Edited by Christos Floros
Ioannis Chatziantoniou

Applications in Energy Finance

The Energy Sector, Economic Activity, Financial Markets and the Environment

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Christos Floros · Ioannis Chatziantoniou
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Preface

The field of Energy Finance is a rapidly growing field of research that has a multitude of motivating empirical applications. There is a wealth of literature on studies investigating the impact of the energy sector on macroeconomic and financial variables, while the implications for stock markets and economic activity in the light of the recent debate on climate change also constitute a promising and topical field for empirical research. It should also be noted that the market for crude oil is very popular in the relevant existing literature; a fact that stands to reason, considering the importance of crude oil as an input of production. What is more, the recent financialization of commodity markets (e.g. crude oil derivatives contracts) has resulted in energy markets and financial markets coming closer together, implying that economic developments that affect either side might further entail contagion dynamics.

The motivation for putting together this Volume is not to offer an exhaustive list of energy markets and of research conducted therein, but rather, to provide a set of illustrative studies that help introduce readers to the empirical approaches currently employed in the broader field of Energy Finance. In this regard, this Volume constitutes a collection of studies relating to Energy Finance that predicate upon contemporary and advanced empirical methods. Our objective is to provide a point of reference for presenting how research is being carried out in the relevant field.

We anticipate that the Volume will be of particular value to researchers with a keen interest in the field of Energy Finance and empirical methods. Students could also benefit from this Volume by adopting the empirical methods presented here in order to develop and answer their own research questions. Furthermore, the topics presented in this Volume are quite popular and relevant for the field of Energy Finance and as such, they could be incorporated as discussion topics or case studies in any program of study that involves the market for energy.

With regard to the underlying structure of the Volume, *Part One* introduces the reader to the field of Energy Finance. *Chapter* 1 is therefore an insightful introduction to the field of Energy Finance by D. Zhang and Q Ji. The authors elaborate on the development of the field and discuss the financialization of energy markets, the linkages between energy and financial markets, micro-firm level issues in the energy sector, as well as, the relationship between the field of Energy Finance and climate change, green financing and investments.

In turn, the Volume breaks down into two closely associated thematic areas. In this regard, *Part Two* of the Volume focuses on empirical applications of Energy Finance on the Macroeconomy and Financial Markets and comprises Chapters 2 to 6. In *Chapter* 2, J. Beckmann and R. Czudaj utilize Cointegration Analysis in order to investigate the relationship between the price of oil and effective USD exchange rates. The authors distinguish between demand and supply-side dynamics and further purport to investigate the extent to which forecasting opportunities of either variable are possible within this setting. *Chapter* 3 by S. Soylu, İ. Sendeniz-Yüncü, and U. Soytas involves an application of the Toda Yamamoto Augmented Vector Autoregression for Granger Non-Causality method. The authors employ this approach in order (i) to investigate the linkages between crude oil prices, real stock returns, exchange rates, and industrial production levels (for emerging countries) and (ii) to make appropriate inferences based on their findings. Next, in *Chapter* 4, authors M. Balcilar, O. Usman, and D. Roubaud employ a non-linear Vector Autoregressive model to study the propagation of shocks through an economy. They particularly focus on crisis episodes and oil supply shocks. *Chapter* 5 by S.M.R. Mahadeo, R. Heinlein, and G.D. Legrenzi, focuses on the relationship between exchange rates and stock market changes under extreme shocks in the market for oil. The authors predicate their analysis upon the combination of a Structural Vector Autoregressive (SVAR) model, a Dynamic Conditional Correlation (DCC) model, as well as, a thorough correlation analysis in the light of the pertinent discrete oil market conditions. Finally, in *Chapter* 6, authors I. Chatziantoniou, C. Floros, and D. Gabauer utilize the Time-Varying-Parameter Vector Autoregressive (TVP-VAR) Extended Joint Connectedness approach in order to investigate volatility contagion. The authors consider the G7 stock markets and the market for crude oil and provide useful insights regarding the connectedness dynamics of the particular network of variables.

In turn, *Part Three* of the Volume, further introduces a green finance/climate policy element to the analysis. This part comprises chapters 7 through 10. In *Chapter* 7, P. Sadorsky employs multivariate Generalized Autoregressive Conditional Heteroskedastic (GARCH) processes, such as the Asymmetric Dynamic Conditional Correlation (ADCC) and the Generalized—Orthogonal (GO) GARCH methods. The overriding objectives of the study are (i) to calculate time-varying conditional clean energy equity betas and (ii) to study the impact that market uncertainty (i.e., captured by implied volatility) has on clean energy equity betas. *Chapter* 8, by P. Tzouvanas, focuses on climate finance and climate change. In particular, the author employs the Panel Data method and examines 1800 companies included in the STOXX Index in order to deduce whether EU firms are being rewarded the most when they decrease their emissions, considering that they pay particular notice on climate change issues. In *Chapter* 9, authors D. Broadstock, I. Chatziantoniou, and D. Gabauer discuss Socially Responsible Investing (SRI) and the market for Green Bonds. The authors consider both the traditional and the Green Bonds market in three different regions of the World (i.e., China, Europe and the US). They initially employ the TVP-VAR method and in turn, they introduce the Minimum Connectedness Portfolio approach as an alternative method for making effective investments. The motivation for the study is to ascertain when and to what extent Green Bonds can be part of an international fixed-income investor's portfolio. Finally, *Chapter* 10, by B. Ghosh, S. Papathanasiou, and V. Gablani, focuses on Greenhouse Gas (GHG) emissions and investigates GHG persistence levels in 186 countries around the World. The authors consider Long Memory Identification through Order of Fractional Differencing (d) and Hurst Exponent (H), utilizing an ARFIMA process. What is more, they are particularly interested in identifying appropriate policy stances that will help reduce GHG emissions, thereby benefiting markets and the economy.

We hope that you enjoy reading the Chapters. We are positive that this Volume will help introduce readers to the relevant empirical applications and will contribute to the development of research in the field of Energy Finance.

Heraklion, Crete, Greece
April 2022

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Part I

Introductory Chapter on Energy Finance

1 Review of the Development of Energy Finance

Dayong Zhang and Qiang Ji

1.1 Introduction

Energy finance has arisen in recent years, and it has become a booming subject of research. A large strand of literature has developed looking into the financial characteristics of energy products, for example, oil (Zhang, 2017). Other researchers have been paying attention to the general financing and investment issues of the energy sector (Haushalter, 2000). New models have been developed to study risk spillovers in the energy sector, and these have been applied to enrich the current models for energy risk management (Zhu et al., 2020). With more attention towards sustainable development and climate change, green finance (or climate finance) has also appeared as the new hotspot (Zhang & Rong et al., 2019).

In fact, studying the links between energy markets and financial markets is not new (e.g., Jones & Kaul, 1996; Park & Ratti, 2008; Sadorsky, 1999). However, these studies follow Hamilton (1983) and generally take oil prices as an external shock to stock markets. As the most important input factor for production, oil price changes will affect firms' cash flows or change expected returns (Jones & Kaul, 1996)—although their empirical results show that the price reaction is higher than what can be explained by the changes of real cash flows or future expected returns. Using a sample of energy firms, Broadstock et al. (2014) proposed the idea that oil shocks may pass through stock markets via a direct and an indirect channel. The variability in oil prices is considered an additional risk factor that enters the

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basic Capital Asset Pricing Model (CAPM); it can also pass to individual stocks by affecting market returns.

Despite the differences in methodology or markets in the studies mentioned above, the fundamental logic of oil shocks is that these firms or markets are price takers. This is consistent with the fact that the global oil markets are largely influenced by the Organization of Petroleum Exporting Countries (OPEC), an intergovernmental organization of 13 oil producers. Although there are some controversies about OPEC's role (Kaufmann et al., 2004; Wirl & Kujundzic, 2004), the general belief is that OPEC has fundamental impacts on the world oil markets, especially in the early years (Gately, 1984). The global crude oil market can be treated as a single market (Adelman, 1984), or prices in different regions tend to move together.

The situation, however, has changed in the new century. The Shale Revolution led by the U.S. is one of the most fundamental shocks. Bataa and Park (2017), for example, showed that the increase of U.S. oil production from shale oil contributes critically to oil price movements. Another important issue contributing to OPEC's weakening power is commodity financialization (e.g., Cheng & Xiong, 2014; Henderson et al., 2015; Tang & Xiong, 2012). While the Shale Revolution changed the general landscape of global oil supplies, the financialization process in the new century has brought fundamental changes to our traditional view of energy markets. It has also directly contributed to the development of energy finance.

In this chapter, we will start from financialization in energy markets, making use of the most recent empirical evidence and theoretical arguments to revisit the relationship between energy and the financial market in Sect. 1.2. In particular, we emphasize the concept that energy products, such as oil, intrinsically have the characteristics of financial products. Its linkage with financial markets is not simply via fundamental shocks but via more complicated mechanisms. Moreover, we also review some recent risk spillover techniques, paying special attention to the implications for energy risk management. Section 1.3 moves to the micro-firm-level issues in the energy sector. Specifically, we will introduce the most recent developments in corporate finance for energy firms. Section 1.4 reviews the literature on green finance and investment, and then the last section summarizes and discusses future directions in this newly developed subject.

1.2 Energy Financialization

1.2.1 Conceptual Issues

As a relatively new concept, there is no clear definition of energy financialization. Nevertheless, we can go back to the idea of commodity financialization, wherein Cheng and Xiong (2014) observed a large inflow of investment into commodity futures markets. They found that the investments go beyond the fundamental role of commodity futures as a risk-hedging instrument. These capital inflows substantially change commodity markets and affect the traditional risk-sharing and information discovery mechanisms. As one of the most important commodities, energy products share similar changes but behave differently, making the need to study energy financialization more urgent.

A few recent collections of articles may present a clue about how energy financialization is defined among researchers. In an editorial introduction on a special issue in *Emerging Markets Finance and Trade*, Ji and Li et al. (2019) stated that "*energy financialization refers to the financial behavior of energy prices and the integration of energy and financial markets considering the increasing innovation of energy-oriented products in the financial markets*". They suggested that energy financialization provides "*new research ideas and directions for the study of price behavior, risk contagion mechanisms and risk management in the energy market*".

In 2020, Ji, Zhang, and Kutan organized another special issue in the *International Review of Financial Analysis* on "Energy financialization, risk and challenges". They further elaborated on the concept of energy financialization in their editorial introduction. Starting from the structural changes due to the 2008 global financial crisis and recent geopolitical risks, they illustrated several clear fundamental changes in global energy markets. For example, extreme price fluctuations, more active energy financial derivatives and the associated high capital flows by hedge funds, and the need to diversify portfolio risks by financial investors. The consequence of these changes is the increasing co-movements among energy markets, commodity markets and financial markets, which lead to more complicated risk spillovers than before and more challenges to energy risk management. In general, they believe that energy financialization brings new risks and challenges to energy markets and inevitably leads to new research issues and the need to develop new methodologies.

1.2.2 Energy–Stock Market Relationship

As mentioned above, the energy–stock market relationship, particularly the relationship between oil shocks and the stock market, has been an interesting topic among researchers for a reasonably long time. While the early researchers took oil shocks as exogenous and tried to understand the channel of oil passing through to stock prices, recent researchers have taken a distinctive approach and found something very different. From the numerous research articles that have appeared in recent years, this section uses Zhang (2017) as an example to demonstrate how to study the energy–stock market relationship in a different way and illustrate the empirical evidence supporting energy financialization.

The first and perhaps the most important contribution of Zhang (2017) is to adopt a network approach to study the oil–stock relationship. A Vector Autoregressive (VAR)-based approach—developed initially by Diebold and Yilmaz (2009) and subsequently refined by Diebold and Yilmaz (2012, 2014)—is the key of this research. In time series models, when we have no prior information about the causality of the variables studied, it is often more appropriate to assume all endogeneity and let the data speak. The VAR model is, therefore, a widely applied empirical method in macroeconomics and financial econometrics. Unfortunately, the standard VAR model is difficult to interpret due to the many estimated parameters. It is also hard to link these estimated coefficients directly to economic meanings.

Diebold and Yilmaz (2009) and their following works have made a very simple twist on interpreting the VAR models, and thus, become an extremely effective tool. We know that the Impulse Response Function (IRF) and the Forecasting Error Variance Decomposition (FEVD) are two commonly used approaches to interpreting VAR estimations. The IRF shows to what extent the system responds to the shock on one (or any) of the variables in the system. In contrast, the FEVD takes an alternative angle by estimating how much the variations of one variable are due to the changes of other variables (including itself). Defining θ_{ij} as the contribution of variable j on variable i, then $\sum_{i=1}^{k} \theta_{ij} = 1$, meaning that the total changes of variable i (normalized as 1) can be decomposed into contributions from the whole system (K variables). Diebold and Yilmaz (2009) repackaged the estimated FEVD (or θ_{ij}) and created a connectedness matrix (see Table 1.1) to illustrate how variables interact with each other.

A few important messages can be extracted from the connectedness matrix: first, the matrix is asymmetric, meaning that $\theta_{ij} \neq \theta_{ji}$. This allows us to calculate the relative importance between any two variables, and then the net contributions can create directional connectedness (defined as the net directional connectedness or **NDC**). The column summation of the matrix (excluding self-contributions or diagonal elements) can be taken as the informational gain from the system (all other variables or **From**). The row summation of the matrix (excluding self-contributions or diagonal elements again) can be taken as the contribution of each variable to the system (all other variables or **To**). The last information from the matrix, and the most important one, is $\frac{1}{K} \sum_{i,j=1}^{K} \theta_{ij}^{H}, i \neq j$. It shows the share of explanatory

Table 1.1 Connectedness matrix (Zhang, 2017)

	y_1	y_2	$\dots$	y_K	From others
y_1	θ_{11}^H	θ_{12}^H	$\dots$	θ_{1K}^H	$\sum_{j=1}^{K} \theta_{1j}^H, j \neq 1$
y_2	θ_{21}^H	θ_{22}^H	$\dots$	θ_{2K}^H	$\sum_{j=1}^{K} \theta_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_K	θ_{K1}^H	θ_{K2}^H	$\dots$	θ_{KK}^H	$\sum_{j=1}^{K} \theta_{Kj}^H, j \neq K$
To others	$\sum_{i=1}^{K} \theta_{i1}^H, i \neq 1$	$\sum_{i=1}^{K} \theta_{i1}^H, i \neq 2$	$\dots$	$\sum_{i=1}^{K} \theta_{i1}^H, i \neq K$	$\frac{1}{K} \sum_{i,j=1}^{K} \theta_{ij}^H, i \neq j$

Note This table is taken from Zhang (2017, Table 1). H is the number of steps ahead in forecasting power other than self-contributions, which can also be interpreted as the level of systemic interaction or systemic risk (Diebold & Yilmaz, 2009).

Following this repackaging, a number of improvements were made by Diebold and Yilmaz (2012, 2014). First, it is well known that the FEVD in a typical VAR model is affected by the ordering of variables, thus making the connectedness matrix unstable. To control for this, Diebold and Yilmaz (2012) adopted the approach suggested by Koop et al. (1996) to use a generalized FEVD or GFEVD. Second, the interactions of any system or the estimation of a VAR model can be affected by structural changes or containing time-varying characteristics. Dividing samples using known structural changing points can solve the first problem, but it is often difficult to identify breaking points, and there is also the possibility of multiple breaks. Diebold and Yilmaz (2009) proposed a simple rolling-window approach to solve this problem, allowing us to evaluate time-varying systemic risks in financial markets. The last improvements in the interpretation of systemic connectedness were by Diebold and Yilmaz (2014), who suggested using a network approach. Using the pairwise NDC as the foundation, we can establish a directional network to give a more intuitive illustration of how the system works.

After these improvements, this approach has been used extensively and has become a powerful tool to study systemic interactions in financial markets. Zhang (2017) is one of the earliest empirical studies using this approach. In this paper, a seven-variable system was established using monthly data from 2000 to 2016. The Brent crude oil price was used together with six major stock market indices, including the Dow Jones Industrial Average, FTSE 100, DAX, Nikkei 225, Singapore Straits Times Index (STI) and the Shanghai Stock Exchange (SSE) composite index.

Unlike previous research taking oil shocks as exogenous, this paper allows all variables to be endogenous in the system, and all of them can interact with each other. Interestingly, the empirical results show that crude oil prices are a net information taker in the system, which contradicts the common finding that oil shocks drive stock market movements. The level of connectedness in this seven-variable system demonstrates clear time-varying patterns. A sharp increase in the total connectedness is found following the 2008 global financial crisis, reaching an overall 49.62%, but the level of connectedness falls back after 2013. We are also interested in whether oil shocks matter and, if so, when they matter. The evidence suggests a positive answer to the first part of this question, and then a large variation was found for oil shocks' contribution to the system. Oil shocks' contribution can range from 10% to 37%, depending on the market conditions.

While several other findings from Zhang (2017) are interesting, this study's key message is that oil shocks are no longer independent from global financial markets. The general situation has changed fundamentally since the 2008 global financial crisis. In recent years, movements in the major global financial markets, especially the rise of the Chinese stock market, have strongly influenced the dynamics of oil prices. This research, together with other subsequent studies (e.g., Degiannakis et al., 2018; Ferrer et al., 2018; Wei et al., 2019; Wen et al., 2019; Xu et al., 2019; Zhang et al., 2018), has established a large amount of empirical evidence supporting the concept of energy financialization.

1.2.3 Price Determination with Financialization

Knowing that energy prices are affected more than their fundamental factors (such as demand and supply), the next step is to rethink the price determination mechanisms of energy products. Obviously, we would expect to see an increasing role of financial factors due to the financialization process in energy markets. Morana (2013), for example, finds that financial shocks have made a sizeable contribution to oil prices. One of the main characteristics of these empirical studies is that the factors influencing energy prices are time-varying.

Following this idea, a strand of works (e.g., Drachal, 2016, 2018) adopts a new approach named the dynamic model averaging (DMA) model to study the determining factors of oil prices. This approach is a useful method to perform empirical analyses when a clear theoretical foundation is lacking. The idea is to let the data tell which factors are important determinants. The DMA approach was further developed by Raftery et al. (2010) and Koop and Korobilis (2011). It has been widely used for forecasting the prices of crude oil and other products. The DMA model's main advantage is that it allows parameters in an estimated model to vary over time, and thus, it can uncover information that a stable model framework cannot (Wang et al., 2019).

In this section, we move from oil to natural gas and illustrate how to rethink price determination with energy financialization. Specifically, we briefly introduce one of our research works on natural gas price determination. This is a study by Wang et al. (2019), who used the DMA approach presented above to study the time-varying determining factors of natural gas prices.

Historically, natural gas was determined by the price of oil, a mechanism called oil-indexation (Zhang et al., 2018). The reason behind this is that oil and gas are substitutable in nature. Brown and Yucel (2008) introduced a "rule of thumb" that the gas and oil price ratio should be one to ten or one to six in the U.S. market. The Shale Revolution in the early 2000s marked a fundamental change that led to a general movement away from oil indexation. Although the oil price remains the most important driving factor of the natural gas price (Zhang et al., 2018), clear evidence of oil–gas price decoupling has been found (Zhang & Ji, 2018). Together with energy financialization, the determinants of natural gas prices can be more complicated.

Taking this question forward, Wang et al. (2019) performed an empirical study using the DMA approach to examine the main driving factors and how their influential power has changed over time. Specifically, financial factors are explicitly introduced to their empirical framework. In this study, monthly data from 2001 to 2018 are used. Some typical fundamental factors—such as gas consumption, production, storage, heating degree days and cooling degree days—are included in the model. An interesting feature of this work is that a number of financial factors are studied.

Following Zhang et al. (2017) and Ji and Liu et al. (2018), the paper includes the Chicago Board Options Exchange Volatility Index (VIX), a couple of speculation factors (long and short) and the weighted U.S. dollar index. These financial factors are then fitted into the regression models together with other factors. Consistent with most of the recent literature (e.g., Ji & Zhang, 2019), the explanatory power of crude oil prices (i.e., the West Texas Intermediate [WTI] oil price) has been declining, especially since the 2008 global financial crisis. Most importantly, the DMA estimation shows that financial factors are becoming more important over time. Among all four financial indicators, the long-speculation proxy is the most important determinant, and it dominates all other financial factors in the model. It is significant for 65.59% of the whole sample period, and the values of inclusion probability are often close to 80% with an increasing trend.

1.2.4 Energy Risk Management

Energy financialization can undoubtedly enrich the traditional energy pricing system by introducing more efficient market mechanisms. It also brings significant challenges to energy risk management. The declining power of OPEC may give a chance for a better-functioned pricing mechanism. Still, it will definitely raise uncertainties and energy security issues in certain oil-importing countries, for example, China, Japan and South Korea (Ji & Zhang et al., 2019). Increased volatility spillovers and risk contagion between energy and financial assets give investors opportunities to diversify their portfolios. However, at the same time, extra financial market activities and speculative trading behaviour can bring serious challenges to standard risk management frameworks.

A set of new models has been developed to model systemic risks since the 2008 global financial crisis (e.g., Acharya et al., 2012, 2017; Adrian & Brunnermeier, 2016). The influence of this crisis on the global economy is fundamental, and its aftermath carries on influencing the global financial system. Financial markets have become remarkably more volatile (Wu et al., 2019), and risks spreading across countries, markets, sectors and individual assets have made systemic risk a much more important issue. Financialization in energy markets means that extreme events are more likely to happen, and risk contagions between financial markets and energy markets will lead to higher systemic risk. Thus, it is much more complicated for individual investors or a nation to form a proper risk management strategy. The need to reconsider the traditional energy risk management framework is more urgent than ever.

The COVID-19 pandemic outbreak in 2020 is a clear example that shook global financial markets and also crude oil markets. On 20 April 2020, crude oil futures for the WTI closed at −$37.63 per barrel, making it an unprecedented event throughout history. Technically, how to form a strategy to hedge against such a "once-in-a-century" pandemic (Gates, 2020) and find safe-haven assets became challenging (Ji et al., 2020).

Indeed, a large volume of research is taking extreme risk spillovers among asset classes (including energy) into consideration. Du and He (2015), for example, apply Granger causality on the Value at Risk (VaR) of the S&P 500 index and WTI crude oil future returns to show extreme risk spillovers between oil and stock markets. Wen et al. (2019) used a VAR for VaR approach and demonstrated that the extreme risk spillovers between oil and stock markets increased after the 2008 global financial crisis. Yang et al. (2020) built VaR into a connectedness network to model extreme risk spillovers between the Chinese crude oil futures and other global crude oil futures markets. They reported a sharp increase in spillovers due to the COVID-19 pandemic.

With new techniques developed, more complicated models are used to study extreme risk spillovers among energy, commodity and financial markets. First, the CoVaR and the Delta CoVaR approach in Adrian and Brunnermeier (2016) are used. Second, copula models or dynamic copula models are adopted to provide a better estimation of extreme risks (Patton, 2012). Third, the estimated extreme risks are further investigated via a network-based approach (Yang et al., 2020). There is also evidence showing asymmetric effects in the spillover (e.g., Ji & Zhang et al., 2018), giving risk management more challenges.

1.2.5 Is Financialization Temporary or Permanent?

Despite abundant evidence found in the literature supporting the financialization of energy markets, our understanding of the underlying mechanism remains limited. The majority of the existing efforts are to build evidence and identify empirical patterns. Without a solid theoretical foundation, it is hardly possible to reconcile the current differences in empirical works. Some have already raised questions about whether energy financialization is the "new normal" or merely a passing trend (Adams & Gluck, 2015). Zhang et al. (2017) studied whether there is de-financialization in energy commodity markets. In Zhang and Broadstock (2020), rising connectedness in the global commodity markets is found to be only relevant to the 2008 global financial crisis period, and certain patterns have disappeared in recent years.

Of course, none of the studies mentioned above provides strong evidence against energy financialization; rather, their findings generally support it. However, these challenges and issues deserve further investigation. Over ten years have passed since the 2008 global financial crisis, but the sample we have is still relatively small and hardly sufficient to give a deterministic confirmation. Nevertheless, we strongly believe that the energy financialization process will be irreversible.

1.3 Corporate Finance in the Energy Sector

Compared to the booming research output in energy financialization, corporate finance issues in the energy sector have received less attention in the energy finance literature. However, it is an essential part, as suggested by Zhang (2018). Given the strategically important position of the energy sector in any nation's economy, financing and investment decisions in the energy sector are critical. These decisions are not only relevant at the macro-level but are also major issues at the micro-level, as firms are the essential units delivering energy products and services.

1.3.1 Why Are Energy Firms Special?

Financing and investment decisions are core elements in corporate finance, and the general issues have already been studied in the mainstream corporate finance literature. Like other industries, the energy industry is often part of the picture and will only be controlled as an industrial dummy in most empirical studies. In theory, energy firms should face the same challenges as other types of firms. They need to invest in projects with positive NPVs, and they also have to choose an optimal capital structure to maximize their value when making financing decisions. At the same time, being a corporation, an energy firm also needs to resolve agency problems by designing an effective governance system. The question of making energy corporate finance a separate issue is whether energy firms are special and in what aspects they should be treated differently. This is the obvious challenge that has limited the development of energy corporate finance (Zhang, 2018).

Back to Jensen (1986), who raises the free cash flow (FCF) problems that lead to the following discussions on the agency problems of corporate decision-making. The example used in his argument is a sample of oil companies. In the 1970s, oil prices went up sharply after several oil crises. Consequently, these oil companies accumulated a large amount of cash. Instead of distributing this cash to their shareholders after investing in good (positive NPV) projects, the managers kept investing in poor-quality projects (negative NPV). Their behaviour brought benefits to themselves at the cost of the shareholders, thus becoming a typical example of agency conflicts. Similar issues have been found recently in China by Zhang et al. (2016a)—average cash flows held by energy firms are substantially higher than other firms in the Chinese stock market. Once again, these firms expand and invest in projects that are not optimal.

Energy is the foundation of the modern industrial economy, and its supply relates directly to general economic development. For countries like China, energy supply relies heavily on the international energy markets (Zhang & Rong et al., 2019), and thus, shocks to energy markets can lead to serious concerns about energy security. To ensure a stable supply of energy, China continues to invest in the international energy market. Tan (2013), for example, showed that a large proportion of international investment from China is in the energy and resource sector. These investments are primarily executed through energy firms. From this perspective, when making decisions, energy firms are different because standard profit maximization may not be the only concern.

In addition to the arguments above, there are potentially other major issues that distinguish energy firms from other sectors. For example, their governance structure can be different; energy firms tend to have large state ownership. Like the banking industry, major energy firms in China are a consequence of a series of reforms. However, they generally have a very significant state presence and operate differently (Zhang et al., 2016a). These differences between energy firms and other firms have clear country-specific features and warrant further investigation.

1.3.2 Investment Decisions by Energy Firms

Bearing in mind that energy firms may behave differently from firms in other industries, we introduce a few studies looking into energy firms' investment decisions. The first issue worth exploring is whether these firms invest according to the standard corporate finance theory. For example, Lang et al. (1991) proposed using Tobin's Q to measure investment opportunities. Q equals the market value of a company divided by its assets' replacement cost. Higher Q is often considered to indicate good investment opportunities for the underlying firm. Lang and Litzenberger (1989) took the unity value of Q as a threshold; in other words, when Q is less than one, the firm's investment opportunity is poor.

Empirically, Fazzari et al. (1988) set up a benchmark regression model:

$$(\mathrm{I}/\mathrm{K})_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 (\mathrm{CF}/\mathrm{K})_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{1.1}$$

where I/K stands for the investment (I) divided by the beginning-of-period capital stock (K), and CF/K stands for the cash flow scaled by the same capital stock. Q is the proxy for investment opportunities, such as Tobin's Q. Both β_1 and β_1 are expected to be positive. Following Lang et al. (1991), an interaction term is created, which then moves to Eq. (1.2):

$$(\mathrm{I}/\mathrm{K})_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 (\mathrm{CF}/\mathrm{K})_{\mathrm{it}} + \beta_3 \left[\left(\frac{\mathrm{CF}}{\mathrm{K}} \right)_{\mathrm{it}} \times \mathrm{D}(\mathrm{Q}_{\mathrm{it}} < 1) \right] + \varepsilon_{\mathrm{it}} \tag{1.2}$$

$\mathrm{D}(\mathrm{Q}_{\mathrm{it}} < 1)$ is a dummy variable that equals one if Tobin's Q is less than unity. Other things being equal, if β_3 is positive, then firms invest even if their investment opportunity is poor. In other words, they tend to have agency problems.

Zhang et al. (2016a) followed these arguments and investigated these models with a sample of energy firms listed on the Chinese stock market. The sample firms cover electricity, coal, oil and gas, the new energy sector and related sectors from 2001 to 2012. One additional contribution of their work is to use a new measure of Q: the fundamental Q. This was proposed by Gilchrist and Himmelberg (1995) to overcome the problems of basic Q in measuring investment opportunity. In general, the empirical analyses show clear evidence supporting the FCF hypothesis for Chinese energy-related firms. These firms tend to overinvest, even when future investment opportunities are poor. Furthermore, Zhang et al. (2016a) controlled for several corporate governance factors, such as degrees of state ownership and managerial shareholder levels. Not surprisingly, these factors can play a role in firms' investment decisions.

Inspired by Zhang et al. (2016a), a series of subsequent works began to further investigate in this direction. For example, Yu et al. (2020) explored the role of political connection on the overinvestment problems of Chinese energy firms. Kong et al. (2020) studied the effects of foreign investment in Chinese energy firms' innovation. Cao et al. (2020) used listed firm data to show that oil price uncertainty can affect renewable energy firms' investment.

1.3.3 Financing Decisions by Energy Firms

An equally important issue for energy corporate finance is firms' financing decisions or how they choose their capital structure. According to the standard corporate finance theory (e.g., the pecking order theory of financing), firms should use internal capital, followed by debt and then equity financing. In a perfect market, firms' value is not affected by their specific capital structure (debt/equity ratio), but the tax benefit of debt and bankruptcy cost bring forward the trade-off theory (see Myers, 2001). The literature in this area is abundant for general corporate finance studies but limited for general energy firms. An exception is renewable energy firms, which will be illustrated later in the next section.

Here, we take a couple of examples to elaborate on what can be done in this area. The first study is by Narayan and Nasiri (2020), who used a sample of 726 energy firms from 56 countries to study whether oil market activities can affect these firms' capital structure. Their first argument is that oil companies are different from non-oil companies, similar to the earlier arguments. Meanwhile, energy firms are more likely to be affected by oil price shocks (see Broadstock et al., 2012; Ma et al., 2019), as price movements in oil markets can directly affect the cost and revenue of these firms. Empirical analyses of this cross-country study demonstrate both statistically and economically significant effects of international oil market changes on energy firms. However, similar effects cannot be found in non-oil companies. Kim and Choi (2019) took a different approach and also showed that hedging can affect oil and gas project companies' capital structure. The capital structure may also affect firms' performance (e.g., Zhang et al., 2016b). Cole et al. (2015) used the data of a sample of U.S. firms covering industrial, healthcare and energy sectors to see whether there is a relationship between capital structure and firm performance. They showed a clear difference in the energy sector relative to others.

The second example is on the financing constraints of energy investment. It is a well-explored area that financing constraints can directly affect corporate investment (Fazzari et al., 1988). Si et al. (2021) used a sample of 230 energy firms from

2003 to 2018 to show that financial deregulation can lower these firms' operational costs by alleviating financing constraints. Once again, this research direction is a much more relevant issue for renewable energy investment, so we will cut it short here and discuss it more in the following sections.

1.3.4 Governance in the Energy Sector

As mentioned above, corporate governance factors can impose a substantial impact on firms' decisions. There are no exceptions for energy firms. Also, due to the special features of the energy industry, it is typically more complicated for the internal governance system to work out properly (Zhang et al., 2016a). Meanwhile, firms' behaviour/performance can also be affected by the institutional environment or external governance. The interaction of internal and external governance can impose a significant impact on firms' behaviour (Liu et al., 2019). For example, a large volume of literature following La Porta et al. (1997) discusses the financial impacts of legal origins. The general idea is that the common law system tends to give higher weight to shareholders' interests, whereas the civil law system emphasizes general stakeholders' benefits. Investment in the energy sector is shown to be affected by legal differences, together with some internal governance issues (e.g., Liu et al., 2019). Of course, there are also other external governance factors to be considered.

The corporate governance system is designed to reduce agency costs and improve the efficiency of firms. The first and perhaps the most widely used governance factor is ownership structure. It is often argued that state ownership tends to bring inefficiency into corporate operations. Thus, empirical findings often demonstrate that private companies outperform their state-owned counterparts (e.g., Ohene-Asare et al., 2017). Conversely, foreign ownership or institutional ownership can improve firms' performance. Kong et al. (2020), for example, studied energy firms' innovation performance and showed that foreign institutional investors can improve energy firms' innovation via three possible channels: investment, governance and human capital. Filippini and Wetzel (2014) used 28 electricity distribution companies in New Zealand to show that separating the ownership of electricity generation and retail operations from the distribution network can improve these firms' cost efficiency. In a cross-country study, Clo et al. (2017) found that public ownership is associated with lower emissions than private ownership in the power industry. The results are obviously different across countries. Wang et al. (2021) reported that equity concentration can improve Chinese energy companies' investment efficiency.

From these studies, we can see that private ownership (or foreign ownership) tends to give more weight to efficiency and thereby improves performance, whereas public ownership may improve energy sectors' environmental performance. Given that energy firms bear more of the burden for carbon reduction or environmental benefits than the general society, they must also be responsible for energy security issues (Zhang & Rong et al., 2019), which is not a major concern for firms in other sectors. Hence, it is important for us to investigate whether there is an optimal ownership structure.

Other issues in the corporate governance literature also have clear, unique features in the energy industry. For example, manager characteristics, political connections and executives' compensation schemes may also differ from other sectors (subject to country-specific institutional environments). Using a sample of Chinese energy firms, Yu et al. (2020) explored the relationship between firms' political connections and investment behaviour, demonstrating a statistically significant relationship. Overinvestment is more likely to happen when local politicians approach promotion lines.

1.4 Green Finance and Investment

The concept of "green finance" has arisen in recent years due to increasing pressure from climate change and the need to pursue a sustainable growth path in the global society. In 2015, the Paris Agreement was signed within the United Nations Framework Convention on Climate Change (UNFCCC). Member countries have agreed to work cooperatively to mitigate the severe problem of greenhouse gas (GHG) emissions.

Five years after adopting the Paris Agreement, the world remains a long way behind the race against climate change. Ambitious commitments and urgent actions are needed for transitioning to net-zero emissions (or carbon neutrality) by 2050. A significant amount of investment is required to solve the problem. For example, maintaining the 2 °C temperature threshold of the Paris Agreement requires $53 trillion in energy-related investments by 2035 (IEA, 2014). The European Commission (2020) estimated that for the EU alone, more than EUR 270 billion of investment per year would be necessary to achieve an 80% reduction of emissions by 2050. Global investments in low-carbon solutions are growing, and the cumulative clean energy investment was around USD 3.7 trillion from 2004 to 2018, although it is still not sufficient to meet the required pace (Climate Finance Leadership Initiative, 2019). A substantial investment gap remains between the current development and the requisite level of emissions.

1.4.1 Green Finance or Climate Finance

In 2010, the Green Climate Fund (GCF) was established by 194 countries, aiming to provide financial support to developing countries to mitigate GHG emissions and adapt to climate change. Since then, the term "green finance" has frequently appeared in the reports of international organizations (e.g., the International Finance Corporation [IFC], 2017) and national governments. Relevant discussions have also attracted enormous attention from academics. Green finance per se, however, remains vaguely defined and is often mixed with climate finance.

Zhang and Rong et al. (2019) reviewed the existing literature in a simple bibliometric analysis. They did not explicitly distinguish the difference between green finance and climate finance but instead used them in the same way. In total, 381 papers were included in their survey, and there has been a clear upward trend of research interest since 2011. Their research may provide some clues about the concept of green finance.

According to the IFC (2017), green finance is defined as the "financing of investments that provide environmental benefits". A related concept named "climate finance" is proposed and defined by the UNFCCC as "*local, national or transnational financing—drawn from public, private and alternative sources of financing—that seeks to support mitigation and adaption actions that will address climate change*". In their simple bibliometric analysis, Zhang and Rong et al. (2019) showed that at the heart of both terms is the financing tools for coping with climate change and other issues for sustainability. Moreover, these two concepts are relevant to energy finance, as major changes are expected to apply to the energy sector, such as developing the renewable energy sector or achieving energy transition to a sustainable regime.

To get a general idea of the current status of the global energy structure, Fig. 1.1 plots the world's total energy production structure from 1980 to 2018.[1] Clearly, total primary energy production keeps increasing to fuel global economic development. Although the renewable energy sector has already experienced a significant increase in recent years, its share remains low, and three main fossil fuel energy sources (i.e., coal, petroleum and natural gas) together account for over 84% of the world's total energy production. To achieve the climate goal, there is obviously much more work to be done to change the energy structure or make a substantial transition towards renewable energy.

1.4.2 Financing the Energy Transition

Speeding up the energy transition process is challenging, and an enormous amount of investment is needed. Note that the information presented in Fig. 1.1 is the status of the whole world; there are clearly regional/country-specific differences. Together with the large variation in the world's economic development, a general improvement is hard to achieve. Taking China, the largest emitter of GHG in the world, as an example, fossil fuel accounts for about 90% of the total energy consumption (Ji & Zhang, 2019). Despite this, the leaders of China made strong commitments and pledged to reach peak GHG emissions in 2030 and achieve carbon neutrality by 2060. To realize such an ambitious plan, a combination of efforts is needed, and one of the major constraints is financing.

Ji and Li et al. (2019) presented a simple empirical study for the case of China. They used historical data to investigate the main contributing factors that

[1] Source: www.eia.gov.

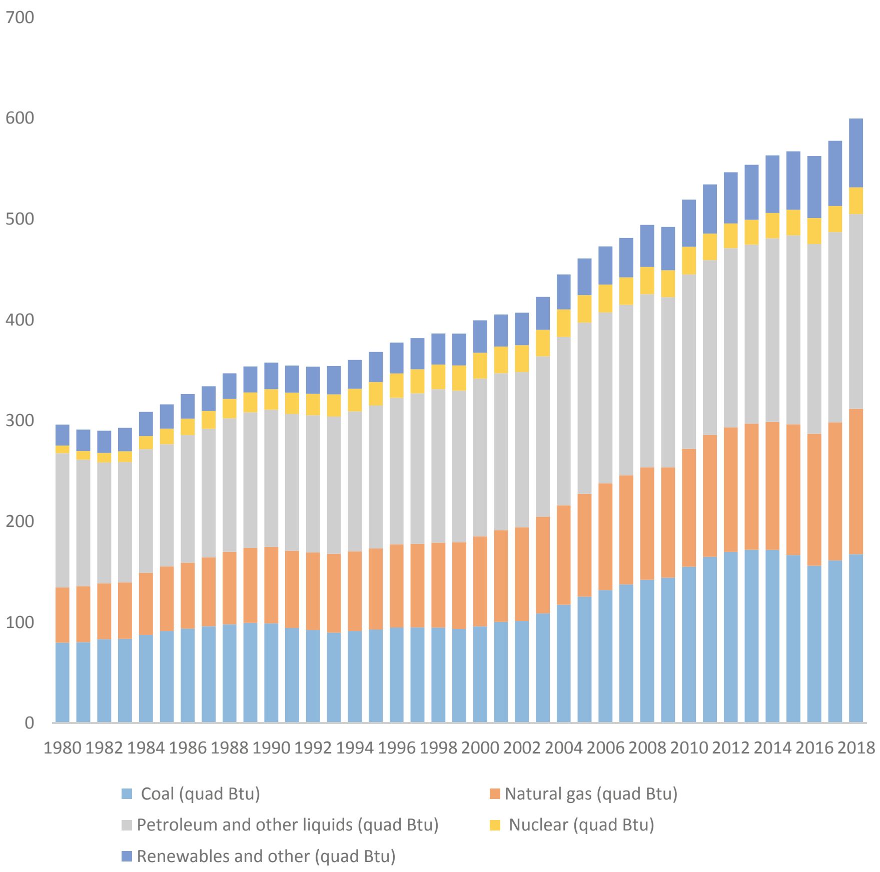

Fig. 1.1 World energy structure (*Source* www.eia.gov)

are pushing China's energy transition. Through the Diebold and Yilmaz (2014) network approach, they found some very interesting results. The main message from this research is that financial development is critical to the development of the renewable energy sector. Among the stock market, the credit market and foreign capitals, the stock market takes the leading position in providing the most explanatory power for the changes in renewable energy growth. An additional analysis using U.S. and EU data shows that they are considerably different. While the U.S. energy transition is mainly due to the stock market, the credit market demonstrates a dominating role in Europe.

Le et al. (2020) further confirmed the role of financial development on renewable energy development using a sample of 55 countries in the 2005–2014 period. They suggested that policymakers should facilitate renewable financing through proper policy designs. Taking Europe as an example, Polzin and Sanders (2020) identified a clear investment gap for the European energy transition and limited participation of institutional investors and risk-carrying capitals. In a sub-regional study, Wang et al. (2020) established a regional-level index for China to show its unbalanced development status and potential for the renewable energy sector. In their study, financial development or support was used as a key dimension of interest. There is clear evidence of unbalanced inter-provincial development in renewable energy development.

These macro-level studies may provide critical information on the big picture; however, a much larger volume of literature using micro-level data has appeared recently. The main objective of these studies is to determine the main issues for the financing of the world's energy transition. Using a bibliometric analysis approach, Elie et al. (2021) surveyed the literature on renewable energy finance and discovered eight clusters based on the type of finance, location and technology. Their results show that policy-relevant studies are the most popular.

It is obvious that renewable energy development or financing depends largely on policy support. Liu et al. (2021) showed that the listed Chinese solar PV firms responded significantly to subsidy policy changes. Understanding capital market responses to policy shocks is essential for policymakers. Financing the renewable energy transition requires private capital participation; a favourable capital market condition can reduce the cost of financing for renewable energy firms. Appropriate policy instruments can also facilitate the financing process by reducing operational risks and providing support for start-ups. Although this study is based on listed firms, it is worth noting that most newly established renewable energy firms rely on equity financing. Thus, the findings on capital market responses to policy shocks matter to more than listed firms.

One has to realize that financing the renewable energy transition also needs financial innovation (Horsch & Richter, 2017). For example, green bonds have emerged in recent years as a major source of financing green development, and they have attracted a great deal of attention in the literature. Since the first green bonds in 2007 by the European Investment Bank, green bond assurance has reached USD 167.3 billion by international organizations, governments, banks and the corporate sector. Initially led by international organizations, corporate green bonds have grown at a much faster pace since 2014, becoming the main player in the global green bond markets. There are numerous issues that have been discussed intensively in the literature. For example, are green bonds different from other traditional bonds (Ferrer et al., 2021)? Can green bond issuance benefit shareholders (Tang & Zhang, 2020)? How do investors respond to the issuance of corporate bonds (Flammer, 2021)? More empirical evidence is needed to provide a solid understanding and make proper policy suggestions. There is also a need for governments to engage further in financial innovation, such as introducing more financial instruments, using derivatives or structuring financial products. Of course, it is also necessary for more sophisticated risk management tools to be developed.

1.4.3 Investment in the Energy Transition

Financing is only one side of the story; how to support investment in energy transition is another major issue. We do expect to see large-scale investment employed in the near future, but challenges remain concerning how to make sure the investment is efficient and how to encourage a sustainable investment strategy. Once again, there is a large volume of literature discussing relevant issues from both the aggregate (Fadly, 2019) and disaggregate (Liu et al., 2019) levels. Relevant issues include how to improve investment efficiency, promote green innovation, invest in energy-efficient projects and so forth.

Like other energy firms, renewable energy firms also tend to be affected by agency costs; in other words, managers may choose investment decisions that are not necessarily optimal (Zhang et al., 2016b). For example, China experienced significant overinvestment in the wind and solar PV industry, resulting in a large volume of wind curtailments and overcapacity. Therefore, proper governance is important. It is also worth noting that renewable energy investment can be affected by external governance or institutional environments (Liu et al., 2019). Using a sample of renewable energy companies around the world, Liu et al. (2019) examined the role of legal systems and national governance on these firms' investment decisions. Firms under the civil law system are more likely to invest relative to those in the common law system. This is consistent with the legal origin literature, which states that the common law system gives more weight to shareholders' interests, whereas the civil law system encourages the broader social responsibilities of firms. The level of national governance can also play a role here.

Technological progress is critical for energy transition and achieving carbon neutrality; therefore, green technology investment is another crucial issue attracting a great deal of attention. Firms are profit maximization entities; thus, they only engage in green innovation if it can create value by sending a positive signal to the investors. Zhang and Zhang et al. (2019) used a sample of Chinese listed firms to examine the famous Porter hypothesis (Porter & Van der Linde, 1995), which suggests that strict environmental regulations can induce efficiency and encourage innovation. Green innovation can then help improve the commercial competitiveness of firms. Based on their empirical analysis, Zhang and Zhang et al. (2019) confirmed the hypothesis that green innovation can improve firms' subsequent performance. In other words, green innovation is associated with higher sales growth and higher net profits. In their study, the evidence also shows that ownership matters: state-owned firms tend to gain more of the economic benefits.

While there is a long way to go to remove fossil fuel energy completely, improving energy efficiency is another major step towards sustainability. In a recent study, Zhang et al. (2020) used firm-level data from the World Bank Enterprise Survey to investigate whether access to credit can affect energy intensity in a sample of Chinese manufacturing firms. Their research is related to the "efficiency paradox" proposed by DeCanio (1998), in which firms may not take profitable investment opportunities in energy efficiency. The underlying reasons for this paradox include market failure, bounder rationality, asymmetric information and inefficient energy management. Zhang et al.'s (2020) empirical results support the paradox that firms with credit access tend to have significantly higher energy use per unit of output, although local government environmental regulations can mitigate this inefficient relationship. This suggests that local government may play an important role in correcting firms' irrational behaviour and pushing for efficient energy use.

1.5 Summary and Looking Forward

This chapter provides a survey of the literature related to energy finance. We hope to provide a general structure that gives readers some general ideas about how this subject has developed over time and what topics energy finance covers. In particular, we focus on three categories of research, namely, energy financialization, energy corporate finance and green finance. We have to acknowledge, once again, that this subject is still emerging, and an accurate conceptual framework remains unavailable. Furthermore, with the ever-increasing pressure of climate change, energy finance as a major element of climate finance will inevitably attract more attention.

Extending from the literature review above, we also list several exciting research directions. First, supported by richer empirical evidence and policy discussions, theoretical investigations are needed to complete the general picture. Up to now, we have accumulated a large volume of empirical literature justifying the need for energy finance research and clarifying its relevance. It is time to consider establishing a more solid theoretical framework that allows us to consolidate this subject area further.

Second, despite the booming literature on green/climate finance, the need to move in this direction is still urgent. This is especially relevant as more countries begin setting up a clear timetable for reaching carbon–neutral. For example, there is enormous demand for research on the pathways to carbon neutrality for China. Being the largest emitter in the world and the biggest emerging economy, balancing the needs of economic development while achieving the tight goal of carbon–neutral in 2060 is almost a mission impossible. Searching for feasible pathways not only requires developing technological advances but also looking for financial solutions.

Third, corporate financial decisions remain an interesting direction of research. Currently, we have very limited information about this due to sampling issues and limited attention. Academic research on corporate social responsibility (CSR) or ESG has already developed rapidly, but linking this to energy-related firms is needed to understand the fundamental decision-making by firms.

Lastly, there is a clear need to make international comparisons. Most current studies focus on a single country or sector, which is not sufficient, given the large variety of institutional environments among countries worldwide. There are also cultural differences yet to be explored.

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Part II

Energy, Economic Activity and Financial Markets

What Do We Know About the Oil Price–Exchange Rate Link?—The Role of Time-Variation and Supply/Demand Dynamics

2

Joscha Beckmann and Robert Czudaj

2.1 Introduction

Oil prices and exchange rates have two things in common: Both have experienced long swings after the breakdown of Bretton Woods and are incredibly hard to predict. There is also an inherent belief that both markets are related with potential causalities going in both directions. If a commodity, such as oil, is denominated in the US dollar, a domestic appreciation against the dollar lowers the price of oil measured in terms of the domestic currency, which increases demand and may result in a general rise in oil prices (Akram, 2009). Changes in the oil price can also affect the exchange rate since oil exporters receive a wealth transfer, which might be invested in international financial markets if the price of oil increases.

Against this background, researchers have analyzed linkages between oil prices and exchange rates over the short-run, the medium-run and also in terms of out-of-sample predictability. Unsurprisingly, the results vary across countries, sample periods and forecasting horizons. This is true for both identifying long-run relationships and evaluating forecasts. When it comes to forecasts, several studies have provided selected evidence for predictability which is encouraging (Lizardo &

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Mollick, 2010). However, no clear pattern has so far emerged except the fact the currencies of oil exporters are affected more frequently. From a general point of view, the main problem a researcher faces when trying to identify an adequate forecasting model is that in-sample explanation power does not necessarily translate into out-of-sample predictability in the presence of parameter shifts (Rossi, 2013). Finding a consensus across studies is also complicated by the fact that neither the distinction between oil supply and oil demand nor the role of common drivers of oil prices and exchange rates is addressed when drawing conclusions about predictability and causalities between both.

Against this background, this paper contributes to the literature on oil prices and exchange rates by analyzing (1) the importance of time-variation in- and out-of-sample, (2) a distinction between oil supply and demand when focusing on long-term dynamics, and (3) a potential link between long-run relationships and out-of-sample predictability. Our empirical evidence is based on a broad set of recursive and rolling estimates for various exchange rates.

The remainder of this paper is organized as follows. The following section provides a brief summarization of theoretical linkages and previous empirical findings. Section 2.3 describes our data set. The empirical framework for analyzing the long-run relationship between oil prices and exchanges rates is presented in Sect. 2.4 together with the discussion of its results. The results of our forecasting analysis are presented and analyzed in Sect. 2.5. Section 2.6 concludes.

2.2 Literature Review

The literature on the link between oil prices and exchange rates covers a notable range of methods, sample periods and countries. The reader is referred to Beckmann et al. (2017) for a detailed literature review and a summarization of theoretical linkages. Taking the aim and scope of our paper into account, this section focuses on the main empirical findings and the existing gaps in the literature we are interested in.

Nevertheless, a brief summarization of the two main transmission channels in nominal terms is useful at this stage. The basic idea of the portfolio and wealth channel which postulates a causality from oil prices to exchange rates is that oil-exporting countries experience a wealth transfer if the oil price rises (Bénassy-Quéré et al., 2007). In such a scenario, wealth is transferred to oil-exporting countries (in US dollar terms) and is reflected in an improvement in exports and the current account balance in domestic currency terms. The opposite effect is observed for oil-importing countries (Beckmann & Czudaj, 2013). The dollar potentially appreciates in the short-run because of the wealth effect—if oil-exporting countries reinvest their revenues in dollar assets. The short- and medium-run effects on the dollar relative to currencies of oil exporters will depend on various factors such as oil exporters' relative preferences for dollar assets (Bénassy-Quéré et al., 2007; Buetzer et al., 2016; Coudert et al., 2008). A reversed causality from exchange rates to oil prices can be derived based on the fact that an

Table 2.1 Data description

Series	Source
West Texas Intermediate	Federal Reserve Bank of St. Louis
Effective Dollar Exchange Rate	Federal Reserve
Oil demand Index / Global Industrial Production	Baumeister and Hamilton (2015)
Oil supply index	US Energy Administration
Federal Funds Rate	Federal Reserve

appreciation of the US dollar increases the price of oil measured in terms of the domestic currency. This lowers demand for oil outside the US, resulting in a drop in the oil price, all else equal (Akram, 2009; Bloomberg & Harris, 1995).

There are different strands of the literature dealing with the link between oil prices and exchange rates. One frequent observation is that oil price and exchange rate dynamics are found to be related over the long-run with the intensity varying across sample periods, countries and methodologies and causalities running in both directions (Beckmann et al., 2017; Chen & Chen, 2007). However, a distinction between oil demand and supply factors has hardly been addressed by the literature. The results of Basher et al. (2016) based on structural VARs show that oil demand shocks have stronger effects on oil exporters exchange rates compared to oil supply shocks while a recent study by De Schryder and Peersman (2015) finds that a decline in oil demand of 65 oil-importers as a result of an appreciation of the US dollar. The out-of-sample evidence in both directions is less conclusive. Alquist et al. (2011) do not find systematic forecasting gains for oil price predictions based on exchange rates and the evidence on exchange rate predictions also do not provide systematic evidence for exchange rate predictability (Rossi, 2013). A natural question therefore is whether significant forecasting results are due to specific sample choices.

There are several explanations for the time-varying evidence between oil prices and exchange rates. Commodity market dynamics and monetary policy and other dynamics are related to both stock prices and exchange rates and therefore affect any empirical investigation on the linkage between exchange rates and oil prices. Nonlinearities constitute another important explanation for the observed time-variation (Beckmann & Czudaj, 2013). Such patterns might be triggered by common factors or specific oil price dynamics, such as a hike and a fall in oil prices. There is also plenty of evidence that the intensity of the link between oil prices and exchange rates has increased over time (Table 2.1).

2.3 Data

Our sample runs from January 1974 until December 2016. Trade-weighted nominal and real effective exchange rates are provided by the Federal Reserve System. The broad index includes 26 currencies while the major index only includes the euro, the Canadian dollar, the Japanese yen, the British pound, the Swiss franc, the Australian dollar and the Swedish krona. The broad index also includes Brazil, Russia, Mexico, Saudi Arabia, Venezuela, Argentina and Colombia as oil-exporting countries. Table 2.2 illustrates that most of them enter with small weights. We use the series of the nominal Brent Crude Oil price expressed in US dollar per barrel provided by the Federal Reserve Bank of Saint Louis. Data on World Crude Oil Production is obtained from the US Energy Administration. As a proxy for global Energy demand, we rely on the extended global industrial production index provided by Baumeister and Kilian (2015). The Effective Federal Funds Rate, Industrial Production of the US and the exchange rate of the Australian Dollar relative to the US Dollar are all obtained via Datastream.[1]

2.4 Empirical Framework and Findings

2.4.1 Framework for Analyzing Long-Run Relationships

A rich amount of studies has dealt with long-run relationships between the price of oil and various exchange rate. Compared to the Engle and Granger (1987) approach, the cointegrated VAR framework proposed by Johansen (1988) and presented in Juselius (2006) has the main advantage that the analysis is carried out without pre-assuming a specific causal structure for long-run relationships. The basic model draws upon the following vector autoregression representation (VAR):

$$\Delta Z_t = \Pi Z_{t-1} + \Gamma(\mathrm{L})\Delta Z_{t-1} + \Phi D_t + \epsilon_t, \quad t = 1, \ldots, T. \tag{2.1}$$

The vector $\mathrm{Z} = (o_t, s_t)$ at the minimum contains the nominal effective exchange rate and the nominal price of oil. We will extend this set in various directions by including measures of oil supply and oil demand as well as industrial production and interest rates as potential common drivers of both the price of oil and exchange rates. The different models will be classified further below. The long-run level matrix Π can be fragmented into two $r \times p$ matrices α and β' ($\Pi{=}\alpha\beta'$), where p denotes the number of lags and r the number of long-run relationships. β' gives the coefficients of the variables for the r long-run relation, while α contains the adjustment coefficients describing the reaction of each variable to disequilibria from the r long-run relations. The $(p \times 1)$ vector ΦD_t, gives the deterministic components while $\Gamma(\mathrm{L})\Delta Y_{t-1}$ describes the short-run dynamics which we do not explicitly address in the following while ϵ_{t} denotes an i.i.d. error term (Juselius, 2006). In the case of a rank equal to one, identification is achieved via normalization. If the rank is larger than one, it is necessary to impose (at least) identifying restrictions on β in order to establish economic long-run relationships. The corresponding hypotheses tests are based on a likelihood ratio procedure described in Johansen and Juselius (1992).

[1] Table 2.1 provides all data sources.

Table 2.2 Country weights for the broad effective dollar exchange rate

Country	2017	2015	2013	2011	2009	2007	2005	2003	2001	1999	1997	1995	1993	1991	1989	1987	1985	1983	1981	1979	1977	1975	1973
Euro area*	17.06	17.06	16.64	16.77	17.61	17.67	17.57	18.65	18.66	18.21	17.49	17.30	17.69	19.26	19.17	20.42	20.07	19.45	19.55	21.09	20.90	20.97	21.10
Canada*	11.98	11.98	12.65	12.89	13.25	15.19	16.47	16.33	16.81	17.42	16.93	16.94	16.92	16.43	17.19	17.23	19.41	19.03	19.13	19.60	20.64	20.84	20.66
Japan*	6.28	6.28	6.84	7.24	7.49	8.75	9.53	10.46	11.65	13.03	14.27	16.54	18.02	18.75	19.63	20.07	19.68	18.74	18.01	16.57	16.83	16.43	17.43
Mexico	12.60	12.60	11.85	11.22	10.37	9.70	9.60	9.97	10.51	9.55	8.50	6.95	6.45	5.77	4.97	4.30	4.34	4.08	5.04	3.92	3.50	3.77	3.53
China	21.89	21.89	21.14	20.25	19.90	17.49	15.26	12.24	8.83	7.34	6.58	5.67	5.01	3.67	2.68	1.95	1.72	1.35	1.43	1.00	0.67	0.76	1.03
United Kingdom	3.68	3.68	3.40	3.57	4.16	4.24	4.46	5.06	5.62	5.85	5.75	5.34	5.54	6.33	6.58	6.96	6.81	6.68	6.36	7.17	7.08	7.44	7.82
Taiwan	2.32	2.32	2.36	2.54	2.41	2.69	2.80	3.06	3.36	3.69	3.77	3.98	4.37	4.64	5.01	5.41	4.25	4.32	3.47	3.37	2.96	2.87	2.97
Korea	3.99	3.99	3.83	3.89	3.69	3.56	3.72	3.92	3.78	3.87	3.68	4.21	3.67	4.18	4.67	4.39	3.43	3.49	2.70	2.60	2.60	2.33	2.39
Singapore	1.69	1.69	1.76	1.98	2.09	2.02	1.92	2.10	2.17	2.41	2.87	3.00	2.69	2.43	2.25	1.83	1.64	1.87	1.45	1.43	1.32	1.22	1.21
Hong Kong	1.38	1.38	1.29	1.27	1.33	1.38	1.62	1.82	2.05	2.12	2.60	2.82	2.93	2.82	2.79	2.78	2.57	2.78	2.51	2.46	2.41	2.25	2.41
Malaysia	1.59	1.59	1.47	1.55	1.74	1.86	2.09	2.18	2.11	2.15	2.25	2.41	2.00	1.47	1.22	1.04	1.10	1.28	1.02	1.14	1.04	0.96	1.02
Brazil	1.81	1.81	2.12	2.22	1.90	1.95	1.99	1.79	1.83	1.61	1.82	1.70	1.69	1.77	2.03	2.10	2.36	2.23	2.45	2.40	2.52	2.79	2.76
Switzerland*	1.98	1.98	1.96	1.66	1.80	1.42	1.39	1.45	1.45	1.47	1.43	1.57	1.64	1.90	1.83	1.96	1.76	1.94	1.89	2.43	2.32	2.25	2.47
Thailand	1.45	1.45	1.38	1.39	1.42	1.40	1.40	1.42	1.46	1.45	1.59	1.67	1.54	1.38	1.03	0.73	0.54	0.58	0.58	0.60	0.56	0.53	0.54
Philippines	0.58	0.58	0.54	0.55	0.57	0.65	0.73	1.00	1.11	1.22	1.18	0.93	0.84	0.69	0.68	0.62	0.68	0.95	0.96	1.01	0.95	0.98	0.99
Australia*	1.16	1.16	1.24	1.43	1.34	1.21	1.21	1.23	1.20	1.21	1.31	1.33	1.45	1.69	1.78	1.62	1.78	1.82	1.69	2.13	2.17	2.20	2.54
Indonesia	0.97	0.97	1.04	1.14	1.03	0.91	0.89	0.91	1.02	1.00	1.24	1.16	1.19	0.96	0.83	0.78	0.93	1.17	1.05	1.08	1.04	1.03	0.95
India	1.98	1.98	1.95	1.92	1.70	1.49	1.25	1.08	0.89	0.91	0.88	0.82	0.84	0.70	0.80	0.67	0.70	0.80	0.69	0.76	0.78	0.92	0.82

(continued)

Table 2.2 (continued)

Country	2017	2015	2013	2011	2009	2007	2005	2003	2001	1999	1997	1995	1993	1991	1989	1987	1985	1983	1981	1979	1977	1975	1973
Israel	1.02	1.02	1.02	1.10	1.14	1.11	1.03	0.98	1.03	0.96	0.84	0.81	0.79	0.76	0.75	0.75	0.76	0.73	0.69	0.72	0.70	0.78	0.83
Saudi Arabia	0.79	0.79	1.01	0.96	0.81	0.87	0.84	0.65	0.71	0.64	0.80	0.70	0.88	1.03	0.69	0.84	1.41	2.48	4.33	3.25	3.58	3.07	1.24
Russia	1.06	1.06	1.35	1.17	1.02	1.22	1.05	0.82	0.74	0.70	0.78	0.83	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sweden*	0.66	0.66	0.67	0.81	0.87	1.00	1.11	1.23	1.15	1.25	1.23	1.28	1.17	1.49	1.66	1.76	1.79	1.64	1.44	1.64	1.66	1.94	1.96
Argentina	0.50	0.50	0.59	0.64	0.55	0.49	0.47	0.43	0.53	0.55	0.61	0.55	0.54	0.50	0.42	0.41	0.53	0.52	0.80	0.87	0.76	0.72	0.85
Venezuela	0.26	0.26	0.38	0.39	0.41	0.43	0.46	0.33	0.47	0.49	0.58	0.49	0.51	0.55	0.50	0.60	0.91	1.03	1.65	1.51	1.82	1.79	1.36
Chile	0.75	0.75	0.86	0.87	0.79	0.83	0.71	0.50	0.52	0.50	0.53	0.51	0.45	0.43	0.44	0.36	0.38	0.48	0.54	0.51	0.46	0.49	0.45
Colombia	0.58	0.58	0.65	0.62	0.62	0.50	0.46	0.40	0.38	0.40	0.49	0.51	0.47	0.41	0.41	0.42	0.48	0.53	0.57	0.77	0.74	0.70	0.69
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source Federal Reserve.

We consider various specifications to disentangle the underlying dynamics between oil prices and exchange rates. As a starting point, we consider both effective exchange rate measures against the nominal oil prices, and measures of oil demand o_t^d and oil supply o_t^s. This results in an estimation of six subsystems:

$Z_t = \left[S_t^m, o_t\right]$, $Z_t = \left[S_t^m, o_t^s\right]$, $Z_t = \left[S_t^m, o_t^d\right]$ for the major effective exchange rate s_t^m and

$Z_t = \left[S_t^b, o_t\right]$, $Z_t = \left[S_t^b, o_t^s\right]$, $Z_t = \left[S_t^b, o_t^d\right]$ for the broad effective exchange rate s_t^m.

We then augment this system in two different directions: One setting includes the interest rate and industrial production of the US if cointegration is detected in the first place. For the broad effective exchange rate model, this results, for example, in $Z_t = \left[s_t^b, o_t, y_t, i_t\right]$. The second extension includes interlinkages between the price of oil, demand and supply into one model, also including interest rates which result in $Z_t = \left[s_t^b, o_t, o_t^d, o_t^s, i_t\right]$. Cointegration tests should be applied to different subsystems to verify that the findings are consistent (Kilian & Lütkepohl, 2017). Restrictions which have been applied to subsystems should continue to hold when additional variables are included (Johansen, 1988; La Cour & MacDonald, 2000).

2.4.2 Preliminary Diagnosis and Tests for Cointegration

A natural starting point is to test for cointegration between the broad and major effective exchange rates on the one hand and either the price of oil, oil demand or oil supply on the other. Table 2.3 summarizes the rank test results for all bivariate

Table 2.3 Rank test results

R	Trace	Trace$^{\alpha}$	p-value	p-value$^{\alpha}$	r	Trace	Trace$^{\alpha}$	p-value	p-value$^{\alpha}$
(a) Broad Effective / Oil Price / Trend					*Broad Effective / Oil Price / Constant*				
0	13.212	13.068	0.724	0.735	0	23.25	22.987	0.017	0.019
1	4.758	4.461	0.637	0.678	1	2.878	1.915	0.611	0.790
(b) Major Effective / Oil Price / Trend					*Major Effective / Oil Price / Constant*				
0	11.647	11.526	0.833	0.840	0	11.07	9.995	0.636	0.646
1	4.743	4.218	0.639	0.711	1	2.159	1.948	0.745	0.784
(c) Broad Effective / Oil Demand / Constant					*Broad Effective / Oil Supply / Constant*				
0	59.921	58.967	0.000	0.000	0	22.24	22.015	0.025	0.027
1	5.809	1.248	0.213	0.902	1	4.41	2.395	0.366	0.701
(d) Major Effective / Oil Demand /Constant					*Major Effective / Oil Supply /Constant*				
0	25.635	25.193	0.007	0.008	0	5.927	5.874	0.946	0.948
1	4.754	0.003	0.322	1.000	1	1.684	1.563	0.831	0.852

Note The Table reports Johansen (1988, 1991) cointegration tests. Trace$^{\alpha}$ and p-value$^{\alpha}$ refer to Bartlett-corrected values. r denotes the cointegration rank settings. A rejection of $r = 0$ implies that there is a cointegrating relationship. A rank of $r = 2$ is naturally rejected since this would imply that both variables are stationary which is rejected by unit root tests.

An important issue corresponds to the choice of the deterministic component D_t in Eq. (2.1). According to Johansen (1988), a major question is whether the cointegrating space contains a deterministic trend. Such a trend is relevant if the underlying variables include a deterministic trend which does not chancel out in the cointegrating relationship. Table 2.3 shows that the test result depends on this choice since the rank test does not reject the null of no-cointegration at the ten percent level for either the major or the broad effective exchange rate and the price of oil. However, additional exclusion tests indicate that a trend should be excluded. This is intuitive considering that the price of oil and the exchange rate measures do not contain a clear deterministic trend.

We therefore choose the setting including a constant as the main setting. The findings in this case suggest that the broad effective exchange rate is cointegrated with the price of oil, oil demand and oil supply while the broad index only displays a cointegrating relationship with the oil demand. These findings reflect the conventional wisdom that the exchange rates of oil and commodity exporters display a stronger relationship with the price of oil. It is also important to take into account that our oil demand measure is simply based on global industrial production which is related to the dollar exchange rate via different potential transmission channels, such as current accounts that are not related to the price of oil.

2.4.3 Long-Run Relationships

We continue our investigation by providing estimates for the broad effective exchange rate and the price of oil, oil demand and oil supply. Table 2.4 provides autocorrelation, ARCH and normality tests for the setting including the broad effective exchange rate and the price of oil. The diagnostics show that the null of no autocorrelation is not rejected at the five percent level and ARCH effects are also partly rejected. Both variables do not display excessive skewness or kurtosis. The diagnostics for the following models are available upon request and show similar results in the sense that the model is well behaved.

Table 2.5 provides the estimation results of long-run and adjustment coefficients for the first model. The hypothesis that the broad effective exchange rate and the price of oil are inversely related is clearly not rejected with a p-value of 0.464. The adjustment coefficient suggests that the exchange rate adjusts stronger compared to the price of oil. However, linear adjustment coefficients often underestimate the speed of adjustment due to various nonlinear dynamics (Beckmann & Czudaj, 2013). We therefore do not elaborate on these findings in the following. Our estimates in Table 2.5 show that the broad effective exchange rate is both clearly inversely related to our proxy of oil demand. This is not surprising considering that although a dollar depreciation tends to improve the current accounts relative to the US and lowers the price of oil while several other causalities also exit. Our estimates show that exchange rate effects on the supply side tend to be

Table 2.4 Estimation results and diagnostics, bivariate setting

(a) Test for autocorrelation			Test for ARCH		
LM(1):	$\chi^2(4)$	8.359 [0.079]	LM(1):	$\chi^2(9)$	22.718 [0.007]
LM(2):	$\chi^2(4)$	9.484 [0.050]	LM(2):	$\chi^2(18)$	34.265 [0.012]
LM(3):	$\chi^2(4)$	2.384 [0.666]	LM(3):	$\chi^2(27)$	43.804 [0.022]
LM(4):	$\chi^2(4)$	9.322 [0.054]	LM(4):	$\chi^2(36)$	93.159 [0.000]

(b)	**Skewness**	**Kurtosis**	**Maximum**	**Minimum**
S_Broad	0.007	−0.11	3.724	−0.025
OIL	0.031	0.122	5.416	0.151

(c):BETA (transposed) TEST CHISQR(1) = 1.856 [0.173]

	S_BROAD	**OIL**	**CONSTANT**
Beta(1)	1.000	1.000	−4.147
	(.NA)	(.NA)	(−20.941)

(d): ALPHA	**Alpha(1)**
S_BROAD	−0.000
	(−3.939)
OIL	−0.000
	(−6.246)

Panel (a) reports LR tests on autocorrelation, which is distributed as χ^2, with degrees of freedom in parentheses [p-value]. The Table also shows hows the estimates of the cointegration vector with t-statistics (Panel c) in parenthesis and the adjustment coefficients towards the long-run equilibrium for both regimes, with t-statistics in parentheses (Panel d). Test reports the test for over-identifying restrictions, which is an LR-test [p-value]

Table 2.5 Estimation results, oil demand

Panel (a): BETA (transposed) CHISQR(1) = 4.828 [0.028]

	S_BROAD	**OIL**	**CONSTANT**
Beta(1)	1.0000	1.0000	−14.943 ***
	(.NA)	(.NA)	(−9.585)

Panel (b): ALPHA

	Alpha(1)	**Alpha(2)**
S_BROAD	0.003	−0.003
	(0.704)	(−1.639)
OIL	0.059*	0.004
	(1.828)	(0.354)

The Table shows the estimates of the cointegration vector with t-statistics (Panel a) in parenthesis and the adjustment coefficients towards the long-run equilibrium for both regimes, with t-statistics in parentheses (Panel b). Test reports the test for over-identifying restrictions, which is an LR-test [p-value].

Table 2.6 Estimation results, extended model

Panel (a): BETA (transposed) TEST CHISQR(1) = 1.856 [0.173]					
	S_BROAD	**OIL**	**IN**	**INUS**	**CONSTANT**
Beta(1)	−0.715***	−0.084**	0.000	1.000	−0.374***
	(−13.446)	(−2.493)	(.NA)	(.NA)	(−4.005)
Beta(2)	0.000	0.000	0.023***	1.000	−2.142***
	(.NA)	(.NA)	(4.138)	(.NA)	(−54.760)

Panel (b): ALPHA		
	Alpha(1)	**Alpha(2)**
S_BROAD	0.003	−0.003
	(0.704)	(−1.639)
OIL	0.059*	0.004
	(1.828)	(0.354)
IN	1.570***	0.326***
	(4.549)	(3.032)
DLINUS	−0.005**	−0.005***
	(−2.120)	(−6.553)

The Table shows the estimates of the cointegration vector with t-statistics (Panel a) in parenthesis and the adjustment coefficients towards the long-run equilibrium for both regimes, with t-statistics in parentheses (Panel b). Test reports the test for over-identifying restrictions, which is an LR-test [p-value]

much weaker with a potentially positive relationship being not rejected with the findings available upon request.

In the following, we extend the oil price model by including industrial production of the US and the Federal Funds rate as potential common drivers. The findings are provided in Table 2.6. We obtain two cointegrating relationships with the first relationship showing that interest rates and industrial production of the US are inversely related as suggested by a standard aggregated demand function while the second one confirming the inverse relationship between exchange rates and oil prices which are both positively related to US industrial production. This implies that an increase in US industrial production coincides with both dollar appreciations and increasing oil prices.

As a final step, we analyze a full model setting which includes the price of oil, oil demand and oil supply with the findings given in Table 2.7. The findings again confirm the robustness of the inverse link between the dollar exchange rate and the price of oil. The three long-run relationships we identify provide different perspectives on the oil market. The first established equation shows a positive relationship between oil supply and oil demand.[2] The second relationship accounts for the global effects of US interest rates with lower interest rates enhancing global industrial production. The inversed oil price–exchange rate relationship is confirmed in the third long-run relationship where the price of oil is positively

[2] The insignificance of the price of oil in the first equation is due to the significance of the link between oil demand and the price of oil in the third equation.

Table 2.7 Estimation results, full

Panel (a): BETA (transposed) TEST: CHISQR(1) = 1.388 [0.239]						
	S_BROAD	**OIL**	**IN**	**OILD**	**OILS**	**CONSTANT**
Beta(1)	0.000	−0.047	0.000	1.000	−2.974***	12.636***
	(.NA)	(−1.041)	(.NA)	(.NA)	(−14.490)	(13.326)
Beta(2)	0.000	0.000	0.184***	1.000	0.000	−1.273***
	(.NA)	(.NA)	(5.836)	(.NA)	(.NA)	−3.937)
Beta(3)	−0.503***	−0.198***	0.000	1.000	0.000	−0.786***
	(−12.978)	(-6.774)	(.NA)	(.NA)	(.NA)	(−10.061)

Panel (b): ALPHA			
	Alpha(1)	**Alpha(2)**	**Alpha(3)**
S_BROAD	0.002	0.001	0.001
	(0.433)	(1.448)	(0.168)
OIL	0.045	0.007**	0.108**
	(1.353)	(2.539)	(2.544)
IN	−1.401***	−0.015	−1.171**
	(−3.731)	(−0.464)	(−2.453)
OILD	−0.003	−0.001***	−0.015***
	(−1.127)	(−3.647)	(−4.778)
OILS	0.028***	0.000	0.018**
	(4.063)	(−0.846)	(2.058)

The table shows the estimates of the cointegration vector with t-statistics (Panel a) in parenthesis and the adjustment coefficients towards the long-run equilibrium for both regimes, with t-statistics in parentheses (Panel b). Test reports the test for over-identifying restrictions, which is an LR-test [p-value]

affected by oil demand and negatively related to the effective dollar exchange rate. This relationship is also characterized by strong oil price adjustment.

2.4.4 Recursive Estimations

When performing a cointegration analysis, a major problem is that a minor change in the sample period under consideration can result in a breakdown of a cointegrating relationship. Therefore, we rely on two recursive tests for the link between the broad effective dollar exchange rate and the nominal oil price based on the methodology proposed by Johansen (1988): One corresponds to the choice of the long-run relationships while the second one relates to the identification of the model via the likelihood ratio test. We run both tests recursively from both the beginning ("recursive") and the end ("backward recursive") of our sample period. Based on these tests, we re-assess the long-term relationship between the nominal price of oil and proxies of oil demand and supply. Figures 2.1 to 2.11 display the corresponding findings.

Figure 2.1 provides the trace test for a cointegrating relationship between the broad effective exchange rate and the nominal oil price. The vertical line reports

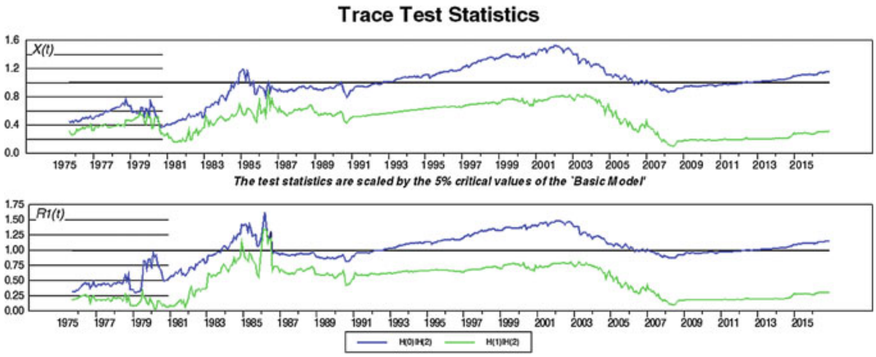

Fig. 2.1 Trace test recursive—broad effective and oil price (*Note* The Graph displays the recursive trace test to determine the cointegration rank. The upper graph refers to the full model and the lower graph to the reduced model without short-run dynamics)

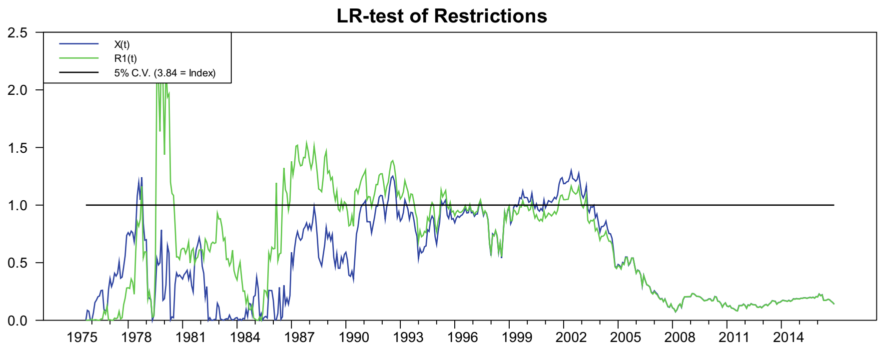

Fig. 2.2 Likelihood ratio test recursive—Broad effective and oil price (*Note* The Graph displays the recursive trace test to determine the cointegration rank. The blue graph refers to the full model and the green graph to the reduced model without short-run dynamics)

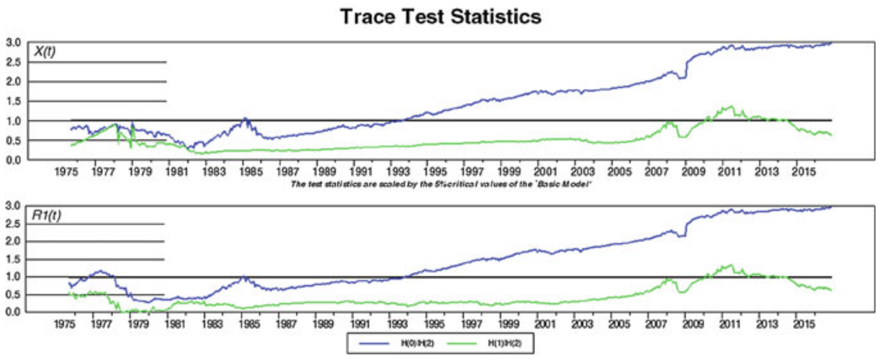

Fig. 2.3 Trace test recursive—Broad effective and oil demand (*Notes* See Table 2.1)

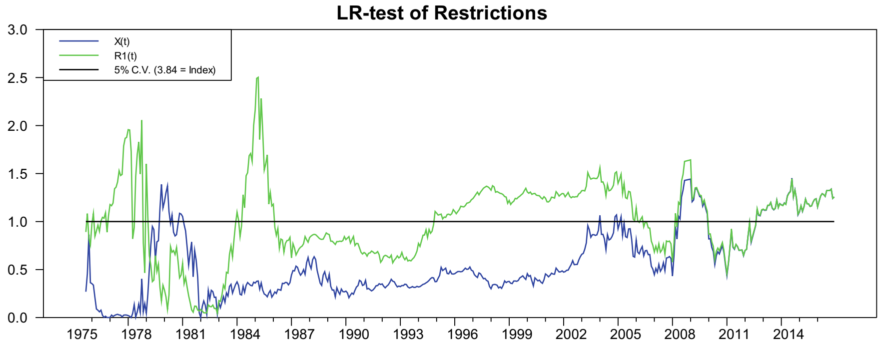

Fig. 2.4 Likelihood ratio test recursive—Broad effective and oil demand (*Notes* See Table 2.2)

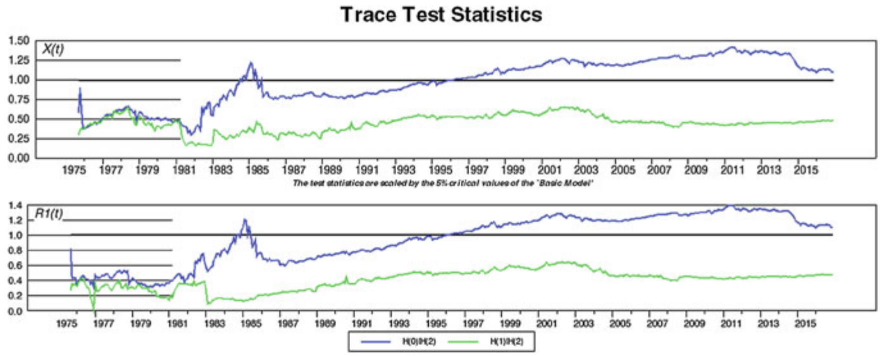

Fig. 2.5 Trace test recursive—Broad effective and oil supply (*Notes* See Table 2.1)

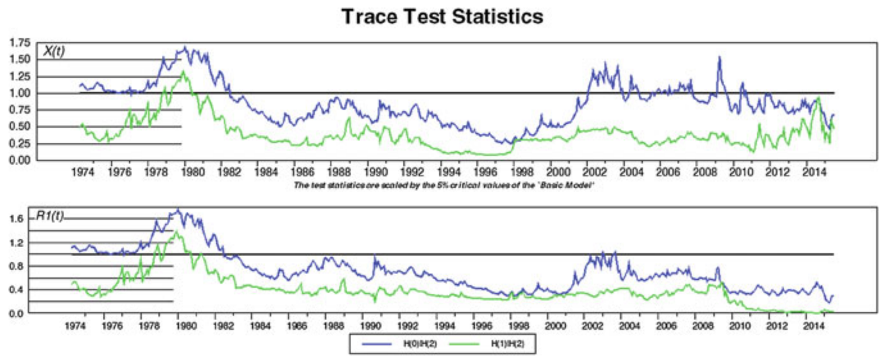

Fig. 2.6 Trace test recursive—Broad effective and price of oil (*Notes* See Table 2.1)

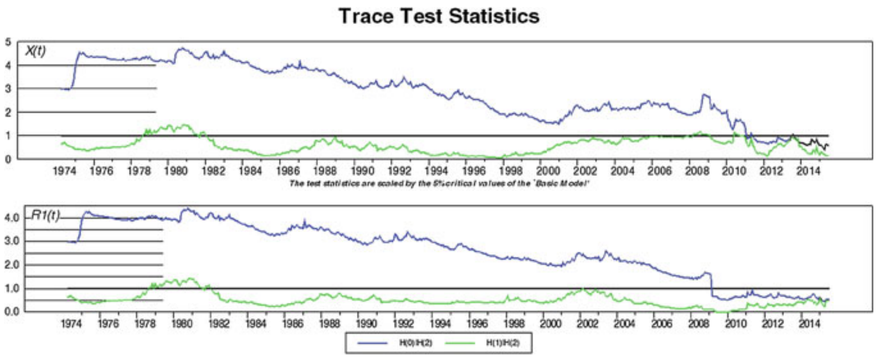

Fig. 2.7 Trace test recursive—Broad effective and oil demand (*Notes* See Table 2.1)

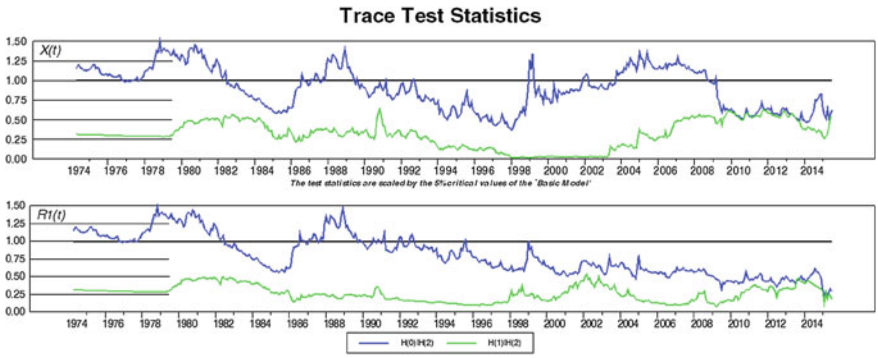

Fig. 2.8 Trace test recursive—Broad effective and oil supply (*Notes* See Table 2.1)

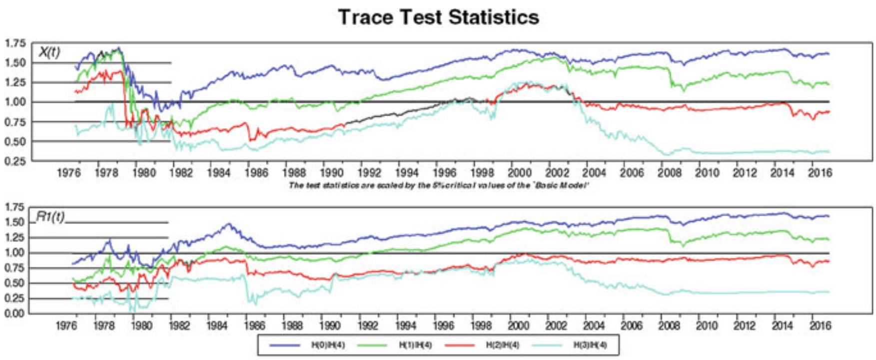

Fig. 2.9 Trace test recursive—Broad effective and oil price extended (*Notes* See Table 2.1)

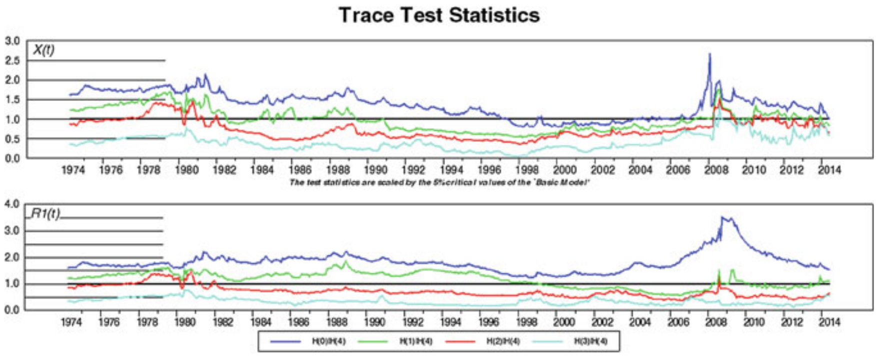

Fig. 2.10 Trace test recursive—Broad effective and oil price extended (*Notes* See Table 2.1)

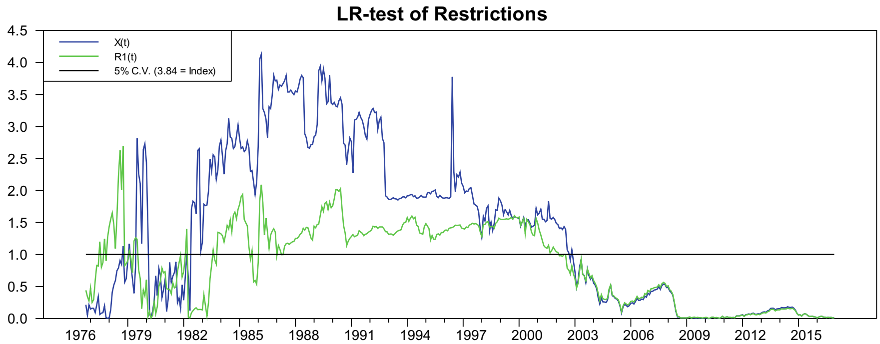

Fig. 2.11 Likelihood ratio test recursive—Broad effective and oil price extended (*Notes* See Table 2.2)

the five percent significance benchmark. A long-run relationship between oil prices and exchange rates is detected if the trace test statistic exceeds this line. Figure 2.2 provides the test statistic of a likelihood ratio (LR) test for the hypothesis that an effective dollar depreciation coincides with a proportional drop in the nominal oil price. A cointegrating relationship is clearly detected around the Millennium while a researcher who conducts an empirical analysis for a sample period ending in 2009 might conclude that none exists. The results again change around the end of the sample period. The LR statistics for a test of the hypothesis that oil price increases and effective dollar depreciations are inversely related also fluctuate over time but is clearly not rejected over the last years. Figures 2.3 and 2.4 show that the link between the broad effective exchange rate and oil demand is much stronger and always detected after 1992. However, a researcher who tests the restriction that oil demand and the effective dollar rate are inversely related ending around 2005 might reject this hypothesis while a similar test shortly afterward would clearly lead to the opposite conclusion. The fact that the p-value of these restrictions wildly fluctuates clearly illustrates the sample dependency of results, even if the starting point remains unchanged and is also intuitive taking the complexity of the link between exchange rates and global industrial production. Figure 2.5 shows that a cointegrating relationship between exchange rates and the price of oil is mostly detected with the evidence becoming slightly weaker at the end of our sample period. The backward-recursive tests reported in Figs. 2.6 and 2.7 confirm that our oil demand proxy is strongly related to the effective exchange rate while the evidence for the price of oil is slightly weaker with evidence for a long-run relationship strongly detected at the beginning and becomes weaker in the middle of our sample period. The findings for oil supply show wild fluctuations, suggesting that a long-run relationship is rejected most of the time (Fig. 2.8).

Unsurprisingly, Figs. 2.9, 2.10, 2.12 and 2.13 also provide some evidence for time-variation in the number of long-run relationships for the extended model. Nevertheless, we find that two and three long-run relationships are identified over the sample period, respectively. While Fig. 2.11 shows that restrictions for the model with two relationships are clearly not rejected after 2000, the recursive

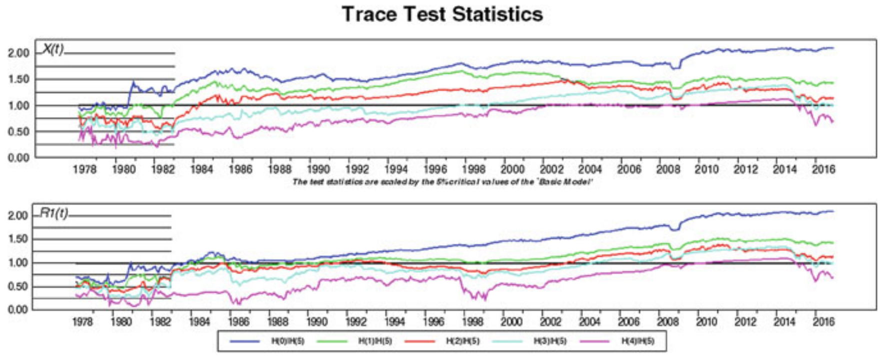

Fig. 2.12 Trace test recursive—Full model (*Notes* See Table 2.1)

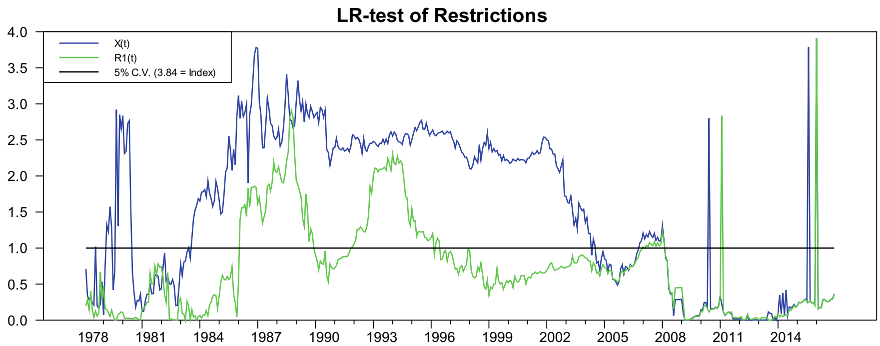

Fig. 2.13 Likelihood ratio test recursive—Full model (*Notes* See Table 2.2)

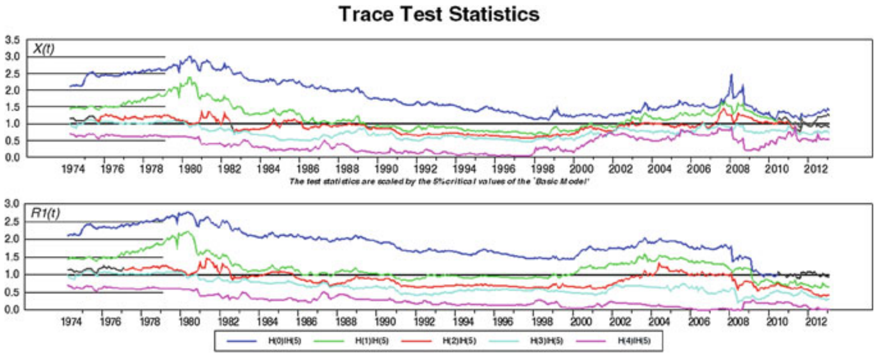

Fig. 2.14 Trace test backward recursive—Full model (*Note* The Graph displays the backward-recursive trace test to determine the cointegration rank. The blue graph refers to the full model and the green graph to the reduced model without short-run dynamics)

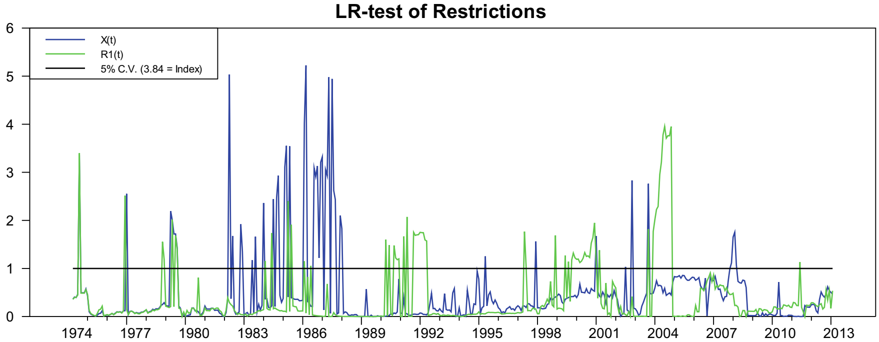

Fig. 2.15 Likelihood ratio test backward recursive—Full model (*Note* The Graph displays the backward-recursive likelihood ratio test)

and backward recursive tests in Figs. 2.14 and 2.15 show that identification for the full model including the price of oil, oil demand and oil supply temporarily breaks down at the end of our sample (Fig. 2.14) and in the middle of our sample (Fig. 2.15) due to large spikes. This suggests that restrictions on the cointegrating space are often not robust to sample period extensions.

2.5 Time-Varying Forecasting Ability

In this section, we analyze the potential of exchange rates and price of oil for forecasting one another out-of-sample. We compare two rolling window forecast models: the first one is a simple ARIMA benchmark model and solely relies on information from the recent past (i.e. 40 observation) of the crude oil price or the exchange rate while the second one additionally includes the recent past of the exchange rate for forecasting the price of oil or vice versa. We use both models for one-month-ahead (h = 1), three-months-ahead (h = 3), six-months-ahead (h = 6) and 12-months-ahead (h = 12) forecasts. We then repeat this exercise in a recursive framework to allow for a comparison with our recursive cointegration results. We do not only focus on effective exchange rates but also adopt the first principal component of one-month-ahead exchange rate expectations from Consensus Economics and the Australian Dollar as a commodity currency.

2.5.1 Time-Varying Forecasting Ability of Exchange Rates for Oil Prices

Figures 2.16, 2.17, 2.18 and 2.19 show the corresponding results for two forecasting horizons, h = 1 and h = 12, and report the actually observed crude oil price and the rolling window forecasts based on both models. We only display findings for the broad effective exchange rate and the Australian dollar with the other ones available upon request. The colored dots display which model is better at which point in time. The turquois dots stand for the benchmark model while the red dots stand for the exchange rate model. For recursive forecasts, the figures look very similar and are therefore not reported to save space but are also available upon request.

As can be seen, the exchange rate model is better than the benchmark model in more than 50% of the cases if we simply count the differences. However, it is important to highlight that even these findings do not necessarily imply that

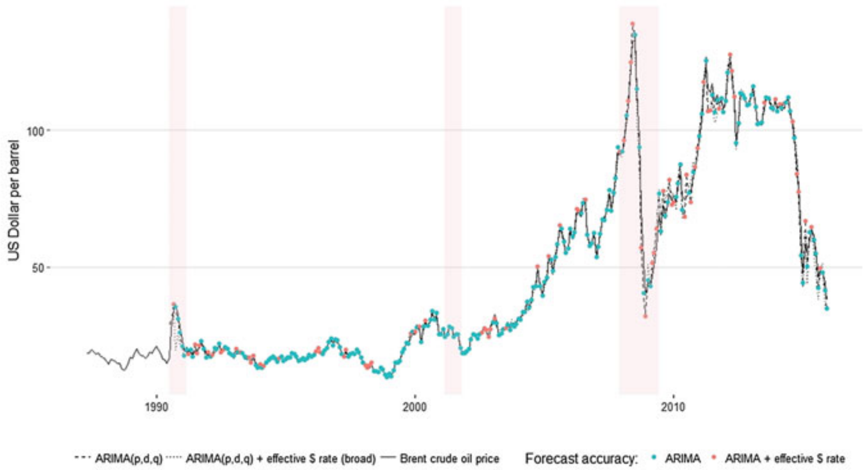

Fig. 2.16 Oil price forecast with broad effective dollar rate (h = 1)—rolling window (*Note* The colored dots display which model is better at which point in time. The turquoise dots stand for the benchmark model while the red dots stand for the extended model)

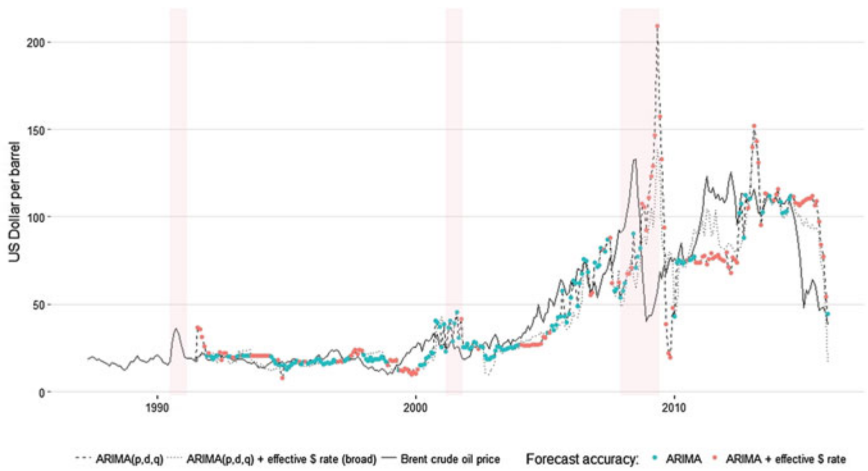

Fig. 2.17 Oil price forecast with broad effective dollar rate (h = 12)—rolling window (*Note* See Fig. 2.16)

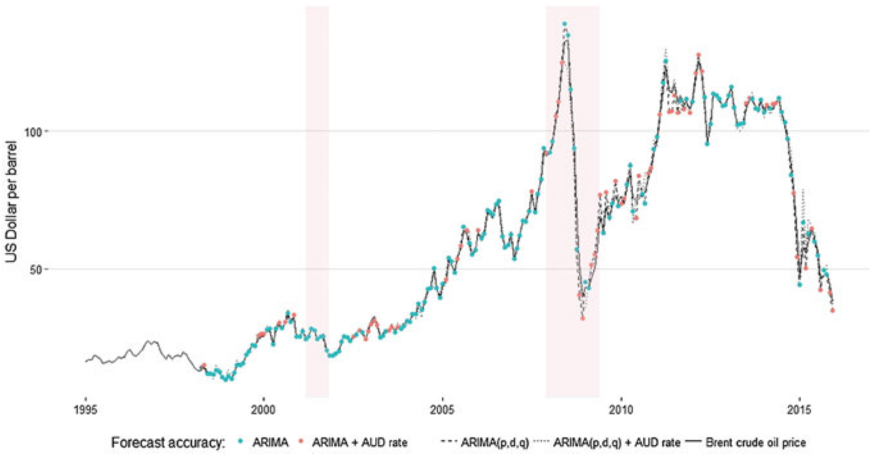

Fig. 2.18 Oil price forecast with Australian dollar rate (h = 1)—rolling window (*Note* See Fig. 2.16)

exchange rates dynamics are useful for oil price predictions for a number of reasons. First of all, trade weights used for calculations of effective exchange rates are not calculated in real time and might exhibit future trade dynamics.

A more important problem is that forecasts from the model including exchange rates partly inflate forecast errors. This is not obvious from the percentages provided from the graphs since those only reflect a binary decision for one of the

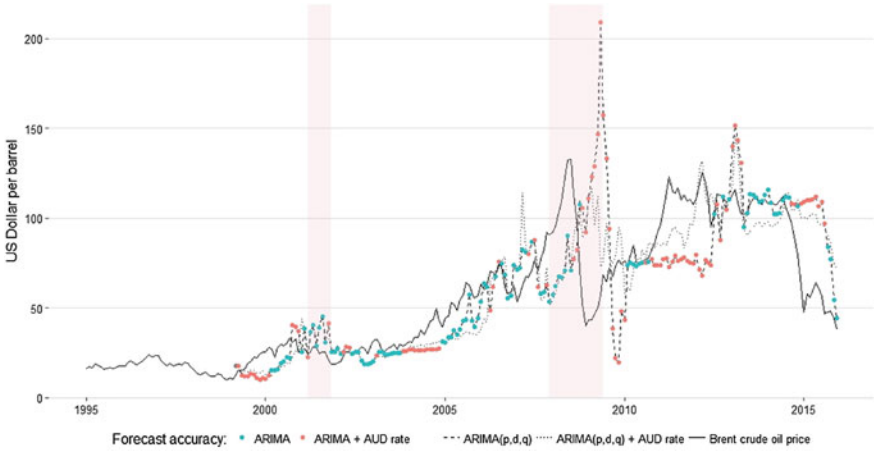

Fig. 2.19 Oil price forecast with Australian dollar rate (h = 12)—rolling window (*Note* See Fig. 2.16)

models. In terms of absolute differences, the exchange rate model hardly outperforms the simpler model to an outstanding degree while the simpler model in many cases outperforms the exchange rate model substantially. A simple example is the case where the simple model correctly proposes a constant oil price while the exchange rate predicts changes which do not materialize. This is reflected in Table 2.8 which provides findings of the Diebold-Mariano test over several horizons. The findings clearly show that exchange rate predictions at best just provide a statistical improvement over simplified benchmark models for one month ahead forecasts.

2.5.2 Time-Varying Forecasting Ability of Oil Prices for Exchange Rates

The seminal work of Meese and Rogoff (1983) which shows that exchange rate models based on economic fundamentals are unable to outperform a simple random walk forecast still constitutes a benchmark result in the international finance literature. The resulting exchange rate disconnect puzzle remains one of the most important topics in international economics (Sarno, 2005). In general, the forecasting performance of fundamental exchange rate models is highly sensitive to the selection of different currencies, sample periods and forecast horizons (Rossi, 2013). Lizardo and Mollick (2010) imbed the real oil price into a simple form

Table 2.8 Share of forecasting superiority of univariate models and Diebold-Mariano tests

		$h = 1$			$h = 3$			$h = 12$		
		Share	DM-statistic	p-value	Share	DM-statistic	p-value	Share	DM-statistic	p-value
Rolling Window	Broad index	0.7401	−2.8533	0.0046	0.5762	−0.6637	0.5074	0.5393	1.3442	0.1799
	Major index	0.6908	−2.2709	0.0239	0.5497	0.1069	0.9149	0.4573	1.3922	0.1649
	AUD/USD	0.7028	−1.7313	0.0849	0.5190	0.6961	0.4872	0.5174	1.2946	0.1969
	PC	0.6780	−0.8305	0.4072	0.5517	0.1919	0.8481	0.3763	1.4633	0.1450
Recursive	Broad index	0.5526	−2.3464	0.0196	0.4437	1.3621	0.1742	0.4403	1.4856	0.1385
	Major index	0.5493	−2.3919	0.0174	0.4967	0.5263	0.5990	0.4369	1.2731	0.2040
	AUD/USD	0.6321	−1.4384	0.1518	0.5476	−0.1615	0.8719	0.5124	0.9864	0.3251
	PC	0.6683	−0.0630	0.9498	0.5517	0.1071	0.9148	0.5155	0.8899	0.3746

Note Share gives the ratio of root mean squared errors of univariate models against models augmented by lagged exchange rates. DM-statistic gives the modified Diebold-Mariano test statistic following Harvey et al. (1997) together with its p-value, which tests the null that the two methods have the same forecast accuracy. A negative (positive) sign indicates that the univariate model has lower (higher) forecast errors. Broad and major indexes are effective exchange rates, AUD/USD denotes the Australian Dollar / US Dollar exchange rates. PC denotes a principal component of exchange rates expectations

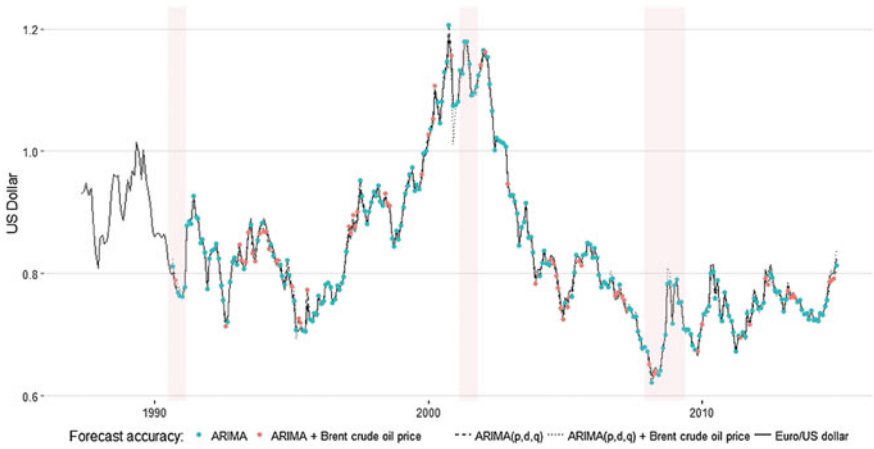

Fig. 2.20 EUR/USD rate with oil price (h = 1)—rolling window

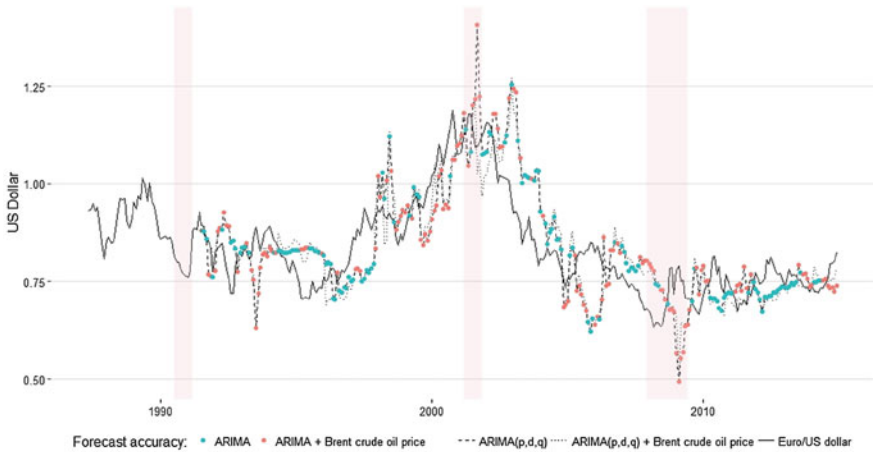

Fig. 2.21 EUR/USD rate with oil price (h = 12)—rolling window (*Note* See Fig. 2.16)

of the monetary model of exchange rate determination and show that it improves exchange rate predictions for several bilateral currencies.[3]

The findings reported in Figs. 2.20, 2.21, 2.22 and 2.23 provide similar evidence as obtained for oil price predictions above: including the oil price temporarily improves forecasts but these gains are often not statistically significant according

[3] Our results do not contradict the results of Kohlscheen et al. (2016) who provides evidence for superior exchange rate forecasts based on commodity prices. However, they conduct "pseudo-out-of-sample" forecasts based on future values.

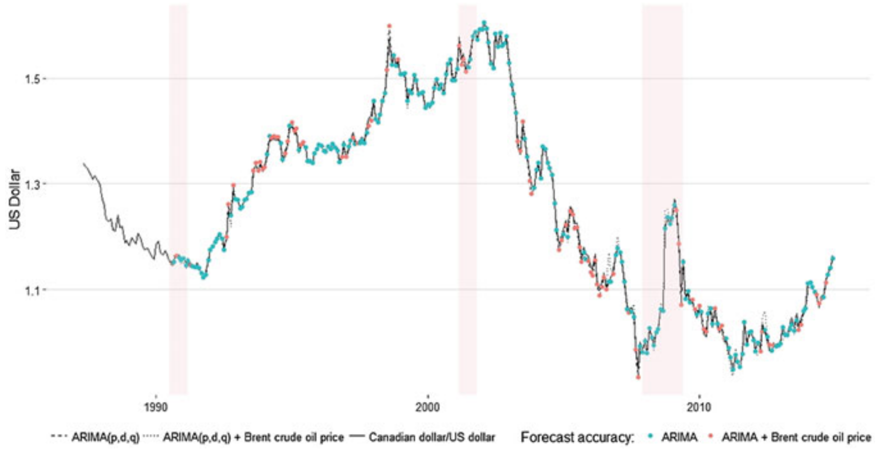

Fig. 2.22 CAD/USD rate with oil price (h = 1)—rolling window (*Note* See Fig. 2.16)

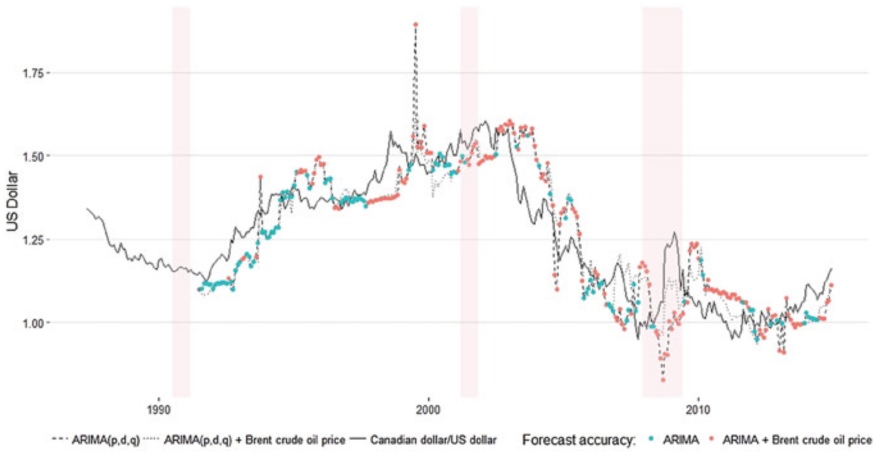

Fig. 2.23 CAD/USD rate with oil price (h = 12)—rolling window (*Note* See Fig. 2.16)

to Table 2.9. The findings reflect the results of Rossi (2013) for exchange rate predictability. A rejection of the null of equal predictability often points to a better performance of the benchmark model. The overall conclusion is that extending a simple benchmark model with either oil prices or exchange rates for forecasting the other potentially inflates statistical forecast errors.

Table 2.9 Share of forecasting superiority of univariate models and Diebold-Mariano tests

		$h = 1$			$h = 3$			$h = 12$		
		Share	DM-statistic	p-value	Share	DM-statistic	p-value	Share	DM-statistic	p-value
Rolling Window	GBP/USD	0.7637	−0.9289	0.3537	0.4621	0.0743	0.9408	0.4448	1.0922	0.2757
	JPY/USD	0.8116	−2.9062	0.0039	0.4793	0.2674	0.7893	0.5267	−0.6341	0.5265
	EUR/USD	0.7705	−2.2213	0.0271	0.5034	0.4460	0.6559	0.4947	2.0499	0.0413
	CAD/USD	0.7123	−2.9917	0.0030	0.5241	0.8377	0.4029	0.4057	1.6886	0.0924
Recursive	GBP/USD	0.8904	−3.1729	0.0017	0.4379	1.8045	0.0722	0.4448	1.5911	0.1127
	JPY/USD	0.8801	−6.3175	0.0000	0.4931	0.3231	0.7468	0.5409	−0.4727	0.6368
	EUR/USD	0.8493	−3.6988	0.0002	0.4276	0.6569	0.5118	0.5445	−1.1583	0.2477
	CAD/USD	0.7260	−3.4188	0.0007	0.4655	2.1161	0.0352	0.3559	1.6369	0.1028

Note Share gives the ratio of root mean squared errors of univariate models against models augmented by the lagged Brent crude oil price. DM-statistic gives the modified Diebold- Mariano test statistic following Harvey et al. (1997) together with its p-value, which tests the null that the two methods have the same forecast accuracy. A negative (positive) sign indicates that the univariate model has lower (higher) forecast errors. GBP/USD, JPY/USD, EUR/USD and CAD/USD are bilateral dollar exchange rates for the British pound sterling, the Japanese yen, the euro and the Canadian dollar.

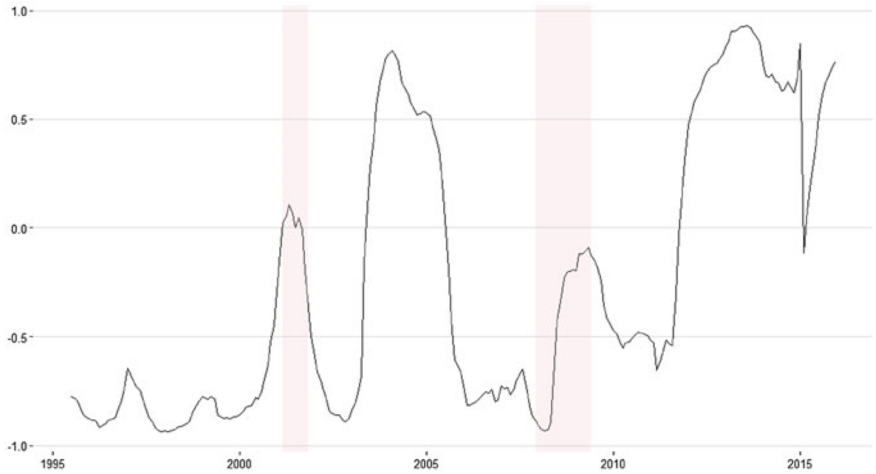

Fig. 2.24 Rolling window correlation between recursively computed Diebold-Mariano test statistic at h = 1 and recursively computed trace test statistic for the broad effective rate (*Note* See Fig. 2.16)

2.5.3 Link Between in-Sample and Out-of-Sample Analysis

As a final step, we assess the question of whether establishing a long-run relationship is related to detecting predictability. This is done via comparing recursive estimates of the cointegrating trace test discussed in Sect. 2.4 and recursive estimates of the Diebold-Mariano test statistic. It is important to take into account that a rejection of equal predictability does not imply that the extended model outperforms the simpler model. Since we are dealing with a two-sided test, a rejection can imply that the extended model is either statistically better or worse (Fig. 2.24).

Quite strikingly, we find that the correlation between the trace test and the Diebold-Mariano test turns out to be negative until early 2000 while the correlation is strongly positive at the end of our sample. Hence, detecting a cointegrating relationship is not consistently related to the out-of sample performance. This is consistent with the difficulty to select an adequate model in real-time based on the in-sample fit. The findings at the end of the sample deserve further attention, for example, by taking a lead-lag relationship in an extended framework into account.

2.6 Conclusion

Previous research has often drawn strong conclusions regarding the relationship between the oil price and exchange rate without taking time-variation into account. We have addressed this issue both in- and out-of-sample while also providing a distinction between oil demand and supply factors.

As a starting point, we have provided an extensive cointegration analysis which does incorporate different dollar exchange rates, oil supply and oil demand factors and potential common drivers. While we have established robust evidence for an inverse relationship between the broad effective dollar exchange rate, we find that the major effective exchange rate index displays a weaker relationship with the price of oil. We also identify links between the broad index on the oil supply and oil demand. However, the link between the effective dollar exchange rate and oil supply is not robust over time while the direction of the link between exchange rates and oil demand approximated by global industrial production is changing over time. An extended version of our model confirms the inverse relationship and displays oil price adjustments even if oil supply and demand factors are considered. Overall, the underlying driver of the long-run link between oil price and exchange rates is therefore not only related to aggregated supply and demand effects with expectations playing a potential role (Beckmann et al., 2017).

Our out-of-sample results show that neither exchange rates nor oil prices are a silver bullet for forecasting each other and often inflate forecast errors. However, they contain potentially useful information and should be taken into account in a broader modeling or forecasting framework, for example, when combing forecasts in a parsimonious framework. Our findings reflect the findings of the seminar paper by Alquist et al. (2011) regarding forecasting the price of oil. It also implies that some studies provide selective forecasting evidence. Finally, we have shown that the probability to find a long-run relationship is not consistently related to the out-of-sample forecasting performance.

Future research should, for example, assess the economic value of predictions in a multivariate setup, for example, in the spirit of Della Corte et al. (2009) for exchange rate models or Alquist et al. (2011) in the context of upside–downside risk for the oil price. Such an exercise potentially sheds some light on the question of whether exchange rates are a useful predictor for oil prices or vice versa. It is also important to emphasize that a structural identification of demand and supply shocks in the context of structural VARs as proposed by Kilian and Murphy (2012) remains on the agenda for further research given the potential drawbacks of the conventional Johansen (1988) approach discussed in Kilian and Lütkepohl (2017).

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Crude Oil Prices, Exchange Rates, Stock Markets and Industrial Production Relationships in Emerging Markets

3

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3.1 Introduction

Oil is an important commodity affecting the economic and financial indicators of a country. A considerable number of studies investigate the effect of oil prices on macroeconomic variables. One of the linkages pointed out in the literature is the one between oil price and exchange rates. There are several channels over which oil prices can have an impact on exchange rates (Beckman et al., 2020; Turhan et al., 2013). One straightforward channel is that any disruption accounting for the change in exchange rates can drive financial pressure for oil-dependent countries. In addition to this effect, trade balance of a country can be vulnerable to exchange

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rate fluctuations. The negative link between oil price and exchange rates is pointed out in Fratzscher et al. (2014). This negative link can be due to 2 channels. One channel is the wealth transfer from oil importers to oil exporters as oil prices rise. Second channel is due to the changes in trade balances in response to a change in oil price, which in turn causes exchange rates to fluctuate. Supply and demand chains are formed according to these fluctuations that directly affect the production processes of countries. Industrial production costs are also a distinctive factor linking oil prices to manufacturing indices.

Relationship between production processes and the returns in stock market is also investigated in the literature. Industrial production is a leading indicator of economic activities. Therefore, economic and financial performances can be linked by using the variables of industrial production and real stock returns. Drobetz (2000) anticipates that not only industrial production provides information about the economic development of a country but also the future expectations of cash flows are formed according to the production level. This suggests that industrial production leads stock returns. Studies carried out by Fama (1990) and Schwert (1990) also support the idea of this relationship between stock returns and industrial production.

Relationship between stock market returns and exchange rates is important since exchange rate fluctuations can change trade dynamics and investment decisions. According to the changes in exchange rate levels, foreign investors may adjust their investment decisions to utilize economic opportunities. For emerging countries, maintaining investment opportunities to attract foreign investors may be crucial for economic development. Hence, understanding how stock market returns and exchange rates of an emerging economy affect each other is important. The production level of a country may have a significant effect on stock market returns due to the close relationship between production and stock market returns, but also due to exchange rates.

While developed countries have more stable economic conditions, emerging economies are more vulnerable to external shocks. This study aims to add to the literature by shedding more light on the relationships between crude oil prices, exchange rates, stock returns, and industrial production in emerging markets.

Fifteen emerging markets are chosen with monthly data ranging from January 1990 to December 2016. Relations between exchange rates, oil prices, stock market returns, and industrial production are estimated and causal relations are tested to determine the direction of long-run causality. Toda Yamamoto procedure is used for this purpose. To complement the analysis with short-run dynamics, generalized Impulse Response Functions are estimated and interpreted.

Paper is organized as follows: Sect. 3.2 presents the literature review, Sect. 3.3 describes the data, Sect. 3.4 presents the methodology and results, and Sect. 3.5 concludes the paper.

3.2 Literature Review

Numerous studies investigated the relationships between energy prices, stock market prices, exchange rate, and economic activity. Researchers focused on both the short-run and long-run effects of the variables with varying time intervals. Most studies look at a subset of these links. In what follows, we try to categorize the literature depending on which link they aim to investigate.

3.2.1 Stock Market and Exchange Rate Relationship

Changes in exchange rate levels can be a leading factor for investment decisions. Their impact depends on the sensitivity of the relationship between the two variables. Several studies have worked on the potential link between stock market activities and exchange rates. Although there exists a large amount of studies ascertaining that there is a causality relationship between the two, in either direction or both, other attained results show that there is no long-run relationship between them. Islami and Welfens (2013), for example, investigate the relationship between stock markets and exchange rates for Poland, Czech Republic, Slovenia, and Hungary. To examine the short-run relationships, VAR model is established and long-run relationship is tested by Johannsen cointegration approach. Depending on the countries analyzed, either short-term or long-term relationship or both appear as the result of the estimations. Alternatively, same relationship is examined by Granger et al. (2000) for 9 Asian countries. They point out the significance of the link between stock markets and exchange rates for all countries except for Indonesia and Japan. Their results show that either stock prices affect exchange rates (Philippines) or vice versa (Hong Kong, Malaysia, Singapore, Thailand, and Taiwan). On the other hand, Abidin et al. (2013) proclaim that stock markets and exchange rates do not have a long-run relationship for Asia–Pacific countries. The Engel-Granger's two-step methodology resulted in cointegration, and hence there is no long-run equilibrium link between them.

In the literature, not only the stock price and exchange rate relationship but also the volatility changes are investigated. Şensoy and Sobacı (2014) study the volatility shifts for Turkey. VAR model and dynamic conditional correlation model results indicate a positive relationship between stock markets and exchange rates. In another study, Hajilee and Nasser (2014) examined the relationship between exchange rate volatility and stock market development for 12 emerging economies. Their results show that for 10 countries in the short run and for 6 countries in the long run exchange rate volatility appears statistically significant. For China, Mexico, Pakistan, and Venezuela the long-run volatility coefficient is negative whereas for Philippines and South Africa it is positive.

Abouwafia and Chambers (2015) investigate the relationship between monetary policy, exchange rates, and stock prices. Their methodology used in the paper is structural vector autoregression (SVAR) and the sample covers the Middle East region, namely Kuwait, Oman, Saudi Arabia, Egypt, and Jordan. They find that for those countries, monetary policy and exchange rate shocks affect stock market prices significantly in the short run. More recently, Tang and Yao (2018) find mixed results for a selected set of emerging markets: Argentina, Brazil, China, India, Indonesia, South Korea, Mexico, Russia, Saudi Arabia, South Africa, and Turkey. They argue that previous results could be misleading due to omitted variable bias. Therefore, they adopt a multivariate Granger causality framework and find significant links between stock market and exchange rate markets for all countries except China.

A brief glance at the literature with mixed results suggests a need for more applied work to identify linkages among stock markets and exchange rates.

3.2.2 Stock Market and Industrial Production, Economic Activity Relationship

Researchers also investigate the linkage between stock prices and industrial production. Production processes and the return to its movements in the stock market remains to be a concern since consumer demands are associated with the production in the sectors and reflect the economic state of a country. Therefore, industrial production is a leading indicator of economic growth and provides insight into the level of overall economic activity.

The literature on emerging markets is relatively smaller compared to the one on developed countries. The stock market and industrial production link for the North and South Euro-zone is examined by Tsagkanos and Siriopoulos (2015). South Euro-zone consists of Spain, Portugal, Italy, Greece, and North Euro-zone countries are constructed as Germany, Belgium, Finland, Austria in their paper covering the period of January 2, 2004 and December 30, 2013. Their data frequency is monthly in the determined period. They use threshold cointegration approach to understand the dynamic links. Equilibrium adjustment speeds of stock prices and industrial production in the case of an expansionary or contractionary shock differ in the long run. In the panel context, North Euro-zone is observed to be adjusted symmetrically but South of the Euro-zone is observed to have an asymmetric adjustment.

Linkage between industrial production and the stock market in the US is examined in Chang and Pinegar (1989). They adopt the Granger causality method to find the relationship after accounting for seasonality. The monthly data used in the study covers from January 1958 to December 1985 period. Their findings indicate that stock returns for large scale firms can lead to seasonal real growth in the long run. Whereas the effect of the stock returns for small firms remains in the short run. Bhuiyan and Chowdhury (2020) confirm the strong link for the US. Using different sector indexes, they find evidence of a strong link for the US, but not for Canada.

Cavenaile et al. (2014) provide evidence of the relationship between stock markets, economic growth, and bank development for five developing countries, namely Malaysia, Nigeria, Mexico, Philippines, and Thailand. They state that there is a cointegration relation in the long run between economic growth and financial development, including both stock market and banking system developments. Causality is running from financial development to economic growth. From this viewpoint, Yu et al. (2012) support the existence of the linkage between financial development, stock markets, and economic growth. They set out a broad country scope to analyze the relation through the panel estimation framework. For each country group, there appears to be a different interpretation of long run or short run results.

3.2.3 Oil Price and Stock Market Relationship

For oil-dependent countries, it is crucial to consider the impact of oil price fluctuations and their reflections on the financial decisions about investments. Since oil prices affect the economic dynamics of a country by forming the future cash flows of firms, the relationship between crude oil prices and stock markets is essential in understanding investment decisions. Degiannakis et al. (2014) investigate the relationship between the oil price shocks and the stock market volatility for the European region. For this purpose, they use the Eurostoxx 50 index, which consists of the most leading and liquid fifty stocks in Europe, as the measurement for the stock market volatility. They use shocks to Brent oil prices and observe their impacts on stock returns. Estimation results of the study are obtained by a Structural VAR model. Oil price shocks are divided into three categories namely supply-side, aggregate demand, and oil-specific demand shocks to offer a better understanding of the relationship. According to the results, supply-side and oil-specific demand shocks do not have a significant effect on stock market volatility. On the other hand, aggregate demand oil price shocks have a significant influence on stock market volatility. Another approach for the same concept is examined by Guesmi and Fattoum (2014), which deals with the effect of oil price changes on stock market returns for ten OECD countries. They establish a dynamic conditional correlation model and use monthly data between the time interval of January 1, 1990 and December 1, 2012. Their findings show that the relationship between crude oil prices and stock markets was affected by mostly oil prices when an oil price shock is observed in the global oil market. They contribute to the literature by revealing the mutual interaction between crude oil prices and stock markets. The strong link between oil and stock markets is also documented for developing countries. For example, Cheema and Scrimgeour (2019) show there are stock market anomalies associated with rising or falling oil prices in China. This suggests that more research is necessary to examine existence and nature of these anomalies. Using an international CAPM model for 21 emerging economies, Basher and Sadorsky (2006) find that oil market risk is significant for stock market returns.

3.2.4 Oil Prices, Stock Market, and Economic Activity

Oil is a leading commodity that can affect several macroeconomic and financial variables as well as policy decisions in an economy. Hence, a multivariate framework is needed to account for this multifactor relationship. Hamilton (1983) can be considered as the pioneering study on the relationships between oil prices and the macroeconomic variables. He examines the oil industry using annual data covering the time interval 1948–1972. According to the Granger causality results, change in oil prices stimulates macroeconomic variables in the following period. There is little evidence that dramatic changes in macroeconomic variables exhibit an essential influence to predict the oil prices, but macroeconomic variables are not found to be completely independent of oil shocks. Papapetrou (2001) aims to identify the relationship between oil prices and economic development including the stock market, industrial production, and employment. Papapetrou shows that oil price shocks have a significant effect not only on industrial production but also on the employment measures. Results also imply that industrial production and employment are influenced negatively when an oil price shock emerged. Moreover, real stock returns are reduced in the case of positive oil price shocks. Smiech and Papiez (2013) investigate a similar nexus with fossil fuel, exchange rate, and stock market for the European region countries as variables. They found significant relation between fuel prices and exchange rates. Similar results hold for the links between stock market and other variables. They report bidirectional causality between variables for the period 2006–2008. Apart from the indicated period, causality between variables appears insignificant. In a similar framework, Seshaiah and Behera (2009) examine Indian data to figure out the linkage between stock prices, exchange rates, and crude oil prices. Data cover the period from 1991 to 2007 of daily frequency. The main finding of this paper is that all the variables are cointegrated. Causality direction is from exchange rates to stock prices and from crude oil prices to stock prices. In addition to this causality, exchange rates affect stock prices. Besides this study, Basher et al. (2012) question the same nexus; however, they use the MSCI emerging stock market index. They establish a structural vector autoregression (SVAR) model for this purpose and their monthly data covers the period from 1988 to 2008. Their finding of the causality between variables partially supports the study of Seshaiah and Behera (2009) indicating that oil prices have an effect on stock prices in the short run. On the other hand, the direction of causality runs from oil prices to exchange rates in the short run. Parallel to this issue, Sarı and Soytaş (2006) examine the link between stock market returns, crude oil prices, and interest rates in Turkey. They use time series analysis, variance decomposition, and generalized impulse response methodology in order to investigate the relation between these variables. Their paper provides evidence that oil price shocks do not have a significant effect on the Turkish stock market. More recently, Olayeni et al. (2020) show that the stock market plays an intermediary role in passing oil shocks to Nigeria–US exchange rate.

Overall, studies have relied on efficient market hypothesis or arbitrage pricing theory to examine the link between stock returns, macroeconomic variables, and energy markets. Recent studies concentrate on the methodological advancements that eliminate the spurious regression problem (Bhuiyan & Chowdhury, 2020). Evidence as to the existence and direction of causality between the variables in concern is mixed. Regardless of the framework in which these linkages are examined, there is a gap in the literature regarding emerging markets. This study attempts to help fill that gap.

3.3 Data

In this study monthly data of exchange rates (EXC), real stock returns (RSR), crude oil prices (OIL), and manufacturing indices (MI) are used for 15 Morgan Stanley Capital International (MSCI) emerging countries are used and data covers the period from 1990:01 to 2016:12. Variables and data ranges are presented in Table 3.1.

Exchange rates (EXC) are natural logarithms of local currencies per US dollar for each country. Real stock return estimation is conducted following Papapetrou (2001) and Sarı and Soytaş (2006). Stock return is computed by taking the difference of the natural logarithm of the related stock market indices (SMI) for each country. Real stock market returns (RSR) are computed as the subtraction of natural logarithm of inflation rates (INF) calculated by Consumer Price Index from the stock market returns. Formulations are constructed as the following:

$$\text{Stock Return} = \text{LN}\ (\text{SMI}_t / \text{SMI}_{t-1})$$

$$\text{Real Stock Return} = \text{LN}\ (\text{SMI}_t / \text{SMI}_{t-1}) - \text{LN}\ (\text{INF})$$

Bloomberg Stock Market Indices are presented in Table 3.2. Stock market index values are in the form of local currencies per US dollar. Data source for EXC and INF is the Bloomberg database.

West Texas Intermediate Spot Crude Oil Prices (OIL) are used and taken from the source of Federal Reserve Bank of St. Louise database in US dollar. Brent Prices (BOIL) are used for robustness check.

Another variable used to measure economic activity is the Manufacturing Index (MI) used in the form of the natural logarithm. Data series are obtained for the majority of the countries from the OECD Statistics. Manufacturing Index of Philippines is taken from the national government data of the Philippines.

Table 3.3 presents the descriptive statistics for exchange rates (EXC), real stock returns (RSR), manufacturing indices (MI), Crude oil prices (OIL), and Brent oil prices (BOIL). Manufacturing index levels persist its upward trend since 1990 resulting in 79.80 average and closest to the maximum value, even though they face with a sudden decrease in 2010:02. Crude oil prices and Brent oil prices display a similar pattern by having an upward trend since 1998:12 but the rise in

Table 3.1 Data ranges of emerging countries

Emerging countries	Exchange rate	Crude oil prices	Brent oil prices	Inflation rate	Real stock return	Manufacturing Index
Brazil	01–1992 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	02–1996 02–2019	01–1990 02–2019
Chile	10–1988 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 12–2018	02–1990 02–2019	01–1991 02–2019
Colombia	09–1992 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	08–2002 02–2019	01–1990 12–2018
Czech Republic	06–1993 02–2019	01–1990 01–2019	01–1990 01–2019	01–1992 02–2019	05–1994 02–2019	01–1991 01–2019
Greece	04–1989 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	01–1990 02–2019	01–1990 01–2019
Hungary	06–1993 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	02–1991 02–2019	01–1992 01–2019
India	11–1988 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 12–2018	08–1990 02–2019	04–1994 12–2018
Indonesia	11–1991 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	01–1990 07–2018
Mexico	08–1989 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	02–1994 02–2019	01–1990 01–2019
Philippines	11–1991 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	01–1990 02–2019	01–2001 01–2019
Poland	06–1993 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	07–1994 02–2019	01–1990 02–2019
Russia	07–1993 02–2019	01–1990 01–2019	01–1990 01–2019	01–1992 02–2019	10–1997 03–2018	01–1999 01–2019
South Africa	04–1989 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	07–1995 02–2019	01–1990 01–2019
South Korea	08–1989 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	01–1990 02–2019
Turkey	04–1989 02–2019	01–1990 01–2019	01–1990 01–2019	01–1990 01–2019	01–1990 02–2019	01–1990 01–2019

Table 3.2 Bloomberg Stock Market Indices

Country	Stock Market Index	Country	Stock Market Index
Brazil	IBRX	Mexico	MEXBOL
Chile	IGPA	Philippines	PCOMP
Colombia	COLCAP	Poland	WIG20
Czech Republic	PX	Russia	IMOEX
Greece	ASE	South Africa	FTSE/JSE
Hungary	BUX	South Korea	KOSPI
India	NSE (NIFTY50)	Turkey	BIST100
Indonesia	JCI		

Table 3.3 Descriptive statistics

Country	Variable	Obs	Mean	Median	St.Dev	Max	Min
Brazil	Exchange rates	300	1.88	1.92	0.93	4.02	0.00
	Real Stock Return	251	−1.83	−1.86	0.43	−0.34	−3.12
	Manufac. Indices	324	94.67	92.47	13.99	118.66	57.31
Chile	Exchange Rates	324	511.26	512.38	107.67	749.25	295.2
	Real Stock Return	314	−1.55	−1.43	0.81	1.24	−3.42
	Manufac. Indices	312	79.88	78.35	16.01	104.30	48.20
Colombia	Exchange Rates	293	1918.5	1949	656.84	3292.9	691.7
	Real Stock Return	173	−1.45	−1.51	0.43	−0.57	−2.28
	Manufac. Indices	324	82.34	77.78	12.54	108.57	61.47
Czech Republic	Exchange Rates	283	25.86	24.95	6.40	41.06	15.16
	Real Stock Return	259	−0.88	−0.97	1.13	2.37	−2.65
	Manufac. Indices	312	70.02	69.64	18.68	105.69	39.99
Greece	Exchange Rates	324	0.83	0.80	0.12	1.18	0.63
	Real Stock Return	279	−1.52	−1.37	0.92	3.73	−3.32
	Manufac. Indices	324	123.2	127.04	14.72	150.30	93.20
Hungary	Exchange Rates	283	210.3	215.30	50.70	310.27	91.76
	Real Stock Return	292	−1.96	−1.94	1.10	2.33	−3.72
	Manufac. Indices	300	64.05	68.74	25.10	103.67	23.13
India	Exchange Rates	324	43.44	44.46	11.72	68.42	16.96
	Real Stock Return	316	−1.93	− 1.97	0.52	0.84	−3.02
	Manufac. Indices	273	62.04	55.34	27.20	106.92	23.23
Indonesia	Exchange Rates	302	8047.79	9072	3597.21	14,950	1980
	Real Stock Return	322	−2.02	−2.00	0.68	1.21	−4.69
	Manufac. Indices	324	69.46	67.73	16.21	107.23	37.43
Mexico	Exchange Rates	324	9.77	10.41	4.04	20.73	2.71
	Real Stock Return	275	−1.83	−1.54	0.76	−0.77	−3.96
	Manufac. Indices	324	80.25	82.94	13.15	103.98	54.55
Philippines	Exchange Rates	302	42.04	43.88	9.86	56.35	23.40
	Real Stock Return	321	−1.60	−1.72	0.72	1.61	−3.13
	Manufac. Indices	192	150.29	152.45	20.05	180.70	110.90
Poland	Exchange Rates	283	3.28	3.25	0.63	4.65	1.76
	Real Stock Return	241	–1.34	−1.37	1.12	1.61	−3.71
	Manufac. Indices	324	54.81	47.50	27.38	108.19	15.59
Russia	Exchange Rates	282	26.83	28.61	15.83	75.45	0.99
	Real Stock Return	231	−2.48	−2.40	0.65	−1.25	−4.98
	Manufac. Indices	216	79.31	82.13	17.44	106.49	46.52

(continued)

Table 3.3 (continued)

Country	Variable	Obs	Mean	Median	St.Dev	Max	Min
South Africa	Exchange Rates	324	6.92	6.84	3.05	15.89	2.52
	Real Stock Return	257	−1.67	−1.77	0.61	1.68	−2.73
	Manufac. Indices	324	89.45	90.11	10.25	111.01	66.91
South Korea	Exchange Rates	324	1038.80	1085.74	195.57	1633	689
	Real Stock Return	324	−1.10	−1.20	0.75	1.69	−2.37
	Manufac. Indices	324	60.40	55.53	28.43	105.50	19.76
Turkey	Exchange Rates	324	1.08	1.33	0.88	3.52	0.00
	Real Stock Return	324	−3.14	−3.12	1.07	−1.33	−4.91
	Manufac. Indices	324	55.98	46.75	22.36	106.10	27.01
For Each Country	Oil Prices	324	46.64	32.64	30.52	133.88	11.35
	Brent Oil Prices	324	47.58	30.91	34.17	132.72	9.82

the prices disrupted and conspicuous falls observed after mid-2008 and mid-2014 which explains the close value to the minimum estimation. For countries like Chile, Columbia, Hungary, Indonesia, and South Korea standard deviations of exchange rates are much higher than deviations in oil prices. These countries may be more vulnerable to oil price shocks due to the highly sensitive local currencies. The standard deviations of all manufacturing indices come close but fall short of the deviations in the oil markets. This is expected as investors in oil markets can shift their positions faster than firms can shift their production levels. Stock returns in Czech Republic, Hungary, Poland, and Turkey have the largest variation compared to other countries. Hence, their stock markets may be more sensitive to oil price movements.

3.4 Methodology and Results

3.4.1 Toda Yamamoto Procedure

Following the Toda Yamamoto procedure, initially maximum order of the integration (d_{max}) for all the variables is determined by implementing a unit root test so as to determine the order of integration for each country. Lag length (m) selection is followed in the procedure, in which the Akaike criterion is the base criteria. As indicated in Grendenhoff and Karlsson (1997), lag length selection is a crucial issue to discuss and construct a model, since lag length criteria can mislead the model estimations. They compare both Schwarz or Bayesian Information Criterion (SC or BIC) and Akaike Information Criterion (AIC) to determine the appropriate lag length. Their conclusion shows that the true lag length of the model is underestimated if Schwarz criterion is employed and interpretations about the result of the model may not reflect the actual conclusions. When hypothesis testing and interpretations about a model are considered, the model may not provide reliable results with the Schwarz lag length criterion selection. Although lag length specification of a model may not be accurately known whether the exact lag length is selected or not, Akaike Information Criterion (AIC) is indicated to perform better inferences than SC criterion.

Akaike (1974) defines the information criterion (AIC) as follows;

$$\mathrm{AIC} = \frac{-2\log(\mathit{maximum\ likelihood}) + 2k}{N}$$

where k is the number of endogenous variables, N is the number of observations.

$$\log(\mathit{maximum\ likelihood}) = -\frac{\mathrm{N}}{2} \cdot \left\{k(1 + \log 2\pi) + \log\left|\sum \epsilon\right|\right\}$$

in which $\left|\sum \epsilon\right|$ is defined as;

$$\left|\sum \epsilon\right| = \det\left(\frac{1}{N - (pk + d)} \sum \epsilon_t \epsilon_t^{'}\right)$$

where p is the lag included, d is exogenous intercept of C and $\sum \epsilon_t \epsilon_t^{'}$ is the sum of the estimates of residuals.[1]

Toda and Yamamoto (1995) states that unit root testing may suffer from the pretest biases unless there exist robust time series processes to test. In order to avoid these circumstances, Toda Yamamoto augmented VAR procedure for Granger non-causality Wald test is used to inspect the relationship between exchange rates, crude oil prices, real stock returns and manufacturing indices. Unit root test is the first step of the Toda Yamamoto procedure to detect the maximum order of integration.

3.4.2 Unit Root Tests

Basic unit root theory provides the simple AR (1) process:

$$\mathrm{y_t} = \rho \mathrm{y_{t-1}} + \mathrm{x_t'}\delta + \varepsilon_\mathrm{t}$$

where $\mathrm{x_t}$ is exogenous regressor, ρ and δ are parameters and ε_t is the white noise. Mentioned in Dickey and Fuller (1979), model is constructed as below;

$$\Delta \mathrm{y_t} = \alpha \mathrm{y_{t-1}} + \mathrm{x_t'}\delta + \varepsilon_\mathrm{t}$$

[1] Lag length criteria are decided by using Eviews tool and results are available upon request.

where $\alpha = \rho - 1$, in a generalized form with p lagged difference;

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \cdots \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + \upsilon_t$$

Even though ADF test is useful to find out the integration order of the variables, in case of trend and mean appears for the time series to be analyzed more developed tool is required. For this purpose, Elliott et al. (1996) has modified traditional approach of Augmented Dickey-Fuller unit root test to improve and ensure the interpretation of the result of testing. As indicated in the paper of Elliott et al. (1996), new modified version of the model is obtained as follows;

Series of y_t is replaced with the residual series of ${y_t}^d = y_t - \beta' z_t$ where $z_t = (1, t)'$ is the linear trend. Thus, the modified model is obtained as;

$$\Delta y_t^d = \alpha_0 y_{t-1}^d + \alpha_1 \Delta y_{t-1}^d + \alpha_2 \Delta y_{t-2}^d + \ldots + \alpha_p \Delta y_{t-p}^d + \varepsilon_t$$

DFGLS procedure is more powerful than ADF unit root testing due to de-trended and de-meaned estimation framework.

Augmented Dickey-Fuller (ADF), Dickey-Fuller Generalized Least Square (DFGLS), and Phillips Perron (PP) unit root tests are applied to find out the order of integration and also to ensure whether the stationary condition is valid for the variables. Unit root tests suggested by Phillips and Perron (1988) allow us an analysis independent from the lag length specification, and also exhibits more robust form of the heteroscedasticity of the error term disturbances.

The hypotheses for ADF, DFGLS, and PP tests for stationarity determination are defined as follows;

H_0: series has a unit root
H_1: series has no unit root

Rejection of the null hypothesis indicates that the series is stationary. Akaike Information Criterion (AIC) is selected to determine the lag length for ADF and DFGLS unit root tests for each of the series. Newey-West Bandwidth automatic selection is preferred for PP unit root testing.

In the level series ADF unit root results show that among 15 emerging countries, Brazil exhibits stationary exchange rate and real stock return series in level by rejecting the null hypothesis at 1% significance. Exchange rates of India, Russia, Turkey and real stock return of Indonesia share the same interpretation with Brazil standing at a 1% significant level to reject the null hypothesis. Only the manufacturing index series of Czech Republic stands in the 5% significant level which remains to be sufficient to reject the null hypothesis and obtained as stationary. All the series for the remaining countries preserve to be nonstationary even at the significant level of 10%. For these countries, the null hypothesis is failed to be rejected and the series have a unit root.

PP unit root results for level indicates that variables for the emerging countries do not satisfy the stationary condition mostly as parallel to the other unit root test results. Exchange rates of Brazil, India, Russia, and Turkey are found to be statistically meaningful at 1% significant level and the null hypothesis of having a unit root is rejected. Hungary, India, and Poland do not have a unit root at 5% significant level for the variable of exchange rates. Exchange rates of the remaining countries are not detected to be statistically meaningful even at 10% significant level and the null hypothesis for this variable is failed to be rejected. Real stock returns of the countries namely, Brazil, Chile, Czech Republic, Hungary, India, Indonesia, Philippines, Russia, and South Korea are found to be meaningful at 1% significant level implying that the variable is stationary for the denoted countries. South Korea and Turkey share the same results with other emerging countries differently at 5% significant level and the null hypothesis is rejected. Remaining are not performed to be statistically significant even at 10%. Moreover, the null hypothesis for manufacturing indices is also tested and the main findings are observed for Czech Republic, Indonesia, and Turkey to be nonstationary at 1% significant level. The null hypothesis of emerging countries Colombia, Greece, and South Africa is rejected to have a unit root at 5% significant level. Remaining countries are observed to be nonstationary.

In the level series according to DFGLS test results, 11 countries fail to reject the null hypothesis at 10% significant level implying that series have a unit root and stationary condition is not satisfied. For the remaining three countries, namely for Czech Republic and South Korea real stock return series is attained to be stationary and reject the null hypothesis at 5% significant level. In the case of Indonesia, series of real stock returns are obtained to be stationary. The null hypothesis is rejected at 1% significant level and stock returns are proved to deny the presence of a unit root.

ADF, DFGLS, and PP unit root results consistently point out nonstationarity of oil prices at 10% significant level.

Regarding first differences, variables are observed to be stationary using ADF, DFGLS, and PP unit root tests. ADF and PP unit root results are consistent with each other except for the stock market returns in Chile and Greece. Unit Root test results for the variable in first differences I(1) are presented in Tables 3.4, 3.5, and 3.6. Stationarity is ensured with all applied unit root tests and the null hypothesis of having a unit root is rejected mostly at 1% significant level.

3.4.3 VAR Stability Detection

VAR $(m + n)$ is established to check the stability of the augmented VAR. According to the VAR $(m + n)$ model, stability of the roots of VAR model is ensured. Diagnostic tests are monitored to check autocorrelation, heteroscedasticity, and stability of the parameters in the form of VAR equations. First m parameters of other variables in the equations are conducted by Wald tests and causality inferences are interpreted by the results. Causality relations are defined as change in one variable lead to a change in other dependent variable. Generalized impulse responses also obtained to get a general picture of the variables.

Table 3.4 Unit root ADF and PP test results

Country			Manufacturing Index		Exchange rate		Real stock return	
		Test	*t*-stat	*p*-value	*t*-stat	*p*-value	*t*-stat	*p*-value
Brazil	Intercept	ADF	−3.624	0.006	−5.385	0.000	−20.738	0.000
		PP	−10.288	0.000	−18.310	0.000	−22.605	0.000
	Trend	ADF	−3.925	0.012	−5.413	0.000	−20.717	0.000
		PP	−11.752	0.000	−18.333	0.000	−22.797	0.000
Chile	Intercept	ADF	−16.058	0.000	−1.113	0.712	−18.802	0.000
		PP	−16.035	0.000	−12.809	0.000	−28.937	0.000
	Trend	ADF	−16.062	0.000	−0.883	0.955	−18.969	0.000
		PP	−16.027	0.000	−12.782	0.000	−30.289	0.000
Colombia	Intercept	ADF	−15.240	0.000	−13.274	0.000	−5.684	0.000
		PP	−15.327	0.000	−13.339	0.000	−32.409	0.000
	Trend	ADF	−15.290	0.000	−13.266	0.000	−5.675	0.000
		PP	−15.330	0.000	−13.325	0.000	−32.378	0.000
Czech Rep	Intercept	ADF	−16.390	0.000	−14.335	0.000	−4.352	0.000
		PP	−16.390	0.000	−14.289	0.000	−27.234	0.000
	Trend	ADF	−16.381	0.000	−14.317	0.000	−4.315	0.003
		PP	−16.381	0.000	−14.270	0.000	−27.613	0.000
Greece	Intercept	ADF	−16.830	0.000	−3.111	0.027	−3.835	0.003
		PP	−16.813	0.000	−15.583	0.000	−35.737	0.000
	Trend	ADF	−16.811	0.000	−3.091	0.111	−3.910	0.013
		PP	−16.794	0.000	−15.669	0.000	−36.001	0.000
Hungary	Intercept	ADF	−8.315	0.000	−17.084	0.000	−6.723	0.000
		PP	−16.525	0.000	−17.234	0.000	−25.818	0.000
	Trend	ADF	−8.374	0.000	−16.938	0.000	−6.853	0.000
		PP	−16.552	0.000	−17.086	0.000	−26.111	0.000
India	Intercept	ADF	−4.048	0.001	−4.863	0.000	−3.817	0.003
		PP	−16.404	0.000	−19.394	0.000	−25.949	0.000
	Trend	ADF	−4.156	0.006	−4.854	0.001	−4.011	0.010
		PP	−16.488	0.000	−19.361	0.000	−26.212	0.000
Indonesia	Intercept	ADF	−4.829	0.000	−3.949	0.002	−4.417	0.000
		PP	−15.362	0.000	−13.615	0.000	−43.779	0.000

(continued)

Table 3.4 (continued)

Country			Manufacturing Index		Exchange rate		Real stock return	
		Test	*t*-stat	*p*-value	*t*-stat	*p*-value	*t*-stat	*p*-value
	Trend	ADF	−4.900	0.000	−3.936	0.012	−4.415	0.003
		PP	−15.354	0.000	−13.601	0.000	−44.003	0.000
Mexico	Intercept	ADF	−9.295	0.000	−6.730	0.000	−7.511	0.000
		PP	−16.007	0.000	−17.698	0.000	−19.633	0.000
	Trend	ADF	−9.313	0.000	−6.603	0.000	−7.504	0.000
		PP	−16.071	0.000	−17.673	0.000	−19.632	0.000
Philippines	Intercept	ADF	−8.677	0.000	−10.268	0.000	−4.975	0.000
		PP	−15.916	0.000	−16.671	0.000	−13.478	0.000
	Trend	ADF	−8.742	0.000	−10.236	0.000	−14.229	0.000
		PP	−15.917	0.000	−16.634	0.000	−14.222	0.000
Poland	Intercept	ADF	−8.175	0.000	−8.809	0.000	−23.010	0.000
		PP	−15.664	0.000	−16.480	0.000	−22.336	0.000
	Trend	ADF	−15.676	0.000	−8.791	0.000	−22.974	0.000
		PP	−15.674	0.000	−16.443	0.000	−22.307	0.000
Russia	Intercept	ADF	−7.154	0.000	−8.532	0.000	−19.659	0.000
		PP	−9.954	0.000	−15.011	0.000	−20.084	0.000
	Trend	ADF	−7.450	0.000	−8.574	0.000	−19.644	0.000
		PP	−10.211	0.000	−14.985	0.000	−20.135	0.000
South Africa	Intercept	ADF	−17.589	0.000	−5.817	0.000	−10.813	0.000
		PP	−17.606	0.000	−12.592	0.000	−28.073	0.000
	Trend	ADF	−17.565	0.000	−5.810	0.000	−10.798	0.000
		PP	−17.582	0.000	−12.575	0.000	−28.033	0.000
South Korea	Intercept	ADF	−16.720	0.000	−7.293	0.000	−18.596	0.000
		PP	−16.715	0.000	−20.384	0.000	−18.596	0.000
	Trend	ADF	−16.709	0.000	−7.247	0.000	−18.661	0.000
		PP	−16.702	0.000	−20.351	0.000	−18.661	0.000
Turkey	Intercept	ADF	−4.381	0.000	−7.559	0.000	−5.099	0.000
		PP	−14.037	0.000	−27.447	0.000	−29.371	0.000
	Trend	ADF	−14.250	0.000	−7.546	0.000	−5.203	0.000
		PP	−14.360	0.000	−27.402	0.000	−29.832	0.000

Maximum lag length is determined by Akaike information criterion for the ADF test. Newey-West Bandwidth is automatic selection criterion chosen to determine the lag length for PP test. Significance intervals are as follows: $p < 0.01$***, $p < 0.05$**, $p < 0.1$*

Table 3.5 DFGLS Unit Root Test results

Country		Exchange rates		Real stock return		Manufacturing Index	
		DFGLS statistic	Lag	DFGLS statistic	Lag	DFGLS statistic	Lag
Brazil	Intercept	−3.561***	3	2.540**	6	−1.719*	12
	Trend	−3.642***	3	−5.016***	3	−7.565***	3
Chile	Intercept	−15.876***	0	−0.024	11	−1.729*	10
	Trend	−15.981***	0	−1.273	11	−2.760*	10
Colombia	Intercept	−2.812***	13	−3.102***	4	−2.113**	6
	Trend	−15.171***	0	−7.765***	1	−3.538***	6
Czech Republic	Intercept	−7.416***	2	−1.990**	7	0.034	15
	Trend	−7.960***	2	−1.406	7	−1.355	15
Greece	Intercept	−16.811***	0	−0.734	13	−0.960	14
	Trend	−16.831***	0	−1.916	13	−2.142	14
Hungary	Intercept	−1.154	15	−1.922*	12	−4.597***	6
	Trend	−7.290***	2	0.43	12	−6.855***	4
India	Intercept	−3.883***	14	−2.585**	11	−1.478	10
	Trend	−4.149***	14	−1.602	11	−2.980**	10
Indonesia	Intercept	−4.836***	13	−2.523**	15	−0.427	13
	Trend	−4.877***	13	−2.278*	15	−1.576	13
Mexico	Intercept	−8.891***	3	−0.555	14	−1.592	13
	Trend	−9.301***	3	−1.206	14	−2.766*	13
Philippines	Intercept	−8.591***	2	−9.268***	1	−4.896***	3
	Trend	−8.631***	2	−1.088	16	−5.106***	3
Poland	Intercept	−3.810***	5	−1.053	6	0.328	15
	Trend	−7.383***	2	−2.473	6	−0.757	15
Russia	Intercept	−7.027***	2	−8.309***	13	−0.742	12
	Trend	−7.105***	2	−8.441***	13	−2.307	12
South Africa	Intercept	−17.162***	0	−1.954**	5	−10.100***	2
	Trend	−17.383***	0	−3.376**	3	−10.661***	2
South Korea	Intercept	−4.468***	8	−4.545***	12	−3.750***	5
	Trend	−16.499***	0	−6.158***	11	−11.562***	1
Turkey	Intercept	−2.005**	14	−0.309	16	−1.682*	16
	Trend	−14.204***	0	−1.745	16	−2.973**	15

Maximum lag length is determined by Akaike information criterion for DFGLS test. Significance intervals are as follows: $p < 0.01$***, $p < 0.05$**, $p < 0.1$*

Table 3.6 Oil Prices Unit Root results

Variable		Test	*t*-stat	*p*-value/[lag]
OIL	Intercept	ADF	−13.027	0.0000
		PP	−12.484	0.0000
		DFGLS	−9.444***	[1]
	Trend	ADF	−13.007	0.0000
		PP	−13.458	0.0000
		DFGLS	−12.496***	[0]
BOIL	Intercept	ADF	−13.524	0.0000
		PP	−13.062	0.0000
		DFGLS	−2.000**	[10]
	Trend	ADF	−13.504	0.0000
		PP	−13.037	0.0000
		DFGLS	−3.264**	[10]

Maximum lag length is determined by Akaike information criterion for DFGLS test. Significance intervals are as follows: $p < 0.01$***, $p < 0.05$**, $p < 0.1$*

Roots of the related VARs are monitored to handle the stability condition. VAR equations are established according to the order of integration and supported the lag length criteria. Equations used in the analysis are denoted as below.

First VAR equation is constructed as;

$$\begin{aligned}\mathrm{EXC} = \sum_{s=1}^{m+n} \alpha_s \mathrm{EXC}_{t-s} + \sum_{s=1}^{m+n} \beta_s \mathrm{OIL}_{t-s} + \sum_{s=1}^{m+n} \gamma_s \mathrm{RSR}_{t-s} \\ + \sum_{s=1}^{m+n} \theta_s \mathrm{MI}_{t-s} + \text{Dummy variable} + \mathrm{C}\end{aligned}$$

where α, β, γ, θ are the coefficients of variables respectively exchange rates, crude oil prices, real stock returns, and manufacturing indices. m is the maximum order of integration for each of the variables as defined formerly and n is the optimum lag length.

Causality direction from crude oil prices to exchange rates is estimated by verifying joint hypothesis, which implies that the first m coefficients of crude oil prices (β_{S}) are not jointly equal to zero. Respectively, causality from the real stock return to exchange rates (γ_{S}) and manufacturing indices (θ_{S}) to exchange rates proceed in a similar fashion.

Second VAR equation is constructed as;

$$\mathrm{OIL} = \sum_{s=1}^{m+n} \alpha_s \mathrm{EXC}_{t-s} + \sum_{s=1}^{m+n} \beta_s \mathrm{OIL}_{t-s} + \sum_{s=1}^{m+n} \gamma_s \mathrm{RSR}_{t-s} + \sum_{s=1}^{m+n} \theta_s \mathrm{MI}_{t-s} + \text{Dummy variable} + \mathrm{C}$$

Causality from all variables to crude oil prices to other variables are detected by using this equation and joint hypothesis tests.
Third VAR equation is constructed as;

$$\mathrm{RSR} = \sum_{s=1}^{m+n} \alpha_s \mathrm{EXC}_{t-s} + \sum_{s=1}^{m+n} \beta_s \mathrm{OIL}_{t-s} + \sum_{s=1}^{m+n} \gamma_s \mathrm{RSR}_{t-s} + \sum_{s=1}^{m+n} \theta_s \mathrm{MI}_{t-s} + \text{Dummy variable} + \mathrm{C}$$

Fourth VAR equation is constructed as;

$$\mathrm{MI} = \sum_{s=1}^{m+n} \alpha_s \mathrm{EXC}_{t-s} + \sum_{s=1}^{m+n} \beta_s \mathrm{OIL}_{t-s} + \sum_{s=1}^{m+n} \gamma_s \mathrm{RSR}_{t-s} + \sum_{s=1}^{m+n} \theta_s \mathrm{MI}_{t-s} + \text{Dummy variable} + \mathrm{C}$$

Breakpoints for each of the VAR equations allow specifying the dummy variables which are added to equations to ensure not to have separate serial correlations in subgroups with the breakpoints and enable them to have a single regression line. Breakpoint determination is used to construct dummy variables in the VAR equations and dummy variables are defined to be independent variables of each equation as denoted in VAR equations not to distort the outcomes. Quandt-Andrews breakpoint test is conducted for each of the VAR equations and results are denoted in Table 3.7.

After the stability of the roots and employing VAR equations, we proceed with autocorrelation, heteroscedasticity, and parameter stability tests. Breusch-Godfrey serial correlation LM test is used to detect whether there is a relationship between the variable and its lagged history. The hypotheses of Breusch-Godfrey test are as follows;

H_0: there is a serial correlation
H_1: there is no serial correlation

Table 3.7 Break points of VAR equations

Countries	Equation	Structural break point	Countries	Equation	Structural break point
Brazil	EQN 1	1999–07	Mexico	EQN 1	1998–01
	EQN 2	2000–10		EQN 2	1999–01
	EQN 3	1999–09		EQN 3	1998–10
	EQN 4	2009–01		EQN 4	2000–08
Chile	EQN 1	2008–11	Philippines	EQN 1	2004–05
	EQN 2	2002–09		EQN 2	2006–05
	EQN 3	2009–04		EQN 3	2014–01
	EQN 4	2013–04		EQN 4	2005–12
Colombia	EQN 1	2014–11	Poland	EQN 1	2008–08
	EQN 2	2008–08		EQN 2	2008–08
	EQN 3	2007–05		EQN 3	2003–05
	EQN 4	2012–11		EQN 4	2003–03
Czech Republic	EQN 1	2008–08	Russia	EQN 1	2014–04
	EQN 2	2007–09		EQN 2	2009–01
	EQN 3	2013–01		EQN 3	2001–12
	EQN 4	2000–02		EQN 4	2001–12
Greece	EQN 1	2008–08	South Africa	EQN 1	2002–01
	EQN 2	2008–10		EQN 2	2007–09
	EQN 3	2009–08		EQN 3	2003–12
	EQN 4	1993–11		EQN 4	2008–09
Hungary	EQN 1	2008–08	South Korea	EQN 1	1998–01
	EQN 2	2008–08		EQN 2	1999–04
	EQN 3	2011–02		EQN 3	1999–08
	EQN 4	2003–03		EQN 4	2009–02
Indonesia	EQN 1	1998–03	Turkey	EQN 1	2001–02
	EQN 2	2001–10		EQN 2	1995–08
	EQN 3	2000–11		EQN 3	2002–03
	EQN 4	1998–04		EQN 4	1997–04
India	EQN 1	2013–05			
	EQN 2	2013–09			
	EQN 3	1999–05			
	EQN 4	2011–04			

When the probability of Chi-Square is detected to be below 5% significant level, the null hypothesis is rejected. It is deduced that serial correlation is not observed and each variable can be defined independently from each other. Variance of the residuals may not be distributed proportionally and stability of the equations can be disrupted for this reason. In order to investigate and observe the distribution of the residuals to check the reliability of the estimations, a heteroscedasticity examination is performed. Breusch-Pagan-Godfrey heteroscedasticity test is conducted for each VAR equation. The hypotheses of Breusch-Pagan-Godfrey heteroscedasticity test are defined as;

H_0: residuals are homoscedastic
H_1: residuals are heteroscedastic

If the probability value of Chi-Square is obtained below 5% significant level, the null hypothesis of having a homoscedastic distribution of the residuals is rejected.[2] Residual tests are useful to take into account since they provide the difference between the observed (actual) value of the exogenous variable and the expected (fitted) value. Heteroscedasticity problems can be detected with the graphical depictions of the VAR equation residuals.

Evaluation of the results exhibits that there exist autocorrelation and heteroscedasticity problems in most of the VAR equations which cause to have a tendency to interpret the outcomes in a biased manner or proceed with an inefficient estimation of parameters. Huber-White and Newey-West estimators are utilized to derive more robust error variances.

Huber (1967) demonstrates the consistency of the standard errors in a maximum likelihood to fit the model in asymptotic normality. The study of White (1980) about heteroscedasticity issue completes the paper of Huber. White (1980) aims to provide an alternative estimation to the covariance matrix to be able to handle with misleading interpretation due to heteroscedasticity. Even though it is not possible to remove the heteroscedasticity factor completely from the model, combined approaches allow having a more proper implication about the results.

Regression equations exposed to autocorrelation problems also have a tendency to give distorted inferences about the results. Newey and West (1987) suggest estimators to overcome autocorrelation by providing a more consistent covariance matrix of the standard errors. For these cases, HAC (Newey-West) covariance method is selected to proceed with more appropriate interpretations.

Parameter stability tests are conducted by Cumulative Sum (CUSUM) and Cumulative Sum of Squares tests to detect if the parameters are changing systematically or abruptly.

[2] Residual Results of the VAR Equations and the diagnostic tests are available upon request.

3.4.4 Wald Test Results

Causality relations which are examined according to the Toda Yamamoto procedure in both directions are analyzed based on the Wald test results provided in Table 3.8.

The hypotheses for Wald coefficient tests to detect the causality between each variable are as follows;

H_0: first *m* parameters of other variable are equal to zero
H_1: first *m* parameters of other variable are not equal to zero

Causality relations those having Chi-square probability value below 5% significant level are considered to be statistically significant. The defined null hypothesis of the Wald coefficient test is rejected which implies that first *m* parameters of other variables are not equal to zero. Wald test result for the tested variable and country concluded that causality relation between two variables exists.

Since emerging countries hold dependent economies to foreign sources, having close relations with foreign investors is regarded as an opportunity for the development of a country. Regarding the economic dependence, it is expected that a shock in exchange rate can be received with a change in other variables conducted for this study. Furthermore, industry of the emerging countries can rely on mostly oil-dependent companies. As the result of this dependence, it is anticipated that there exists a strong relationship between oil prices and the production both from oil prices to production and from production to oil prices.

As reported in Table 3.8, test results reveal that the strongest causality relationship is observed running from exchange rates to manufacturing indices. Eight emerging countries namely Brazil, Colombia, Indonesia, Mexico, Philippines, Poland, South Korea, and Turkey supports causality claim with the significant probability values. Nevertheless, Colombia, India, and South Korea are the only countries with a reverse causality direction mostly standing at the 1% significant level.

Furthermore, causality from manufacturing indices to oil prices is observed to be the second strongest linkage with six emerging countries when the general picture about the outcomes are evaluated. Brazil, Chile, Mexico, Poland, Russia, and South Korea exhibit meaningful causality relations for the indicated direction. In the reverse direction from crude oil prices to manufacturing indices, five emerging countries namely Brazil, Hungary, Philippines, Poland, and Russia appear to have a close relationship between the variables in the mentioned direction. On the contrary, few relationships between the variables show statistically insignificant or weaker outcomes. None of the emerging countries is estimated to be meaningful for the causality from manufacturing indices to real stock returns. Conversely, only Indonesia shows a considerable linkage from real stock returns to manufacturing indices at 5% significant level.

Table 3.8 Wald Test causality results

Country	Causality between EXC and RSR				Causality between EXC and OIL				Causality between RSR and OIL			
	From EXC to RSR		From RSR to EXC		From EXC to OIL		From OIL to EXC		From RSR to OIL		From OIL to RSR	
	F-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value
Brazil	4.045	0.019	0.213	0.308	4.647	0.011	2.721	0.068	0.291	0.748	1.559	0.213
Chile	2.114	0.123	0.209	0.312	2.668	0.071	0.877	0.417	2.339	0.098	2.068	0.128
Colombia	1.951	0.124	0.356	0.785	4.558	0.004	0.461	0.710	1.494	0.219	0.543	0.654
Czech Republic	1.499	0.226	0.276	0.759	1.904	0.151	2.086	0.127	0.376	0.687	0.571	0.566
Greece	0.919	0.432	0.130	0.942	2.642	0.050	1.756	0.156	0.336	0.763	0.218	0.884
Hungary	0.936	0.394	0.436	0.647	2.600	0.076	0.885	0.414	1.037	0.356	2.424	0.091
India	1.081	0.358	1.282	0.281	1.389	0.247	0.862	0.461	3.500	0.016	0.565	0.638
Indonesia	3.115	0.006	1.526	0.170	0.852	0.531	1.882	0.084	2.493	0.023	0.187	0.980
Mexico	2.970	0.013	0.474	0.795	1.190	0.315	1.415	0.219	1.629	0.153	1.165	0.327
Philippines	0.913	0.436	0.205	0.393	0.843	0.472	0.882	0.452	0.280	0.840	1.957	0.123
Poland	0.961	0.384	5.416	0.005	2.162	0.118	1.851	0.160	0.937	0.394	1.975	0.141
Russia	1.454	0.236	1.326	0.268	7.722	0.001	1.881	0.155	0.736	0.481	0.599	0.550
South Africa	0.366	0.422	1.293	0.276	1.497	0.226	5.018	0.007	0.769	0.465	2.608	0.076
South Korea	3.305	0.021	0.523	0.667	4.128	0.007	1.208	0.307	0.621	0.602	3.302	0.021
Turkey	0.138	0.871	1.500	0.225	0.525	0.592	0.600	0.550	3.311	0.038	0.171	0.843

(continued)

Table 3.8 (continued)

Country	Causality between RSR and MI				Causality between MI and OIL				Causality between MI and EXC			
	From RSR to MI		From MI to RSR		From MI to OIL		From OIL to MI		From MI to EXC		From EXC to MI	
	F-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value	*F*-stat	*p*-value
Brazil	1.673	0.190	0.590	0.555	5.798	0.004	5.674	0.004	1.263	0.285	6.493	0.002
Chile	1.671	0.190	1.747	0.176	6.364	0.002	1.708	0.183	0.421	0.657	2.704	0.069
Colombia	1.118	0.344	0.752	0.523	0.853	0.467	2.484	0.063	3.311	0.022	3.775	0.012
Czech Republic	0.108	0.898	1.415	0.245	0.125	0.882	1.465	0.233	0.823	0.440	0.740	0.478
Greece	0.124	0.946	2.395	0.069	0.577	0.631	1.901	0.130	0.199	0.897	0.429	0.733
Hungary	0.893	0.411	0.304	0.738	0.464	0.629	4.099	0.018	2.065	0.129	0.233	0.792
India	1.346	0.260	0.729	0.536	1.049	0.371	1.156	0.327	5.196	0.002	2.425	0.066
Indonesia	2.593	0.019	1.876	0.085	1.383	0.222	0.697	0.652	1.213	0.300	2.951	0.008
Mexico	2.115	0.064	0.097	0.993	2.787	0.018	1.039	0.396	1.987	0.081	3.593	0.004
Philippines	1.060	0.368	0.634	0.594	1.411	0.241	13.387	0.000	0.329	0.804	2.874	0.038
Poland	0.598	0.551	0.376	0.687	4.613	0.011	3.773	0.025	2.103	0.125	3.047	0.050
Russia	0.983	0.376	1.321	0.269	6.415	0.002	4.332	0.014	2.370	0.096	1.939	0.147
South Africa	0.485	0.616	0.923	0.399	0.747	0.475	2.429	0.090	1.176	0.310	1.694	0.186
South Korea	0.258	0.855	2.386	0.069	2.806	0.040	1.512	0.211	4.124	0.007	3.201	0.024
Turkey	1.766	0.173	0.367	0.693	0.263	0.769	1.207	0.301	0.386	0.680	4.993	0.007

Meaningful linkage from crude oil prices to exchange rates is observed only for South Africa; however, in the reverse direction, which is defined as the causality from exchange rates to crude oil prices, emerging countries Brazil, Colombia, Greece, Russia, and South Korea are observed to have meaningful relations in the long run. Additionally, Poland is found to be the unique country to be evidenced to have a causal relation from real stock returns to exchange rates at 5% significant level. Whereas, in the opposite direction, 4 emerging countries indicate a statistically significant causal relationship from exchange rates to real stock returns, which are evidenced as Brazil, Indonesia, Mexico, and South Korea. These empirical results and claims are confirmed with the work of Chkili and Nguyen (2014) for the BRICS countries proving the statement that real stock returns are not affected by exchange rate changes.

Last causal relation considered between real stock returns and crude oil prices can be explained in the same framework. Linkage among emerging countries is observed with the causal direction from crude oil prices to real stock returns at the 5% significant level of Wald test result only for South Korea. Remaining emerging countries do not contribute to the results with a potential causality relation. Results are consistent with the analysis of Sarı and Soytaş (2006) conducted primarily for Turkey that oil price shocks do not explain the change in the real stock returns. On the other hand, real stock returns are evidenced to Granger cause crude oil prices at 5% significant level for three emerging countries. Causality results of India, Indonesia, and Turkey confirm the relation in the long run. This is in line with Soytas and Oran (2011) results for Turkey.

3.4.5 Generalized Impulse Response Results

In addition to causality analyses, as discussed in Lüktepohl (2005), impulse response analysis provides the general picture of the dependences of the variables to each other. Generalized impulse response function is derived for each country to observe how one variable affects others and how reaction changes over time the horizon.

Although the response of crude oil prices to real stock returns is positively plotted for all the countries conducted except for Brazil and the Philippines, causality results are estimated to be insignificant.[3] Only South Korea is found to be statistically significant by holding the causality relation. The initial response of Brazil to the same impulse impacts negatively and the response turns to be positive in period 4. Similarly, in the case of the Philippines, initial response starts in the negative region and changes its direction in period 7.

Responses of crude oil prices to exchange rates are observed to be positive assisting to explain the causal relationship between the denoted variables in the long run. South Africa is the only emerging country having an analysis of causality

[3] Impulse response graphs for emerging countries are available upon request.

relation that is evidenced to be significant. Despite its close relationship between crude oil prices and exchange rates, responses of oil prices are observed to be negative as time period progresses.

Remarkably, Wald coefficient test results state that meaningful causal relations are not estimated between manufacturing indices and real stock returns in the long run however response of real stock return to manufacturing indices changes varies from country to country. Any shock in manufacturing indices is received with a negative response for the countries Greece and the Philippines. On the other hand, responses of India, Mexico, Russia, South Africa, South Korea, and Turkey are captured to be positive to real stock returns. Plotted graphs show that responses alter their directions in the confidence intervals for the remaining countries. Initial response of Brazil changes its direction to positive in the second period. Similar frameworks are observed in Chile, Hungary, and Turkey but they change their direction of the responses in different periods respectively in period 3, period 4, and period 6. Positive impact of Colombia alters its direction two times in the second time horizon. Similarly, real stock returns responses to any unanticipated shock in any manufacturing indices of Poland start on the positive side and changes its direction two times in period 3. Responses of Indonesia begin its path in negative and immediately turn to positive in period 1. In period 5, responses alter two times and continue its path on the positive side over the time horizon.

3.4.6 Robustness Checks

Conclusions derived from the defined variables are replicated with Brent oil prices to check for robustness. Outputs are mostly consistent with previous analysis.[4] Conducting the relationship between Crude oil Brent oil prices and exchange rates, causality from Brent oil prices to exchange rates results holds for all the countries as in the test of crude oil prices. Causality from real stock returns to exchange rates keeps having a weak relationship claim with the former argument. Statement that draws a conclusion as no strong relationship between real stock returns and crude oil prices is found to be valid also for Brent oil prices. Besides, the linkage between manufacturing indices and Brent oil prices remain the same as interpreted for most of the countries, but the results of Colombia, Mexico, and South Korea indicate contradictory results. Outcomes of the causality between real stock returns and manufacturing indices do not distinguish from previous results when WTI was used.

[4] Causality results estimated with Brent Crude oil prices are available upon request.

3.5 Conclusion

This paper investigates the relationship between exchange rates, real stock returns, crude oil spot prices, and manufacturing indices as a representation of the production factor of the emerging countries. Toda Yamamoto procedure is pursued by checking the order of integration for each country, and VAR equations are conducted to establish the significant causality relations between variables showing the long-run relationship.

One of the most important relationships for emerging countries that allow revealing more insight interpretations about countries is the linkage between manufacturing indices and WTI spot oil prices. According to the findings conducted in this paper, not only from manufacturing indices to oil prices but also on the contrary direction, change in one variable affects other variables in a meaningful measure. Analysis of Ayres et al. (2013) supports the importance of the energy prices for economic growth estimated in this paper as the manufacturing indices. However, no significant relation is found for Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Philippines, South Africa, and Turkey that can be explained as the dependence of the economy to outsources, which can be expressed as the foreign investments, or not having a powerful industrial production process to be affected by the oil price changes.

As examined in the paper of Fratzscher et al. (2014), fluctuations in foreign currency put pressure on importers to adapt their budget decisions to be voluntary to produce or make investments. Exchange rates are expected to have a potential relation with the production of the emerging countries that can be associated with the non-US dollar pricing factor of production processes. Causal relationship results for manufacturing indices and exchange rates seem to support the analysis made by Fratzscher et al. (2014). In Brazil, Colombia, Indonesia, Mexico, Philippines, Poland, South Korea, and Turkey there exists a strong causal relation from exchange rates to manufacturing indices. Countries not having a linkage between variables may not have an accessible trade opportunity or may not have effective channels for importation and exportation. The inverse relationship appears to be not as significant as the former relationship for most of the countries. Since manufacturing indices and crude oil prices comprise close relationships explaining the effects of each other, exchange rate movements can be interpreted with a similar approach stated by Fratzscher et al. (2014). Wald test causality results for exchange rates and crude oil prices verify the mentioned relation by obtaining significant statistical measures for the emerging countries of Brazil, Colombia, Greece, Russia, and South Korea.

Another result found to be crucial to denote is the linkage between real stock returns and exchange rates. Brazil, Indonesia, Mexico, and South Korea present meaningful causal relation from exchange rates to real stock returns, which can be explained by holding financial development with close investor contact for the stated countries.

For none of the emerging countries there is evidence of causality running from manufacturing indices to real stock returns. Conversely, only Indonesia shows a significant link from real stock returns to manufacturing indices. Findings of manufacturing indices and real stock returns are in line with the research of Hondroyiannis and Papapetrou (2001) supporting the claim that association between the industrial production and stock market returns is not significant to be linked. Their empirical results demonstrate that economic activity do not have an influence on the stock market returns. Similarly, meaningful linkage from crude oil prices to exchange rates is observed only for South Africa; however, in the reverse direction, which is defined as the causality from exchange rates to crude oil prices, emerging countries Brazil, Colombia, Greece, Russia, and South Korea are observed to have meaningful relations in the long run.

This study extends the literature on the energy, production, stock returns, and exchange rate nexus in emerging economies. It combines previous empirical literature conducted on different parts of the nexus to improve our understanding with a more complete picture and to provide insights to policy makers in the selected emerging markets. Causal relationships provide an overall view of the dynamic links between the variables in emerging markets. In that respect, this study contains many financial and development policy implications.

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How Do Energy Market Shocks Affect Economic Activity in the US Under Changing Financial Conditions?

4

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4.1 Introduction

The evidence of energy poverty arising from the turmoil in the Middle East and global warming has demonstrated large fluctuations in the energy market vis-à-vis energy prices in the U.S economy.[1] Economic theory predicts that a shock to the energy market has negative consequences on the macroeconomy through an increase in the level of inflation and unemployment as well as deteriorating economic activities. However, following a classic paper by Hamilton (1983), a conclusion had emerged from a voluminous empirical literature, confirming the theoretical standing that oil price changes negatively affect macroeconomic aggregates (see Cuñado & Pérez de Gracia, 2015; Ferderer, 1996; Jimenez-Rodriguez & Sanchez, 2005; Lardic & Mignon, 2006; Mork, 1989; Mork et al., 1994; Papapetrou, 2001). In extending the literature, Kilian (2008) accounts for not only the effects of the oil price shock but also supply and demand shocks in the oil market using a shock to oil production as a proxy for supply shock and shipping prices as a proxy for demand shock. This is because oil prices are

[1] As argued in the literature, oil prices are a major significant determinant of energy prices, hence most studies apply only oil prices as all classifications of energy prices are strongly correlated (see Balcilar et al., 2019).

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directly driven by demand and supply shocks, which may have significant effects on the economy. To classify demand and supply shocks, one commonly associated problem is the failure to classify periods that oil prices witness small increases (i.e. below a certain threshold value) due to a fall in the quantity of crude oil produced. These small price increases are as powerful supply shocks like those caused by major disruptions like a natural or political event (see Ready, 2018).

With the 2007–2008 global financial crisis, the financial market instability has become a distinguishing feature of the world economy. This instability is more evident in the US economy with all its attendant consequences demonstrated clearly on the cost of credit and decisions taken by households, business firms, and financial institutions. These consequences have not only led to credit market disruptions but also powerfully generating uncertain shocks in the economy. Recently, a significant amount of empirical research has revealed that financial markets generate shocks that have a recessionary effect even more than shocks from the business cycle (see Alessandri & Mumtaz, 2019; Arellano et al., 2010; Balcilar & Rangan et al., 2021; Caggiano et al., 2014; Caldara et al., 2016; Stock & Watson, 2012).

Given that the question of how financial market shocks affect economic activity is central to macroeconomic analysis (see Balcilar et al., 2016; Balcilar & Rangan et al., 2021; Caldara et al., 2016), there is renewed interest from researchers and policymakers in the dynamic role of financial shocks over the oil price shocks–output growth nexus and how these shocks have reshaped macroeconomic outcomes. In this paper, we investigate the effects of economic uncertainty and energy market shocks on economic activity in the US under changing financial conditions. In other words, we examine the impact of uncertainty and energy market shocks in the US by considering whether economic activity responds differently during periods characterized by "normal" and "crisis" financial conditions. To reach this end, we extend the literature by augmenting the Kilian's (2008) framework with oil shocks identification scheme newly proposed by Ready (2018).[2] In this classification, demand shocks are identified as the index of oil-producing firm returns that are orthogonal to unexpected changes in the Chicago Board Options Exchange (CBOE) volatility index (VIX) while supply shocks are the remaining oil price variations. Risk shocks are captured by innovations to the VIX index (VIX). Therefore, our study contributes significantly to the literature by not only examining the impact of economic uncertainty and energy market shocks on the US economic activity but also decomposing oil prices shocks into oil supply, oil demand, and risk shocks under different financial conditions. Moreover, this study (to the best of our knowledge) is the first to consider the energy market shocks-economic activity nexus during different periods of financial conditions/regimes within the framework of a nonlinear dynamic model. Particularly, by using a

[2] Ready (2018) argues that there are three variables required to construct demand and supply shocks: an oil-producing firms index, a measure of oil price changes, and a proxy for changes in expected returns. For robustness, Ready proposes "the World integrated oil and gas producer index, 1-month returns on the second nearest maturity NYMEX crude–Light Sweet Oil Contract, and VIX Index".

Bayesian threshold vector autoregressive (TVAR) model with stochastic volatility component, we allow for modeling the time-varying effect of energy market shocks and uncertainties stemming directly from the volatility of the structural shocks in the economy. Furthermore, unlike the method of generalized autoregressive conditional heteroscedasticity (GARCH) which is deterministic, our approach allows time-varying stochastic volatility shocks. Hence, it provides more robust outcomes compared to the GARCH approach commonly used.

The remainder of this study is structured as follows: Sect. 4.2 which follows the introduction undertakes a review of related literature. Section 4.3 presents the data description and econometric methodology used, which is based on the Bayesian threshold VAR model with stochastic volatility. Section 4.4 analyses the empirical results while Sect. 4.5 contains concluding remarks and policy implications.

4.2 Review of Related Literature

The literature on energy market shocks seems to almost entirely support a hypothesis that shocks to energy prices hurt economic activity through increases in the level of inflation and unemployment (Cunado & Pérez de Gracia, 2005; Ferderer, 1996; Hamilton, 1983; Jimenez-Rodriguez & Sanchez, 2005; Lardic & Mignon, 2006; Lee et al., 1995; Mork, 1989; Mork et al., 1994; Papapetrou, 2001). There are some reasons why energy price shocks affect economic activity. One reason boils down to the fact that a change in energy prices has a positive contagious effect across other prices since these prices are commonly faced by households and firms. This, in turn, increases the level of inflation and unemployment and hence reduces macroeconomic performance (Davis & Haltiwanger, 2001; Edelstein & Kilian, 2009; Herrera et al., 2019; Kilian, 2008; Punzi, 2019; Ramey & Vine, 2006). Second, energy prices are usually characterized by sharp and sustained increases, which affect the investment decision of firms and households (Kilian, 2008).

While energy market shocks have negative effects on the macroeconomy, there are channels through which this occurs. One of these channels is through the negative effect of oil price shock on the level of investment (see Baumeister & Kilian, 2016; Kilian, 2014; Lee et al., 2011). A theoretical model developed based on a firm-level investment theory relates oil price uncertainty shock to a decline in current investment (see Aguerrevere, 2009; Bernanke, 1983; Triantis & Hodder, 1990). In testing this theory, Elder and Serletis (2010) show that cyclical fluctuations in the macroeconomic levels are attributed to firm-level investment decisions. Lee et al. (2011) examine the effect of oil price shocks on investment level by focusing on the direct effect of oil price volatility based on firm sales growth. The findings demonstrate that oil price shocks affect investment negatively. This finding is contrasted with those documented by Kilian (2014) and Baumeister and Kilian (2016) who both find little support for the theory that future oil price uncertainties have a significant effect on investment only in non-oil sector industries.

Another channel of oil price shock-trigger economic dislocation is through dampening consumption (see Edelstein & Kilian, 2009; Herrera et al., 2019). Edelstein and Kilian (2009) show that personal consumption expenditure is negatively affected by energy prices at both aggregate and disaggregated expenditure components. This finding is also supported by Davis and Haltiwanger (2001), Ramey and Vine (2006), and Baumeister and Kilian (2016). Despite a large number of studies supporting the negative effect of energy market shocks on economic activity through consumption, recent papers have focused on the question of asymmetry and the oil price uncertainty impact. Edelstein and Kilian (2007) provide evidence of asymmetry concerning positive and negative responses of investment to oil price shocks. Similarly, Alsalman and Karaki (2019) find evidence in support of asymmetry on how personal consumption expenditure responds differently to positive and negative shocks in the oil market.

The extent to which oil price shocks affect economic activity may depend on the effects of demand and supply shocks. This is a recurring theme in the thorough analysis by Kilian (2008, 2009), Bodenstein et al. (2012), and Lippi and Nobili (2012). These works disentangle demand and supply shocks-driven effect on real output. Furthermore, Kilian and Murphy (2014) reveal that the effect of oil price disruptions is smaller in proportion to changes in real oil price compared to speculative demand shocks. This finding is also echoed in a study by Aastveit (2014). A thorough analysis conducted by Baumeister and Hamilton (2019) seemingly demonstrates that a larger effect of oil supply could be explained by the assumption of the model used, while, on the contrary, Alsalman and Karaki (2019) show that the effect of supply on aggregate personal consumption expenditure is however limited. In addition, Herrera and Rangaraju (2020) while applying a SVAR model, examine the effects of oil price and the US gross domestic product (GDP) on oil supply disruptions. Their results establish a large response of oil prices with a larger and longer-lived contraction in the US real GDP.

Following severe impacts of financial distortions during the period of global financial crises, many studies have emerged and a great deal of these studies seeks to examine the role of financial market conditions on real output growth. For example, Chen et al. (2014) extend the framework of Kilian (2009) by focusing on the changes in financial market conditions and the macroeconomic imports of oil price shocks. The results show that financial market conditions are necessary and must be explicitly considered in the analysis of oil shocks' impacts. Also, studies like Arellano et al. (2010), Christiano et al. (2014), and Caldara et al. (2016) have documented the role of financial frictions on the uncertainty-macroeconomic nexus. Gilchrist et al. (2014) demonstrate that innovations to uncertainty significantly affect the outcomes of the macroeconomy through financial instabilities. Also, studies like Hubrich et al. (2013), Balcilar et al. (2016), and Kiley (2020) all show that the impacts of financial shocks on real output growth are characterized by asymmetries. Particularly, Hubrich et al. (2013) reveal strong negative consequences of financial shocks on real output growth during financial crises. Balcilar et al. (2016) show that the response of inflation to financial shocks during recessions is significantly high. In recently, Polat (2018) applies a structural VAR model to account for the link between oil price shocks and financial stress based on the US data. The study finds evidence in support of the oil price-financial stress sensitivity with a stronger impact in the short run. Alessandri and Mumtaz (2019) divulge in their study based on a nonlinear VAR model that shocks to uncertainty display recessionary effects on the economy irrespective of the financial market conditions. Also, the impact of uncertainty shocks on output growth is six times larger during periods of financial instability. Furthermore, Balcilar & Rangan et al. (2021) present a study on the impact of uncertainty shocks in South Africa by extending Alessandri and Mumtaz (2019) model. Their empirical results show that the output growth deterioration emanating from uncertainty shocks is larger during the normal period compared to the period of financial stress—although this impact is more persistent during periods the economy experiences financial stress.

Given the foregoing literature, our intention in this paper is to provide empirical evidence on how energy market shocks and related economic uncertainty affect real economic activity in the US during normal financial regime periods and stressful financial regime periods. Therefore, this paper is the first to consider the effect of financial market conditions/regimes in quantifying the impact of energy market shocks on real economic activity within the context of a nonlinear model by accounting for not only uncertainty shocks but also oil supply- and demand-driven shocks.

4.3 Data and Methodology

4.3.1 Data

In this study, we use a dataset based on monthly observations over the period 1987:M11 to 2021:M1. The choice of the sample period is influenced by data availability. The dataset includes three group of variables of interest namely, the energy market shocks, economic activity, and financial conditions. We measure energy market shocks based on the oil market shock identification scheme proposed by Ready (2018) which is based on the decomposition of oil price changes into oil supply, demand, and risk shocks. In doing this, we utilize the monthly price data on the index of oil-producing firms measured as monthly returns of the World Integrated Oil and Gas Producer Index (R_t^{Prod}), changes in oil prices captured by 1-month returns on the second nearest maturity NYMEX–Crude-Light Sweet Oil contract (Δp_t), and changes in the market discount rate corresponding to the CBOE Volatility Index (VIX). We proxy economic activity with the industrial production (IP) index (q_t) while the US financial conditions index (FCI) (F_t), being a transition variable in the model, is the Chicago Fed's National Financial Conditions Index. Other variables included in the model are the inflation (π_t) captured by the changes in the US consumer price index CPI, and shadow short rate

(SSR) (r_t), which measures the US interest rate,[3] oil supply shock (s_t), aggregate oil demand shock (d_t), and risk shock (ν_t). Furthermore, we retrieve all the data used in our empirical analysis from the Thomson Reuters DataStream except shadow short rate which is obtained from Krippner (2013) and Wu and Xia (2016). The time series plots of the major variables are given in Fig. 4.1.

We include the shadow short rate as measure of interest rate in the model. We need a measure of interest rate in the model to control for the effect of monetary policy. Empirical macroeconomic studies usually employ federal funds rate (Fed rate) as a measure of the interest rate or the policy rate. During the global financial crises that started in 2007–2008, central banks all over the world including the Federal Reserve Bank of the US (Fed) have reduced the policy rates to near zero levels and further introduced unconventional monetary policy measures through large scale asset purchases. In an era when nominal interest rates constrained by zero lower bound, unconventional monetary policy measures made the Fed's monetary policy not evaluable with the Fed rate. The SSR first introduced by Krippner (2013) and further extended by Wu and Xia (2016) represents the stance of monetary policy when the conventional policy rate is at the zero lower bound. The SSR is a model-based measure obtained as the shortest maturity from the estimated shadow yield curve. We use the SSR of Krippner (2013) and Wu and Xia (2016) as a measure of the interest rate. Figure 4.1 shows that SSR becomes negative during the July 2009–October 2015 and November 2020–January 2021 periods.

Most studies use crude oil price as representative of the energy market shocks. As Kilian (2009) shows including oil or energy prices directly in a model has two significant drawbacks. First, because of reverse causality from macroeconomic aggregates to oil prices cause and effect is not well defined in a model linking oil prices to macroeconomic variables. Second, the price of oil like any other commodity is determined by supply and demand forces. Therefore, oil price shocks in a dynamic model are driven by both demand and supply shocks and as supply and demand shocks have different dynamic effects, it introduces an indeterminacy. In order to solve this problem Kilian (2009) proposes a recursive identification methodology based on a Cholesky identification in structural VAR (SVAR) model. Kilian's (2009) methodology is known to give too much weight to oil-specific demand shocks, lessening the importance of supply shocks. This happens because the method suffers from identifying oil-specific demand shocks that are ultimately generated by concerns about the future supply of oil and shocks caused by changes in oil-specific aggregate demand. Ready (2018) proposed an alternative approach to overcome his drawback.

Ready (2018) uses returns on an index of oil-producing firms, a measure of oil price changes, and a proxy variable for changes in expected price of risk to construct oil demand, oil supply, and risk shocks. The risk shocks are associated

[3] Shadow short rate (SSR) simply quantifies the monetary policy stance when the nominal interest rate is near zero lower bound as shown by Krippner (2013) and Wu and Xia (2016). To resolve the zero lower bound problem, we use the SSR as the actual short term interest rate.

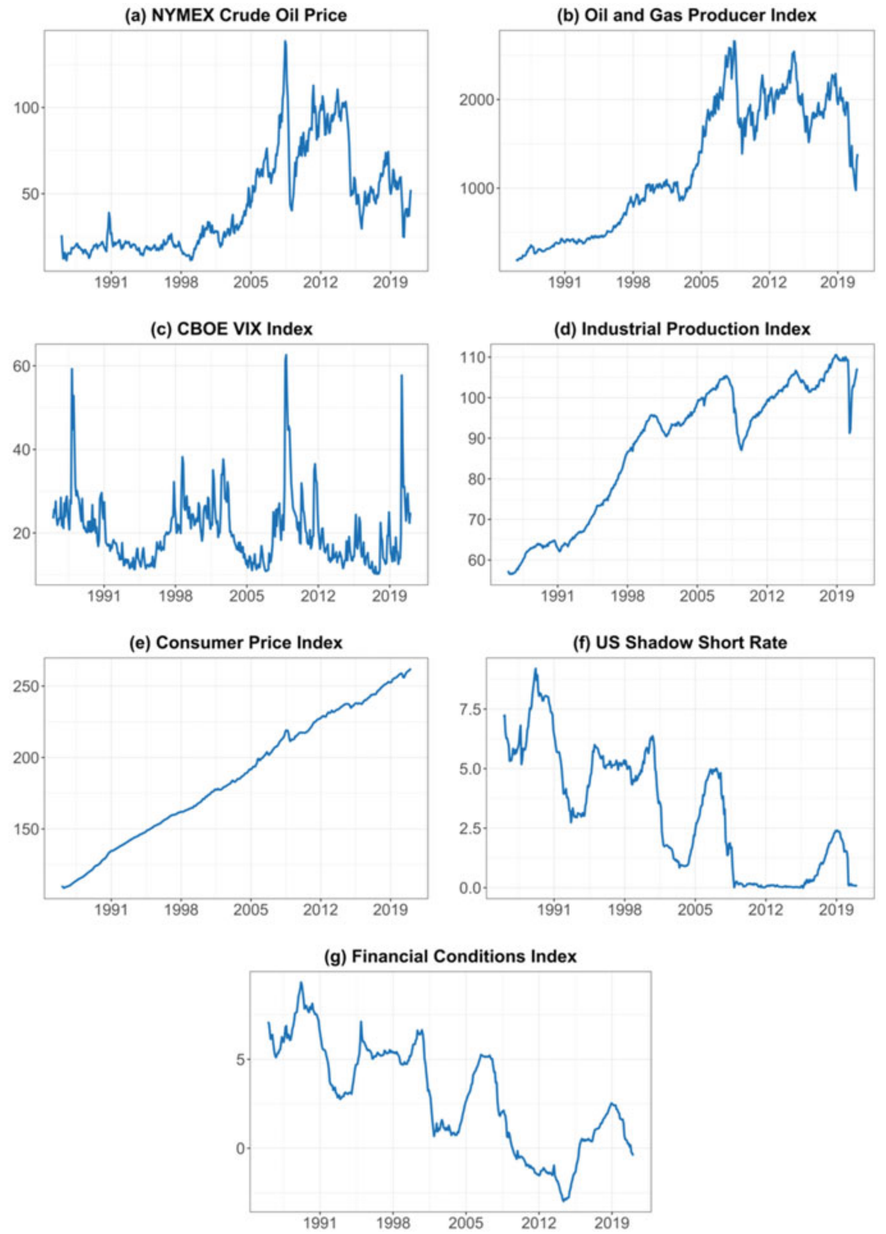

Fig. 4.1 Time series plots of the data in levels (*Note* The figure plots the levels of the CBOE Volatility Index (VIX, $\xi_{\mathrm{VIX},t}$), NYMEX Crude–Light Sweet Oil 1-month contract price, the World Integrated Oil and Gas Producer Index, industrial production (IP) index, consumer price index (CPI), interest rates (r_t) represented by the shadow short rates (SSR; Krippner, 2013; Wu & Xia, 2016), and the Chicago Fed's National Financial Conditions Index (FCI) for the period 1986:M1–2021:M1)

with expected future aggregate demand changes. Oil demand shocks are defined as the proportion of returns on a global index of oil producing firms orthogonal to unexpected changes in the logarithm of the VIX index. The VIX index is used as a proxy for aggregate changes in market discount rates which are potentially driven by varying attitudes toward risk. Thus, the unexpected portion of the VIX index is the risk shock which serves as a proxy for shocks to the price of risk associated with aggregate demand shocks. Oil supply shocks are then defined as the innovations in oil price changes orthogonal both to demand and risk shocks.

In this study risk shocks (ν_t) are obtained from residuals ($\xi_{\text{VIX},t}$) of an autoregressive moving average model fitted to the log of the VIX index with orders 1 and 1 for autoregressive and moving average orders, respectively. Then, we orthogonalize one month returns on the World Integrated Oil and Gas Producer Index (R_t^{Prod}) with respect to risk shocks ν_t to obtain oil demand shocks (d_t). Lastly, oil supply shocks (s_t) are obtained by orthogonalizing changes in the NYMEX Crude–Light Sweet Oil contract price (Δp_t) with respect to supply and risk shocks. Figure 4.2 displays oil supply, oil demand, and risk shocks obtained using this procedure. Visual pattern in Fig. 4.1 evidence the orthogonal nature of these three shocks. The Pearson correlation coefficient estimates in Table 4.1 between pairs of these three shocks are also all zero, indicating their orthogonal property. Pairwise correlation coefficient estimates between oil price change and three shocks indicate that 99.93% of the variance of changes in oil prices is accounted by these three shocks. With a correlation coefficient of 0.862, supply shocks account 74.36% of variability in oil price changes followed by demand shocks which accounts 25.22% of the variance of the oil price changes. Risk shocks have a negative correlation with oil price changes with an estimate of −0.065 and they account 0.42% of the variance of oil price changes.

Considering the descriptive statistics in Table 4.1, we observe that risk shocks have the largest variability with a standard deviation of 16.156 (giving a coefficient of variation estimate of −198.362) followed by oil price change (standard deviation of 10.724). The next two variables with highest variability are the supply and demand shocks with standard deviation estimates of 9.246 and 5.126, respectively. The CPI inflation and short shadow rate display the least volatility with respect to their observed mean with coefficient of variance estimates of 1.245 and 1.010, respectively. Comparing the volatility of oil market related shocks, we see that risk shock are 3.2 times more volatile than demand shocks and 1.7 times more volatile than supply shocks, while supply shocks are 1.8 times more volatile than demand shocks.

Table 4.1 also shows that all variables we consider in the model display positive excess kurtosis implying fat tailed distributions except short shadow rate which has an excess kurtosis of −1.042. In terms of skewness, VIX, risk shocks, demand shocks, and financial conditions index has positive skewness estimates, while oil price change, oil producer index returns, supply shocks, IP growth, CPI inflation, and SSR have negative skewness estimates. Given the estimates of excess kurtosis and skewness the Jarque–Bera normality test strongly rejects normal distribution for all variables. The Ljung-Box autocorrelation statistics also

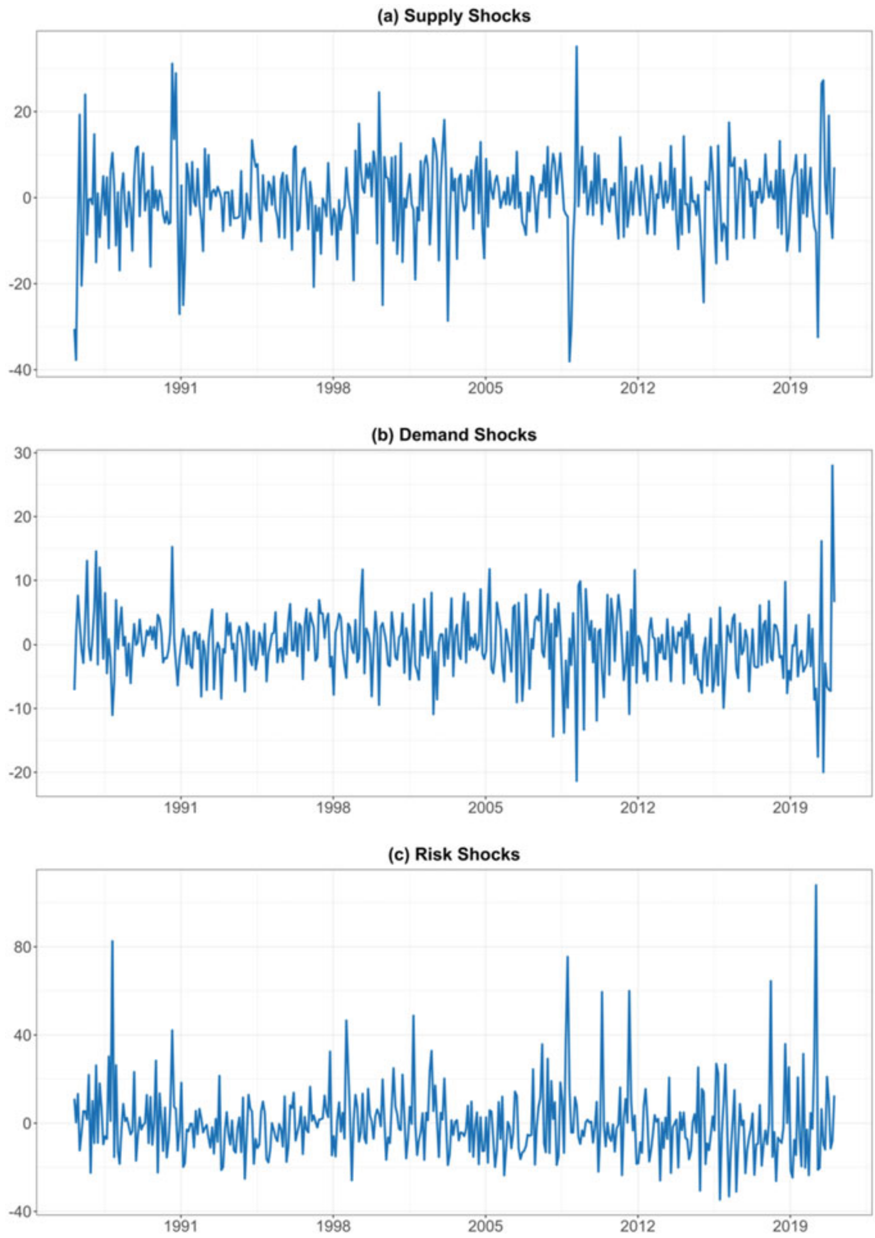

Fig. 4.2 Time series plots of oil supply, oil demand, and risk shocks (*Note* The figure presents the plots of risk shocks associated with expected shocks to future aggregate demand, oil supply shocks, and oil demand shocks calculated using the approach of Ready [2018])

Table 4.1 Descriptive statistics

	VIX ($\xi_{\mathrm{VIX},t}$)	Oil Price Change (Δp_t)	Integrated Oil and Gas Producer Index (R_t^{Prod})	Industrial Production Index (IP) (q_t)	CPI (π_t)
Mean	20.283	0.167	0.462	0.149	0.207
S.D.	8.100	10.724	5.471	1.000	0.258
Min	10.125	−49.791	−21.895	−13.562	−1.786
Max	62.639	45.502	29.403	6.049	1.367
Skewness	1.906	−0.366	−0.411	−6.070	−1.356
Kurtosis	5.778	2.611	3.305	87.440	10.576
JB	848.873***	131.177***	206.569***	137725.216***	2110.934***
Q(1)	301.190***	4.330**	0.416	33.755***	83.809***
Q(6)	975.969***	10.882*	6.059	43.094***	86.241***
ARCH(1)	161.904***	11.170***	4.093**	5.930**	67.814***
ARCH(6)	161.471***	47.772***	52.957***	18.208***	73.253***
	SSR (r_t)	FCI (F_t)	Risk Shock (ν_t)	Supply Shock (s_t)	Demand Shock (d_t)
Mean	2.930	−0.370	−0.081	0.000	0.000
S.D.	2.959	0.497	16.156	9.249	5.126
Min	−2.986	−1.066	−34.663	−38.071	−21.372
Max	9.335	2.720	107.948	35.136	28.012
Skewness	−0.080	2.656	1.877	−0.397	0.061
Kurtosis	−1.042	10.539	7.724	2.663	3.220
JB	19.101***	2465.308***	1306.343***	137.772***	185.064***
Q(1)	417.192***	392.403***	0.000	1.974	0.555
Q(6)	2390.520***	1745.122***	4.498	11.654*	10.569
ARCH(1)	408.236***	355.358***	1.042	15.441***	3.319*
ARCH(6)	405.322***	380.630***	1.553	37.190***	58.221***
Pearson correlation coefficient estimates					
	Δp_t	s_t	d_t	ν_t	
Δp_t	1.000				
s_t	0.862	1.000			

(continued)

Table 4.1 (continued)

Pearson correlation coefficient estimates					
	Δp_t	s_t	d_t	ν_t	
d_t	0.502	0.000	1.000		
ν_t	−0.065	0.000	0.000	1.000	

Note The table reports descriptive statistics for the Chicago Board of Exchange Volatility Index (VIX), 1-month returns on the second nearest maturity NYMEX Crude–Light Sweet Oil contract (Δp_t), monthly return on the World Integrated Oil and Gas Producer Index (R_t^{Prod}), growth rate of the industrial production (IP) index (q_t), inflation (π_t) based on consumer price index (CPI), interest rates (r_t) represented by shadow short rates (SSR; Wu & Xia, 2016), and the Chicago Fed's National Financial Conditions Index (FCI, F_t) in addition to descriptive statistics for risk shocks (ν_t) associated with oil demand shocks, oil supply shocks (s_t), and oil demand shocks (d_t) calculated using the approach of Ready (2018). The Pearson correlation coefficient estimates among the oil price change and orthogonal risk, supply, and demand shocks are also presented in the table. The data is at monthly frequency and covers the period 1986:M2–2021:M1 with 420 observations. In addition to mean, standard deviation (S.D.), minimum value (Min), maximum value (max), skewness, excess Kurtosis, Jarque–Bera normality test (JB), the table reports first [Q(1)] and sixth [Q(6)] order serial correlation test, and also first [ARCH(1)] and sixth [ARCH(6)] order autoregressive conditional heteroskedasticity test

indicate strong autocorrelation for majority of the series except oil producer index returns, risk shocks, and demand shocks. All series display strong autoregressive conditional heteroskedasticity (ARCH) except risk shocks. In sum, distributional characteristics of all series imply strong nonlinear effects in all series.

4.3.2 Model Specification

In this section, we present a nonlinear vector autoregression (VAR) within the framework of a threshold vector autoregressive (TVAR) model. To reach this end, we follow the oil price shocks identification scheme proposed by Ready (2018) so that structural shocks driven by oil demand, oil supply, and risk shocks can be disentangled within the framework of Alessandri and Mumtaz (2019) model. This model has time-varying, stochastic volatilities, which allow the first-moment dynamics of the system to have two separate regimes namely, normal and crisis regimes. Basically, we define the model as follows:

$$\begin{aligned} Z_t =& \left(\mu_1 + \sum_{i=1}^{p} \Phi_{1i} Z_{t-i} + \sum_{i=1}^{k} \theta_{1i} \ln h_{t-i} + \Omega_{1t}^{1/2} u_t \right) \tilde{R}_t \\ &+ \left(\mu_2 + \sum_{i=1}^{p} \Phi_{2i} Z_{t-i} + \sum_{i=1}^{k} \theta_{2i} \ln h_{t-i} + \Omega_{2t}^{1/2} u_t \right) \left(1 - \tilde{R}_t \right) \end{aligned} \quad (4.1)$$

where $Z_t = (Z_{1t}, Z_{2t}, \ldots, Z_{Nt})'$ and u_t is an *i.i.d.* innovation with an identity covariance matrix. N represents the number of variables in the model which include the risk shocks (ν_t) as represented by the innovations in the CBOE VIX index ($\xi_{\text{VIX},t}$),[4] growth rate of industrial production index (IP) (q_t), inflation based on consumer price index (CPI) (π_t), shadow short rate SSR (r_t), and financial conditions index (FCI) (F_t). Thus, Z_t is a (7×1) vector given by $Z_t = (\xi_{\text{VIX},t}, s_t, d_t, q_t, \pi_t, r_t, F_t)'$. Within the framework of this model, h_t appears to capture uncertainty, which is customarily treated as an unobservable state-variable, where uncertainty is estimated as the average volatility of the structural shocks over the period under consideration. This is perhaps different from the procedure in a two-step approach commonly applied in the literature where uncertainty series is first generated from a forecasting model and then explore in a separate regression. $\tilde{R}_t$ is included in Eq. (4.1) to allow for the possibility of two distinct financial regimes–normal financial regime periods and crisis financial regime periods. These regimes are bounded between zero and one. The introduction of $\tilde{R}_t$ also allows all economic variables in the model to shift endogenously with respect to potentially different states of financial conditions. In addition, we allow the level of financial conditions to determine regime in relation to unobserved threshold variable selected as $Z^* = F_{t-d}$, where the transition variable is the US financial conditions index, d represents the delay, and t is the time period. In this setting, $\tilde{R}_t = 1 \Leftrightarrow F_{t-d} \leq Z^*$. Here, Z^* is the unknown threshold parameter in Eq. (4.1). The parameters in the model are all allowed to adjust across regimes as found in the conventional threshold models. Furthermore, the covariance matrix of the stochastic terms $e_{it} = \Omega_{it}^{1/2} u_t$, $i = 1, 2$, is defined as $\Omega_{1\text{t}} = A_1^{-1} H_t A_1^{-1'}$ and $\Omega_{2\text{t}} = A_2^{-1} H_t A_2^{-1'}$, and the lower triangular matrices are represented by A_1 and A_2, $H_t = h_t S$, where $S = \text{diag}(s_1, s_2, \ldots s_N)$.[5] The process of volatility which represents uncertainty in our case follows an AR(1) process, defined as follows:

$$logh_t = \alpha + \varphi logh_{t-1} + \epsilon_t, \text{var}(\epsilon_t) = Q \tag{4.2}$$

where ϵ_t denotes an innovation with variance Q which is $i.i.d$. The time variation of the variance–covariance matrix of the structural shocks is driven by the assumption of a single, scalar volatility process h_t. This assumption is a reoccurring argument in Carriero et al. (2016) and the process is represented by uncertainty in our case. This intuitively implies that a shock to volatility or uncertainty $\epsilon_t > 0$ pushes h_t upward thereby resulting in an upward adjustment in the covariance matrix of the innovations u_t. This in turn deteriorates the level of accuracy upon which an agent predicts future economic variables, Z_{t+n}. The inclusion of h_t in Eq. (4.1) possibly provides a fertile ground for economic variables in the model to adjust endogenously to a new state of the economy where it is uncertain and less

[4] We use innovations in the VIX ($\xi_{\text{VIX},t}$), which is obtained as the residuals of an ARMA(1,1) model fitted to the logarithm of the VIX index, instead of the risk shocks ν_t because ν_t is a constant multiple of $\xi_{\text{VIX},t}$.

[5] In this model, to achieve identification, it is assumed that lags of endogenous variables do not affect state-variable h_t in any way. Further, the first- and second-moment shocks are orthogonal, hence; $E(u_t \epsilon_t) = 0$. For more details, see Alessandri and Mumtaz (2017, 2019).

predictable. The two regime shifts correspond to periods of calm financial condition and tense financial condition, which capture the time-varying component of the underlying transmission mechanisms. Therefore, the nonlinear VAR parameters in the two regimes are given by μ_1, $\Phi_{11}, \ldots, \Phi_{1p}$, $\theta_{11}, \ldots, \theta_{1k}$, A_1 and μ_2, $\Phi_{21}, \ldots, \Phi_{2p}$, $\theta_{21}, \ldots, \theta_{2k}$, A_2. The way and manner primitive shocks u_t and ϵ_t operate in different regimes display no evidence of placement of restrictions as shown by Alessandri and Mumtaz (2019).

In estimating our model, Alessandri and Mumtaz (2019) suggest the use of the Gibbs sampling algorithm. Given draws for the unobserved state-variable h_t, the model collapses to a conventional threshold VAR through the generalized least squares (GLS) transformation of the variables in the system, which eliminates heteroscedasticity. After this transformation, the conditional posterior distributions in the case of regime-dependent VAR parameters, the delay parameter, and the threshold are indistinguishable from those of a conventional threshold VAR as shown by Alessandri and Mumtaz (2017). Furthermore, following the description in Chen and Lee (1995), the threshold value of the VAR can be apparently drawn through a Metropolis step from the non-standard posterior of the threshold while the delay parameter's conditional posterior is simply a multinomial distribution. In essence, the conditional posterior distribution for the coefficients of the VAR model in each of the two regimes is given by $N(B_i^*, \overline{\Omega}_i \otimes (X_i^{*'} X_i^*)^{-1})$. Here, $B_i^* = (X_i^{*'} X_i^*)^{-1}\left(X_i^{*'} Y_i^*\right)$, where both Y_i^* and Y_i^* denote the transformed variables in the system apparently attached with dummy observations and $\overline{\Omega}_i = A_i^{-1} S A_i^{-1'}$. Given the VAR's residuals and the state-variable h_t, the conditional posterior distribution for A_i is standard, and as such the variance S can be drawn from inverse Gamma distribution. With all parameters given, the framework for the model apparently takes the form of a nonlinear state-space where a state-variable h_t is selected using the independence Metropolis algorithm first introduced by Jacquier et al. (1994) and recently extended to stochastic volatility models by Jacquier et al. (2002).

Having obtained all the posterior distribution of all parameters, we examine the potential impact of energy market shocks on economic activity under specific financial conditions by employing generalized impulse-response functions (GIRFs) described in Koop et al. (1996) since the coefficients estimates of the TVAR model seem to provide no much substantial economic meaning and insights (see Balcilar et al., 2018; Balcilar & Roubaud et al., 2021; Rahman & Serletis, 2010). The GIRFs are obtained using the Monte Carlo integration as described in Koop et al. (1996), which is defined as follows:

$$GIRF_t^{\tilde{R}} = E\left[Z_{t+n}|\Psi_{t,} Z_{t-1}^{\tilde{R}}, \delta\right] - E\left[Z_{t+n}|\Psi_{t,} Z_{t-1}^{\tilde{R}}, \delta\right], \quad n = 0, 1, 2, \ldots \tag{4.3}$$

where Ψ_t denotes all VAR model parameters and hyperparameters, δ denotes the shock vector, n represents the forecast horizon, $\tilde{R} = 0, 1$ represents the regimes (calm financial regime vs. tense financial regime) and $Z_{t-1}^{\tilde{R}}$ is the regime-specific history. In this setup, switching from one regime to another and vice versa is treated as endogenous. This implies that the transition from the regime of a calm (normal) financial system to a tense (crises) financial system happens freely without disruptions over the horizon in the economy depending on the sign and size of such shock.

The GIRFs in Eq. (4.3) shows in essence that the impulse responses are computed as differences between two conditional expectations, i.e. the forecast of the endogenous variables conditional on a structural shock on the one hand and the other hand the forecast of the endogenous variables conditional on a baseline where there is no evidence of a shock. As noted by Alessandri and Mumtaz (2017), while this approach for computing impulse responses adequately accounts for unexpected endogenous changes in both regimes, the conditional expectations are approximated through a VAR model stochastic simulation.

4.4 Empirical Results

4.4.1 Estimate of Economic Uncertainty

Figure 4.3 presents the US financial conditions index and the estimated economic uncertainty measured by the median log stochastic volatility over the period

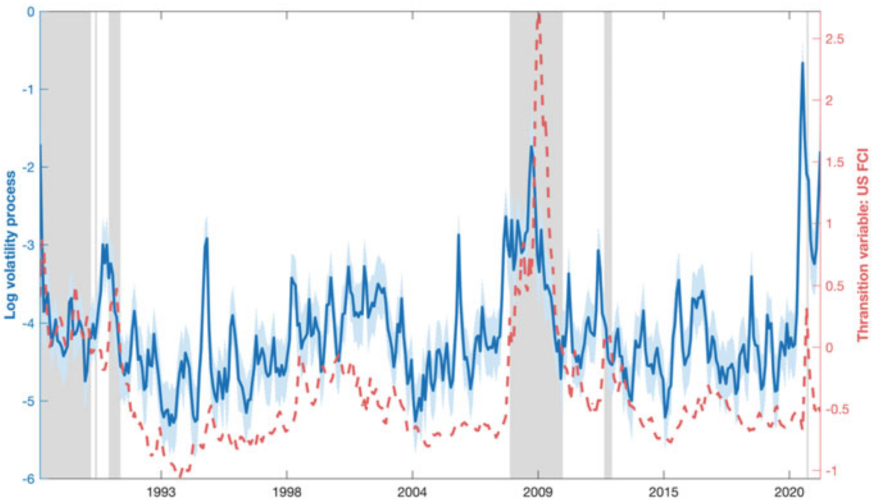

Fig. 4.3 The US financial regimes and estimated economic uncertainty (*Note* The figure displays the US financial regimes index [US FCI, right axis and dashed line in red color] and the estimated economic uncertainty measured by the median log stochastic volatility [left axis and solid line in blue color]. Gray shaded regions signify the sub-periods when the US economy is characterized by financial crises i.e. the period when the economy is said to have witnessed an index exceeding an estimated threshold of 0.0115. For the interpretation of the color references in this figure, the reader may refer to the web version of this figure available at https://dataverse.harvard.edu/dataverse/fin_regimes_oil)

1987:M11–2021:M1. The log volatility is estimated by the threshold VAR model (TVAR) explained in Sect. 4.3. The estimated threshold value is −0.0115. Periods with the values of FCI above −0.0115 are identified as the financial distress or crisis regime periods. The light blue band around the log volatility designates the 68% confidence band. The gray shaded regions mark the financial crisis regime periods identified by the TVAR model. The TVAR model is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A training sample of 20 observations is used for the initialization of priors. The lag order of the TVAR is 2 and the delay for the transition variable is 2.[6] As can be rightly seen, we identify two sub-periods when the FCI is above the estimated critical threshold value of −0.0115, suggesting that the US economy has witnessed financial crises. This is more evident during the outbreak of the sub-prime crisis in the US that culminated into the global financial crisis in 2008–2009. Moreover, the overall volatility h_t suggests that a higher level of economic uncertainty is observed in the US in the early eighties due to several factors ranging from the US stock market crash and subsequent energy crisis in 1979 as well as the Iranian revolution that led to oil price upheavals between 1980 and 1981. These factors also harm the financial markets in the US. In addition, the global financial crisis during the 2008–2009 period suggests also that the economic uncertainty is high. However, it reaches its peak in 2020 due to the outbreak of the COVID-19 pandemic. A closer examination of the relationship between financial conditions index and economic uncertainty suggests that the two variables co-move over time in the US.

4.4.2 Impact of Overall Economic Volatility Shocks on the US Economy

This section presents the responses of macroeconomic variables [(output growth proxied by monthly change in the industrial production (IP) index (q_t), CPI inflation (π_t), shadow short rate (SSR,r_t), and financial conditions index (FCI, F_t)] in the US following an exogenous increase in uncertainty, which in our case, is a one standard deviation increase in the US overall economic volatility in normal periods (first row) and crises periods (second row). As earlier defined, normal periods, which correspond to regime where the value of a threshold variable is below the estimated threshold value (i.e. −0.0115) while the crises periods correspond to regime where the value of a threshold variable exceeds the estimated threshold value, which in our case is −0.0115.

Figure 4.4 displays the impulse responses of the macroeconomic variables following a one standard deviation increase in the US volatility shocks. We find that a one standard deviation increase in volatility shocks instantly deteriorate output growth and financial conditions as explicitly shown by an immediate jump

[6] Replication codes for all results in the paper is available at Harvard Dataverse at address https://dataverse.harvard.edu/dataverse/fin_regimes_oil.

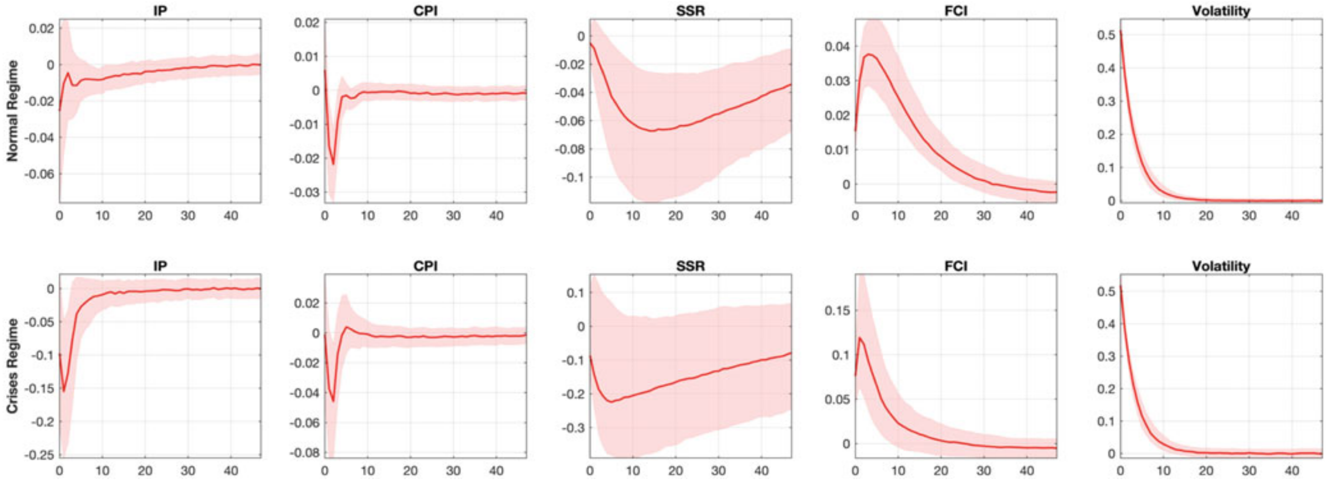

Fig. 4.4 Impact of volatility shocks on the US economy (*Note* The figure presents the median impulse responses [solid line] and 68% confidence bands [shaded regions] of the macroeconomic variables for a one standard deviation increase in the overall economic volatility in normal [first row] and crises periods [second row]. Specifically, impulse responses of the IP growth rate, CPI inflation, shadow short rate, and financial conditions index as well as the overall economic volatility are given in the figure. Horizontal axes are time in months measured from 0 [contemporaneous effect] to 47. The 2-regime TVAR model is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A training sample of 20 observations is used for the initialization of priors. The estimation period is 1987:M11–2021:M1. The lag order of the TVAR is selected as 2 by Schwarz's Bayesian information criterion and the delay for the transition variable is 2. The crises or financial distress regime corresponds to the periods where the FCI exceeds the estimated threshold of -0.0115)

in the output growth and financial conditions index. This impact is found to be larger and statistically significant during periods of financial crises compared to the normal financial regime. However, the contraction impact of volatility shocks is longer lived. Furthermore, the contraction in output growth during periods of the financial crises is quite larger than the contraction in output growth during the normal financial periods. This suggests that financial stress amplifies the impact of volatility shocks on output growth as confirmed by Arellano et al. (2010), Gilchrist et al. (2014), Caldara et al. (2016) and the recent study by Alessandri and Mumtaz (2019). On the contrary, our finding disagrees with Balcilar & Roubaud et al. (2021) who find no evidence to support that an uncertainty shock seemingly amplifies economic activity in South Africa. Our finding also reveals that an increase in volatility in periods of financial crises would pave way for financial conditions to increase further and the negative response of output growth to occur sharply but when the economy experiences normal financial regime with an increase in volatility, there will be no much room for financial conditions to increase further. This finding is consistent with Popescu and Rafael Smets (2010) who aptly suggest that an increase in uncertainty has an impact on credit spreads and risk levels, but the extent of this impact is relatively modest.

In furtherance to the above explanation, we find empirically that the impact of overall economic volatility shocks on inflation is positive (i.e. inflationary) and significant but short-lived in periods of the normal financial regime. The same cannot be said to have occurred during periods of a tense financial regime where the impact is negatively significant and more persistent, suggesting that a volatility shock is anti-inflationary during financial crises. This result perhaps finds no evidence in supporting the aggregate demand effect on prices as contradicted by the finding described in Mumtaz and Theodoridis (2015) and Redl (2018). The intuition behind this finding is traceable to the credible monetary policy stance and achievement of price stability in the US. Comparatively, even though the shape of the response of the inflation to volatility shocks in both regimes looks similar, it is clear that such response is larger during periods of financial crises as also demonstrated in Balcilar et al. (2016) where it is documented that inflation reacts significantly to financial shocks more at the time of recessions. Moreover, the shadow short rate which measures short-term interest rate, responds negatively to a one standard deviation increase in volatility shocks with evidence of a larger response during the period of financial crises. The plausible explanation to this result is that during financial crises, monetary policy authorities especially in advanced countries work counter-cyclically to drop interest rates toward zero lower bound and engage in large-scale asset purchases (LSAPs) and long-term treasury bills to stimulate output and stabilize prices as also find in Bernanke and Reinhart (2004), Borio and Disyatat (2010), Bowman et al. (2015) Lim and Mohapatra (2016), and Balcilar et al. (2020).

Furthermore, it is worthy of note that the process of stochastic volatility in the TVAR does not depend on a regime, hence the dynamic volatility in the normal and crises financial regimes are identical as shown in Fig. 4.4. Basically, an increase in volatility corresponds to a negative shock in demand, which in turn dampen prices, output growth, inflation, and interest rate in the economy through the reaction of economic agents such as households, firms, and governments as shown by Bloom (2009).

The analysis of the forecast error variance decomposition (FEVD) for the effect of volatility shocks on the US economy is displayed in Fig. 4.5. This analysis helps to assess the shares of variance in endogenous variables explained by the overall economic volatility shocks in the US business cycle over the period under consideration. As we can see from Fig. 4.4, the effect of volatility shocks is largely noticeable in the variance of the macroeconomic variables captured especially during the episodes of financial crises with much more pronouncement on the output growth and financial conditions. The contribution of the volatility shocks to the FEVD of output growth and financial conditions during the financial stress or crisis regimes accounts for more than double their variance in the normal financial regime periods. This result, therefore, confirms Alessandri and Mumtaz (2019) and demonstrate disagreement with Balcilar et al. (2020). The validation of the earlier finding of Alessandri and Mumtaz (2019) could be traceable to the debates in the literature that the way and manner volatility shocks contribute to the FEVD of output growth may differ significantly. The impact of the volatility shocks with respect to inflation and short-term interest rate captured by the shadow short rate also reveals more prominence of the impact during the episodes of financial crises.

4.4.3 Impact of Oil Supply and Oil Demand Shocks on the US Economy

Figures 4.6 and 4.7 report the impact of oil supply and oil demand shocks on the macroeconomic variables in the US. As reported in Fig. 4.6, the impact of oil supply shocks is negative on output growth, suggesting that a shock to oil supply, which is a reduction in oil supply since the supply shock is identified as a shock increasing oil price, significantly deteriorates output growth at all times. In the case of oil demand in Fig. 4.7, the impact of oil demand shocks on output growth during financial crises and normal financial periods is positive and short-lived, and afterward deteriorates as explicitly shown by the immediate sharp jump in the response of the industrial production index. Comparatively, the contraction impact of the oil supply shocks is stronger and longer lived in the normal regime compared to the contraction impact of oil demand shocks which displays an immediate positive but short-lived impact on output growth in both the normal and crisis periods. However, the impacts of the oil supply and oil demand shocks on output growth are significant and persistent after two month horizon. Therefore, our results resonate the finding documented by Kilian (2008), wherein oil supply and oil demand shocks have different effects on output growth. Similarly, Lippi and Nobili (2012), Kilian and Murphy (2014), and Herrera and Rangaraju (2020) find contraction of output growth traceable to oil supply shocks.

Furthermore, the impact of oil supply and oil demand shocks on inflation is positive and significant both in the normal and crisis financial regimes. This implies

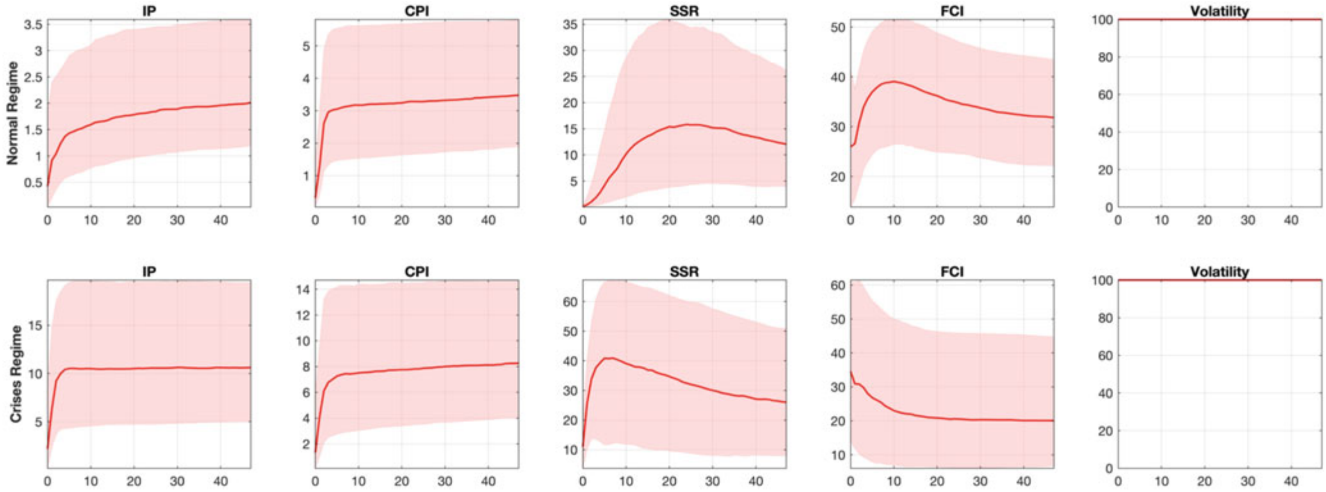

Fig. 4.5 Forecast error variance decomposition for the effect of volatility shocks on the US economy (*Note* The solid line in each panel shows the fraction of median forecast error variance explained by volatility shocks for one of the variables [first to fourth columns] and volatility shock itself [fifth column]. Shaded regions mark 68% confidence bands for median forecast error variance. Horizontal axes represent time in months measured from 0 [contemporaneous effect] to 47 months. The first row corresponds to triangular periods identified by the regime where the FCI is below the endogenously determined threshold estimate of −0.0115. The second row presents the forecast error variance decomposition for the financial distress periods where the FCI is above the threshold value. The TVAR model with two regimes is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A sample size of 20 is used for initial training to initialize priors. The data for the period 1987:M11–2021:M1 is used for the estimation. The lag order of the TVAR is 2, which is selected by Schwarz's Bayesian information criterion, and the threshold delay is also 2)

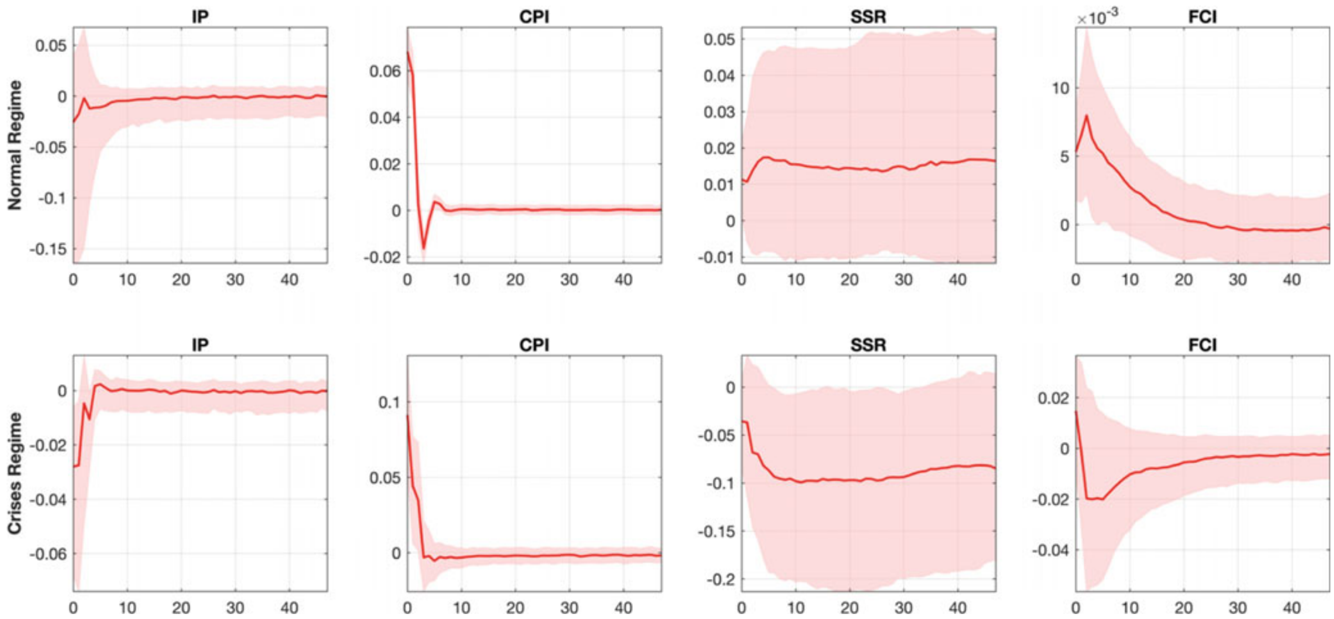

Fig. 4.6 Impact of oil supply shocks (*Note* The figure presents the median impulse responses [solid line] and 68% confidence bands [shaded regions] of the US macroeconomic variables for one standard decrease in oil supply in normal [first row] and crises periods [second row]. See note to Fig. 4.4 for further details)

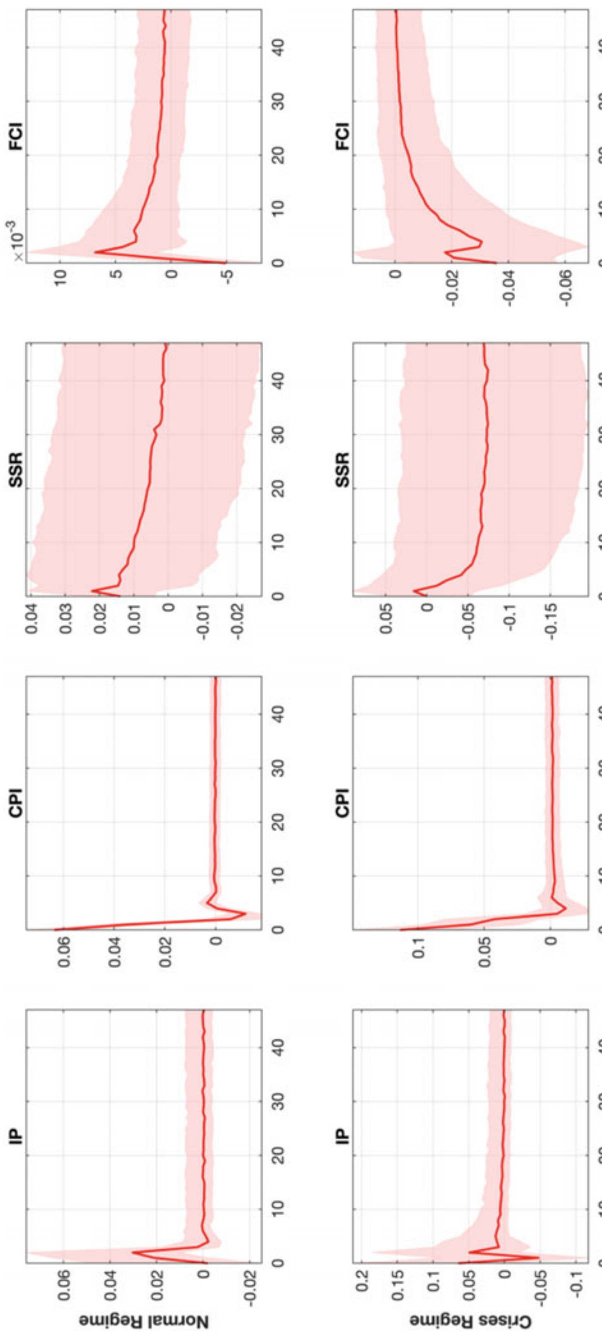

Fig. 4.7 Impact of oil demand shocks (*Note* The figure presents the median impulse responses [solid line] and 68% confidence bands [shaded regions] of the US macroeconomic variables for a one standard deviation increase in demand in normal [first row] and crises periods [second row]. See note to Fig. 4.4 for further details)

that oil supply and oil demand shocks increase prices at all times in the US with evidence of a dramatically sharp and short-lived fall in prices during the episode of a normal financial regime. Again, the impacts of both shocks are stronger during the financial crisis regime. This finding offers support to the previous studies documented by Fernández-Villaverde et al. (2015) and Mumtaz and Theodoridis (2015) that supply shocks are inflationary while this finding contradicts Leduc and Liu (2016) and Basu and Bundick (2017) who establish the opposite (i.e. supply shocks are anti-inflationary). In the case of the impact of oil supply and oil demand shocks on the short-term interest rate, we observe dramatic changes across the regimes: interest rate increases in normal periods and falls in crises periods. This finding agrees with the position of recent literature that reducing the short-term interest rate to a zero lower bound especially in an advanced economy may tend to accelerate economic recovery and stabilize prices (see Bowman et al., 2015; Lim & Mohapatra, 2016).

Given the impact of oil supply and oil demand shocks discussed in the recital, we step further, to quantitatively examine their FEVD to all the macroeconomic variables in the model as reported in Figs. 4.8 and 4.9, respectively. Specifically, the contribution of oil supply and oil demand volatility shocks to the FEVD of the macroeconomic variables in the threshold VAR appear to be more pronounced on all the variables except the short-term interest rate. For example, the fraction of output growth variance accounted for following the oil supply and oil demand volatility shocks in the episode of financial crises is roughly three times larger. Generally, the contribution of volatility shocks resulting from the oil supply and oil demand to the FEVD of all the macroeconomic variables is much more prominent during the period of financial crises except in the case of oil supply volatility shocks where its role is more prominent in the variance of inflation and financial conditions in the normal financial regime. This result is consistent with not only the finding of Caldara et al. (2016) but also Alessandri and Mumtaz (2019) who recently estimated the output growth variance to be larger in the period of crises with approximately 8% against 4% in normal periods.

4.4.4 Sign and Regime Asymmetry

Unlike linear dynamic models, various shocks likely to have asymmetric effects on variables in nonlinear dynamic models. For instance, impulses responses may vary across regimes and negative shock might have different effects from positive shocks. In order to assess sign and regime asymmetry we plot impulses responses of output and financial conditions to uncertainty, supply, and demand shocks both in normal and crises periods in Figs. 4.10–4.12. Regime asymmetry of uncertainty shocks is presented in Fig. 4.10. Response of output (IP) to uncertainty shocks look more asymmetric than response of financial conditions. The size, shape, and persistence of response of output to uncertainty shocks differ for negative shocks than positivize shocks, with positive shocks having larger and longer effects. On

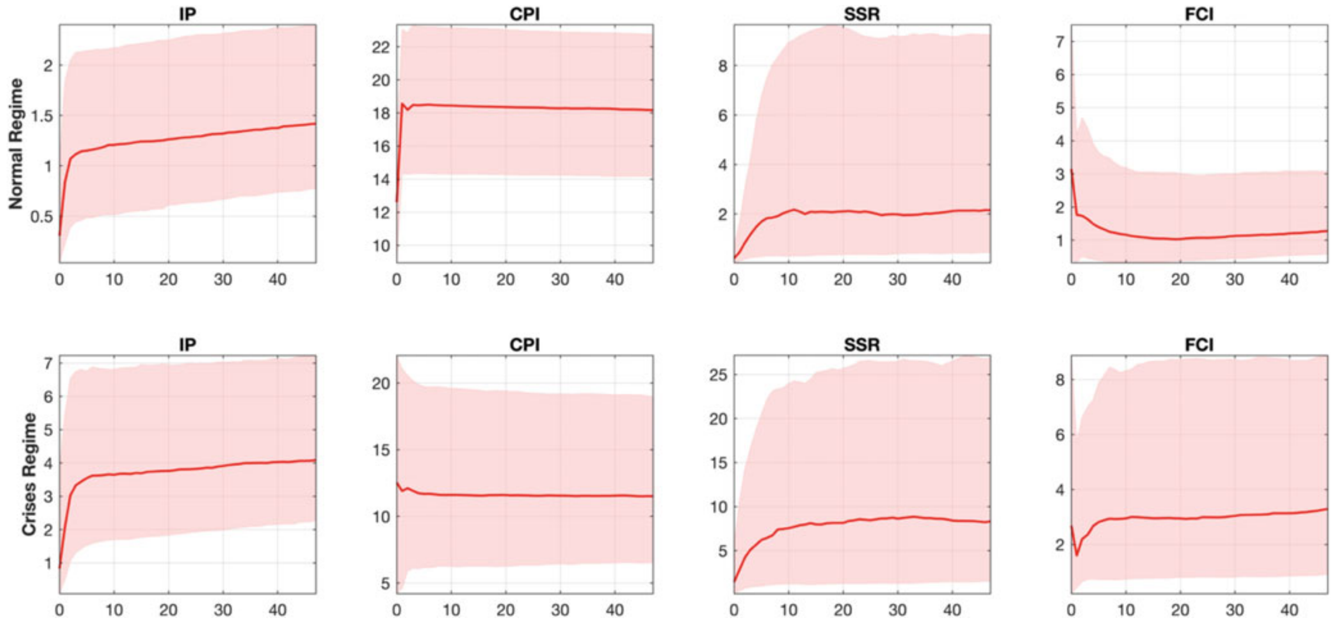

Fig. 4.8 Forecast error variance decomposition for the effect of oil supply shocks (*Note* Each panel of the figure presents the fraction of median forecast error variance explained by oil supply shocks in calm periods [first row] and financial distress periods [second row] for one of the variables of the US. Shaded regions represent 68%, confidence bands. Horizontal axes are in months from 0 to 47. See note to Fig. 4.5 for further details)

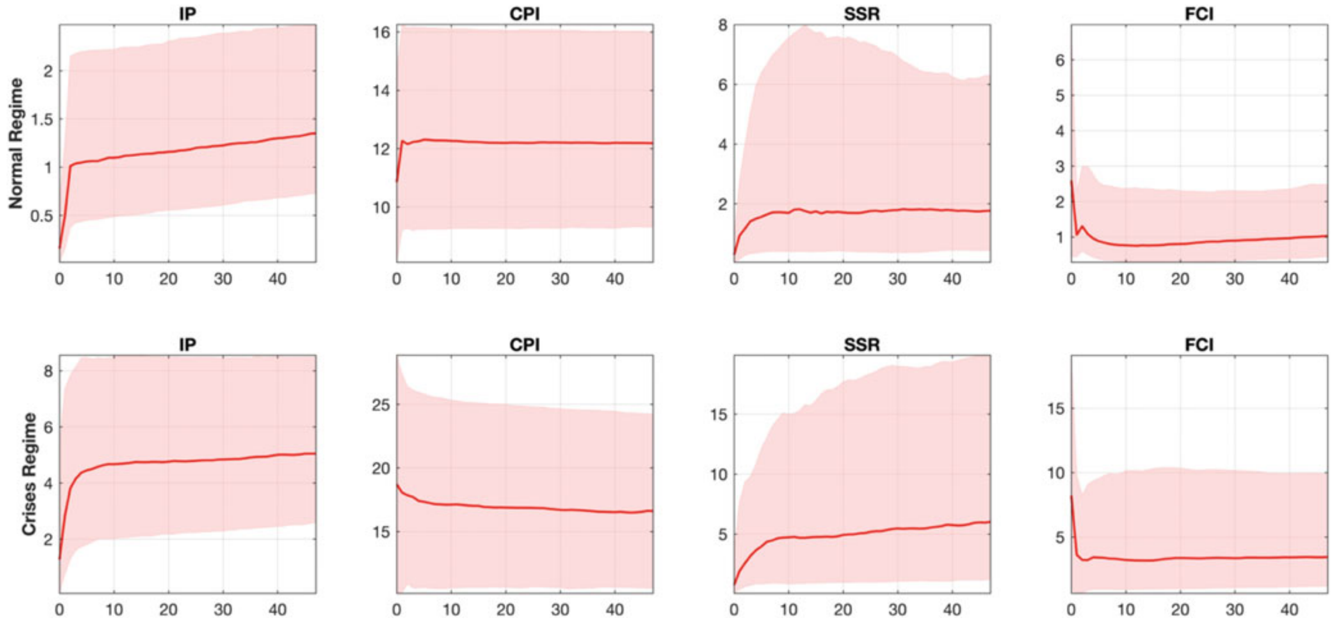

Fig. 4.9 Forecast error variance decomposition for the effect of oil demand shocks (*Note* Each panel of the figure presents the fraction of median forecast error variance explained by oil demand shock in calm periods [first row] and financial distress periods [second row] for one of the variables of the US. Shaded regions represent 68%, confidence bands. Horizontal axes are in months from 0 to 47. See note to Fig. 4.5 for further details)

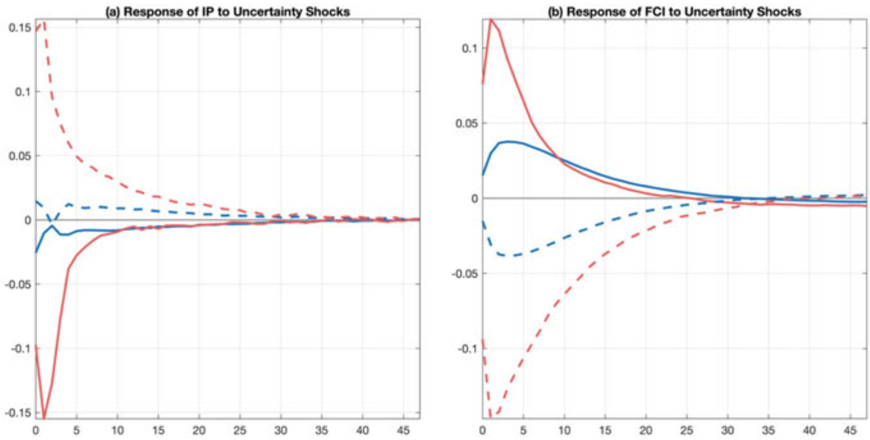

Fig. 4.10 Asymmetry in uncertainty shocks (*Note* The figure presents median impulse responses of industrial production [left panel] and financial conditions [right panel] to one standard deviation positive [solid lines] and negative [dashed lines] shock in economic uncertainty in normal [blue color] and crises periods [red color]. See note to Fig. 4.4 for further details. For the interpretation of the color references, the reader may refer to web version of this figure available at https://dataverse.harvard.edu/dataverse/fin_regimes_oil)

the other hand, financial conditions show a stronger response to reduced uncertainty than increased uncertainty. Response of both output and financial conditions is much stronger during crises periods than normal times.

Figure 4.11 compares the effect of oil supply shocks on output and financial conditions. Both output and financial conditions show a higher and longer lasting response to oil supply shocks in crises periods. We also observe a significant asymmetry in terms of response to negative shocks compared to positive shocks. In general, shocks increasing the oil supply—shocks that reduce the price of oil—have stronger effect than supply shocks that increases the oil price due to reduced oil supply shocks. An important observation is that the effect of a supply shocks in the direction of improving financial conditions—a shock that reduces the oil price—during crises periods is reversed in a month or so, implying that oil price reductions do not help much to improve financial conditions during recession or crises periods.

Lastly the response asymmetry of output and financial conditions to aggregate demand shocks is presented in Fig. 4.12. A noteworthy observation is the much stronger response of both output and financial conditions to both positive and negative shocks during crises or financial distress periods. This is particularly more pronounced in the response of financial conditions. The response of financial conditions in terms of sign of the aggregate demand shock does not show any noticeable asymmetry. On the other hand, the response of output to demand shocks shows significant shape asymmetry to the sign of the aggregate demand shocks. Moreover, the output response to negative demand shocks is much more

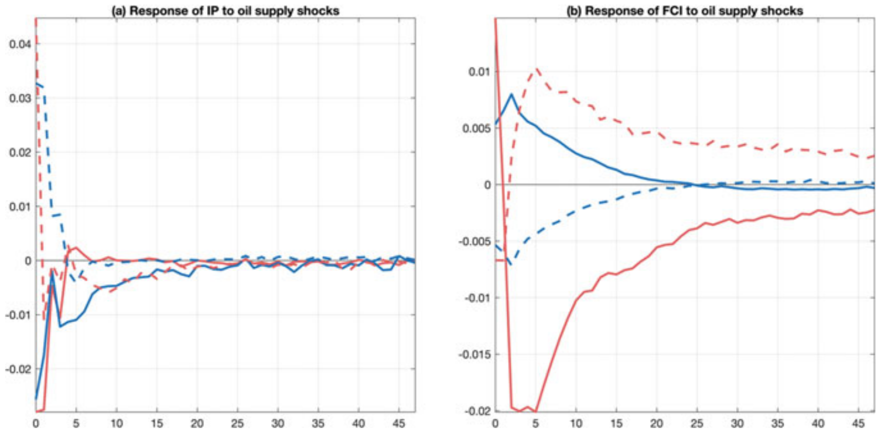

Fig. 4.11 Asymmetry in oil supply shocks (*Note* The figure presents median impulse responses of industrial production [left panel] and financial conditions [right panel] to one standard deviation positive [solid lines] and negative [dashed lines] shock in oil supply in normal [blue color] and crises periods [red color]. See note to Fig. 4.4 for further details. For the interpretation of the color references, the reader may refer to web version of this figure available at https://dataverse.harvard.edu/dataverse/fin_regimes_oil)

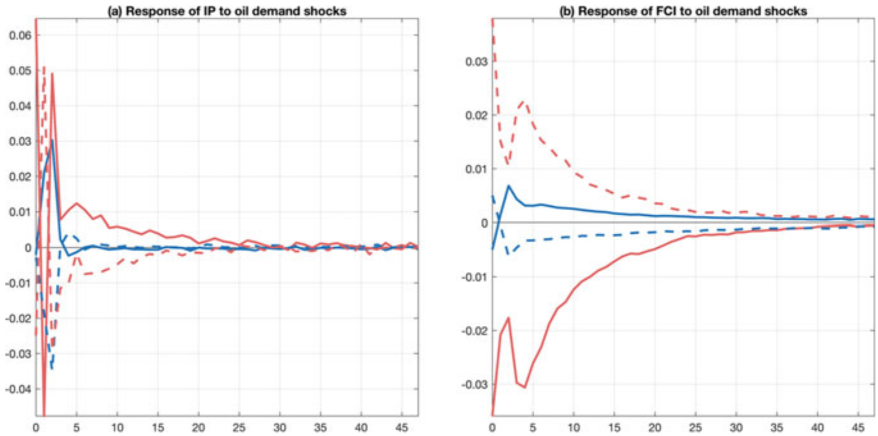

Fig. 4.12 Asymmetry in oil demand shocks (*Note* The figure presents median impulse responses of industrial production [left panel] and financial conditions [right panel] to one standard deviation positive [solid lines] and negative [dashed lines] shocks in oil demand in normal [blue color] and crises periods [red color]. See note to Fig. 4.4 for further details. For the interpretation of the color references, the reader may refer to web version of this figure available at https://dataverse.harvard.edu/dataverse/fin_regimes_oil)

persistent during crises periods. Response of output to aggregate demand shock that reduces oil prices is reversed in a month, but reduces the output growth afterwards. The strongest and longer lasting output response is observed for positive demand shocks during financial distress periods.

4.5 Conclusions

Our understanding of sources of oil price fluctuations and their effects on the US economic activity has undergone important changes since the initial work of Kilian (2009). The oil market uncertainty has been also seen to have a significant effect on economic activity. Not only uncertainty, but oil supply and oil demand shocks also have different dynamic effects on economic activity. Magnitude and shape of these effects also show changing behaviors over time.

Eventhough the interaction between energy market shocks and real output growth has been well-known established in the literature, the extent to which this interaction occurs under the changing financial conditions/regimes remain contentious and unclear. This paper, therefore, develops a new aspect of the interaction between oil price shocks and economic activity in the US under the changing financial regimes. The study further examines the effect of overall uncertainty shocks, which are largely driven by financial conditions as well as the state of the oil market. Using monthly a dataset from the US economy over the period 1986:M1–2021:M1 and a threshold VAR model with stochastic volatility component, we provide evidence that volatility shocks have a contractionary impact on output growth at all times with evidence of such impact largely pronounced during financial crises. This suggests that financial crises amplify the impact of volatility shocks on output growth. Comparatively, the impact of the overall economic volatility shocks is much larger, and longer lived compared to when volatility is disentangled to oil supply- and oil demand-driven shocks.

Our findings further indicate that the shares of the variance of macroeconomic variables explained by volatility shocks are mostly larger during financial crises. We also find that volatility shocks driven by oil supply and oil demand are inflationary while those volatility shocks driven by the overall economy are anti-inflation but their impact on inflation is short-lived in both normal and financial crises periods. Complimentary to the previous literature, we find that oil supply shocks–identified as shocks that reduce the oil supply and causing the price of oil to rise–are contractionary, while aggregate oil demand shock are expansionary. However, we find that the response of the US economy to uncertainty and oil market shocks is strongly asymmetric with larger and more persistent effect during periods of financial stress.

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Tracing the Sources of Contagion in the Oil-Finance Nexus

5

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5.1 Introduction

In this chapter, we posit a novel approach for tracing the sources of extreme oil market shocks to assess whether changing conditions in the international crude oil market can characterise changes in the relationships between oil, exchange rates, and the stock market. The origins of extreme shocks matter because there is convincing empirical evidence suggesting that different types of oil market shocks have different consequences for financial markets (see, e.g., Basher et al., 2018; Güntner, 2014; Kang et al., 2015b; Kilian & Park, 2009). A principal innovation of our procedure is a new rule-based specification to classify supply and demand shocks in the international crude oil market into relatively calm and extreme shock episodes. This specification consolidates non-linear oil price measures in the empirical oil economics literature to identify the most profound movements in oil market shocks over the preceding year (see, e.g., Hamilton, 1996) and deviations in oil market shocks which reside outside a normal range (see, e.g., Akram, 2004), given that such crude oil market episodes are considered to be the most consequential to the economy. Our procedure is also flexible to further filter extreme

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oil market shocks into positive and negative states, which facilitates the detection of asymmetric behaviours in market relationships during extreme times.

To identify the extreme shocks, the rules are applied to an off-the-shelf method to disentangle structural (i) oil supply, (ii) global aggregate demand, and (iii) oil-specific demand innovations in the international oil market. In particular, we use the structural vector autoregression (SVAR) model suggested in Kilian (2009). The identification of discrete calm and extreme conditions can be useful to understand the genesis of oil market contagion. Contagion characterises the intermittent marked increase in cross-market linkages which occur in the wake of a shock to one market, whereas interdependence refers to consistent co-movement between markets under pre- and post-shock conditions (Forbes & Rigobon, 2002). The idea behind contagion analysis is that closely linked markets are more vulnerable as negative shocks are able to propagate and proliferate more in these markets than in weakly associated markets (Kritzman et al., 2011). *Energy* contagion, which is pertinent to countries whose financial and macroeconomic fate are tied to hard commodity prices, refers to the deepening of energy-finance linkages under crisis periods in energy markets (Mahadeo et al., 2019).

We demonstrate the usefulness of our novel procedure by reappraising the energy contagion analysis of Mahadeo et al. (2019), who examine how the relationship between the international crude oil market and the exchange rate and stock market indices of the small open petroleum economy of Trinidad and Tobago change under oil market crises. Wang et al. (2013) argues that the relative influence of oil market shocks is based on the degree of importance of oil to national economy. Trinidad and Tobago provides an appropriate case for contagion analysis when the crude oil market is the source of adverse shocks: small open economies are particularly vulnerable to developments in the international oil market (Abeysinghe, 2001); and small resource-rich economies have a documented legacy of underachievement relative to both their larger counterparts and small resource-poor countries (see Auty, 2017 and references therein).

In addition to using our rule-based specification, we also extend the work of Mahadeo et al. (2019) by considering time-varying rather than static relationships in the oil-finance nexus. As contagion is a phenomenon which appears and disappears relatively quick, we are able to evaluate whether there is additional evidence of contagion that can be diluted in a static correlation analysis. Filis et al. (2011) use a dynamic conditional correlation (DCC) model and examine how the oil-stock market correlations for a selection of countries change during momentous episodes in the crude oil market collated from Kilian (2009) and Hamilton (2009a, 2009b). We estimate a DCC model not only to acquire the time-varying oil-stock market relationship like Filis et al. (2011), but by including exchange rates we are able to also obtain the oil-exchange rate and the exchange rate-stock market relationships. Such an inclusion is important because little is still known about the dynamic relationship between oil prices, exchange rates, and emerging market stock prices (Basher et al., 2012), in spite of the relevance of such variables in financial stabilisation policies. In fact, recent evidence suggests that exchange rates have been found to be the most significant macroeconomic fundamental in the transmission channel of oil prices on the stock market in emerging markets (see, e.g., Wei et al., 2019). Indeed, it is crucial to understand the dependence structure between several variables interacting simultaneously, since essential omissions provide incomplete information (Aloui & Aïssa, 2016), potentially misleading policymakers.

Hence, another original contribution of our work is that we are the first to explicitly consider how the exchange rate-stock market relationship evolves under alternative global crude oil market conditions. The trade flow-oriented model characterises the influence exchange rates can have on the stock market, while the portfolio balance approach establishes that stock prices affect exchange rates (see Chkili & Nguyen, 2014) and references therein), and the correlation between these two variables can be either positive or negative (Tang & Yao, 2018). Lin (2012) finds that exchange rate and stock price relationship increases during crisis episodes in comparison to tranquil periods, which is consistent with contagion between financial asset classes.

The economic significance of the oil-stock market relationship is well-established in the energy-finance literature given the impact oil price changes have on costing associated with consumption and investment, which are factors affecting stock returns. Furthermore, because stock prices are assumed to reflect all available market information, the oil-stock market relationship is considered to be a high-frequency data proxy for the oil-macroeconomy connection. Although there is no consensus on whether the relationship between oil price shocks and aggregate stock returns are positive or negative (Chen et al., 2014), a reasonable assumption held is that oil price shocks create uncertainty for firms which is reflected in higher stock market volatility (Degiannakis et al., 2018b). In particular, many studies find that oil price increases due to oil demand shocks are positive news for markets, while oil price increases due to oil supply shocks hurt the real and financial sectors (Cheema & Scrimgeour, 2019). In the case of oil-exporting economies, the empirical evidence suggests that the sign and magnitude of responses to oil market shocks are country-specific (Basher et al., 2018).

While the importance of the oil-exchange rate relationship is also well-known, how the different types of extreme crude oil market shocks influence this correlation remains unexplored. The oil-exchange rate linkage has implications for the international competitiveness of an oil-exporter via the wealth effects (see, inter alia, Basher et al., 2016; Bjørnland, 2009) and Dutch disease (see, inter alia, Corden, 1984, 2012) channels. Both such channels detail the mechanisms by which oil price increases lead to exchange rate appreciations for oil-exporters, making their exports (imports) more expensive (cheaper).

Comparing our results with Mahadeo et al. (2019), we are able to highlight the further insights gained from employing our innovative rule-based specification for filtering oil market shocks into discrete calm and extreme scenarios, as well as using dynamic rather than static correlations. Our results for the relationship between the crude oil market and the stock market of Trinidad and Tobago serve as an example. Static correlation analysis shows that this is a relatively weak relationship but dynamic correlations reveal that this market linkage strengthens intermittently during international financial crises events, such as the late 1990s Asian flu, the crash of the internet bubble in the early 2000s, and the 2008/2009 global financial crisis. Furthermore, our rule-based specification shows that, from disentangling oil market shocks and classifying them into calm and extreme conditions, it is demand-side rather than supply-side shocks which are more relevant to this small open energy economy.

The rest of this chapter is organised as follows: Sect. 5.2 details the methodology and data; Sect. 5.3 is devoted to the empirical applications; and conclusions are presented in Sect. 5.4.

5.2 Methods and Data

Our empirical procedures can be outlined in three parts. In the first part, we estimate global oil market shocks with a recursive SVAR model and, using our novel rule-based specification, we classify these shocks into relatively calm and extreme episodes. We also decompose crude oil prices into bull and bear market phases, similar to Mahadeo et al. (2019), to determine which extreme oil market shocks dominate periods of rising and falling oil prices. Using such a complementary tool provides a fresh way of conveying which extreme oil market shocks have tended to dominate historical booms and busts in crude oil prices.

For the second part, we estimate a DCC model to obtain three pairs of dynamic financial correlations: the oil-exchange rate, the oil-stock market, and the exchange rate-stock market relationships.

In the third part, we compare how the dynamic correlations change under these calm versus extreme and bull versus bear conditions in the crude oil market. This is accomplished by both qualitative (graphical) and quantitative (statistical) analysis of the correlations during these alternative oil market conditions.

There are a number of reasons why the contemporaneous nature of the time-varying correlations is appropriate for our analysis. First, contagion tends to appear and vanish quickly unlike interdependence and cointegrating relationships which are maintained over a much longer horizon (Reboredo et al., 2014). Second, stock prices absorb all available information relatively instantaneously including developments in international oil markets (Bjørnland, 2009), particularly in oil-dependent economies (Wang et al., 2013). Third, crude oil is mainly indexed in US dollars (Kayalar et al., 2017), implying that this commodity is likely to be affected by movements in this currency (Zhang et al., 2008). At the same time, currency markets are one of the most liquid classes of financial assets and the Trinidad and Tobago dollar is anchored to the US dollar. As such, the oil-exchange rate relationship is expected to promptly adjust to reflect the changes in this common factor.

The period under investigation is January 1996 to August 2017.[1] At each step of our methodology, we explain the data required and their respective descriptions, sources, and transformations. All data are monthly, primarily because the approach for identifying the structural oil market shocks is based on delay restrictions which are only economically plausible at this frequency (see Kilian, 2009).

5.2.1 Identifying Discrete Oil Market Conditions

The two complementary rule-based approaches to identify discrete oil market conditions are subsequently detailed.

5.2.1.1 Discrete Calm and Extreme Oil Market Shock Conditions from a Global Oil Market SVAR Model

We derive oil supply, global aggregate demand, and oil-specific demand shocks from an international oil market SVAR model postulated in Kilian (2009). This step requires monthly data from January 1994 to August 2017 on the growth rate in global oil production, which we proxy with the per cent change in world petroleum production[2]; a Kilian (2019) correction of the global index of real economic activity introduced in Kilian (2009)[3]; and the log of real oil prices calculated from the European Brent crude oil spot prices deflated using the US CPI.[4] Equation (5.1) gives the Kilian (2009) SVAR representation:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \tag{5.1}$$

[1] A switch to a dirty floating exchange rate from a fixed exchange rate regime in Trinidad and Tobago occurred in April 1993. On this grounds we start our analysis in January 1996, to allow for some time for the economy to acclimatise to the new exchange rate regime.

[2] The data are available from the US Energy Information Administration at www.eia.gov/international/data/world and accessed in November 2018.

[3] It is important to note that Hamilton (2018) points out a data transformation error in the index of nominal freight rates underlying the Kilian (2009) global real economic activity measure, where the log operator is performed twice. Kilian (2019) acknowledges this coding error and corrects the global business cycle index. We use this updated data, which are available at https://sites.google.com/site/lkilian2019/research/data-sets and accessed in November 2018.

[4] These data are available from the Federal Reserve Economic Data (FRED) at fred.stlouisfed.org/, accessed in November 2018. Like Broadstock and Filis (2014), we use the Brent benchmark instead of the West Texas Intermediate (WTI) to represent the global price of oil. The latter has been traded at a discounted price since 2011 due to the US shale boom (Kilian, 2016). In light of such developments, Brent oil has further fortified its prominence as global benchmark, while the WTI price increasingly reflects US-specific dynamics (Manescu & Van Robays, 2016). Moreover, Trinidad and Tobago produces water-borne crude which is pegged to the Brent crude oil price benchmark, trading at either a premium or a discount to this international reference price.

where ε_t is a vector of serially and mutually uncorrelated structural errors; and A_0^{-1} is recursively identified so that the reduced-form errors e_t are linear combinations of the structural errors of the form $e_t = A_0^{-1}\varepsilon_t$, as described in Eq. (5.2). Consistent with the empirical literature, we use a lag length of 24 months to remove residual autocorrelation and account for the possibility of delays in adjusting to shocks in the international oil market (see Kang et al., 2015a; Kilian & Park, 2009 and references therein).

$$e_t \equiv \begin{pmatrix} e_t^{\Delta global\ oil\ production} \\ e_t^{global\ real\ activity} \\ e_t^{real\ oil\ price} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil-specific\ demand\ shock} \end{pmatrix} \tag{5.2}$$

The identification strategy of the SVAR assumes a vertical short-run oil supply curve. This indicates that demand innovations in the oil market are contemporaneously restricted from affecting oil supply, as implied by the zeros imposed in the a_{12} and a_{13} positions of the A_0^{-1} matrix in Eq. (5.2). Kilian (2009) argues that such a specification is reasonable, as the cost associated with adjusting oil production disincentivises oil-producers to adjust to high-frequency demand shocks. Further, aggregate demand shocks are innovations to global real activity unexplained by oil supply shocks. Another zero restriction is imposed in the position of a_{23} to delay real oil prices from affecting the aggregate demand within the same month. Lastly, oil-specific demand shocks are the unexplained innovations to the real price of oil after oil supply and aggregate demand shocks have been accounted for.

Subsequently, to classify each of the structural oil market shocks into calm and extreme disturbances, we propose a new discrete rule-based specification which consolidates two veteran measures for identifying extreme oil prices: outlier oil prices outside a normal range and net oil price increases over the preceding year. Regarding the former measure, the idea that oil prices are important if found to be atypically high or low stems from the work of Akram (2004), who constructs extrema bands based on a normal range of oil prices with lower and upper bounds of USD 14 to USD 20, respectively, where values within the band are forced to zero and values outside the band are retained. Akram (2004) and Bjørnland (2009) use this oil price band to investigate the asymmetric effects extreme oil price changes have on the Norwegian exchange rate and stock market, respectively. However, this range is an artefact of oil price behaviour during the 1990s and much has changed since this period with unprecedented oil booms and busts characterising the twenty-first-century energy markets. Therefore, we augment this approach by using the standard deviation value of the three structural oil market shocks to determine the maximum and minimum values of the band.

On the other hand, the net oil price increases measure is proposed by Hamilton (1996) as an extension of the positive and negative oil price transformation suggested in Mork (1989), in an effort to preserve the empirical importance of oil prices in the US macroeconomy. The net oil price increases measure compares the current growth rate in the price of oil with the rate over the preceding year and censors the current observation if it does not exceed the values observed over that period. It is straightforward to extend this approach beyond oil prices to consider net increases from all oil market shocks. We also invert this approach to also allow for net oil market shock decreases, which are also expected to have influential implications if, for instance, a small energy-exporting economy is being considered as is the case here.

We combine these rules to filter the oil market shocks into discrete calm and extreme oil market conditions defined in Eq. (5.3):

$$shock_{i,t}^{dummy} = \begin{cases} 1, \text{ if } |\varepsilon_{i,t}| > \sigma; \\ \quad \text{if } \varepsilon_{i,t} > \max(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \ldots, \varepsilon_{i,t-12}); \\ \quad \text{if } \varepsilon_{i,t} < \min(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \ldots, \varepsilon_{i,t-12}); \\ 0, \text{ otherwise} \end{cases} \tag{5.3}$$

where i represents the oil supply, global aggregate demand, or oil-specific demand shocks derived from the oil market SVAR model. In the first rule, σ is the standard deviation of the structural shocks, which is equal to 0.850 across all structural oil market shocks. Any value outside this standard deviation band is characterised as an extreme shock. The second and third rules correspondingly detect the presence of net oil price positive increases and negative decreases over the previous 12 months. To acquire the extreme positive and negative oil market shocks, from the rule-based specification described by Eq. (5.3), involves a further filtering of all periods identified as 1 into episodes where $\varepsilon_{i,t} > 0$ and $\varepsilon_{i,t} < 0$, respectively. Considering both symmetric or asymmetric movements in the crude oil market are especially useful, given that the conclusions in applied studies tend to vary depending on which has been used (Degiannakis et al., 2018a). The months which are consistently identified as 0 by the rule-based specification in Eq. (5.3), across all three structural oil market shocks, form a relatively calm sample. Such a common calm sample is useful for identifying periods to compare how financial returns and the relationships between returns behave in calm times (0) to periods otherwise identified as extreme (1).

5.2.1.2 Classifying Bull and Bear Oil Market Phases

Much of the literature has been devoted to debating and testing the asymmetric effects of oil prices (see, inter alia, Kilian & Vigfusson, 2011a, 2011b; Cheema & Scrimgeour, 2019). A novel and interesting way to consider this issue in energy contagion analysis is with bull and bear market phases, which captures an environment when oil prices are increasing or decreasing, respectively (Mahadeo et al., 2019). Rule-based algorithms are more appropriate for in-sample identification of bear and bull market states than Markov-switching models (Kole & Dijk, 2017). We use the Pagan and Sossounov (2003) semi-parametric rule-based algorithm to identify bull and bear oil market phases, as it is one of the most popular of such approaches (Hanna, 2018). Hence, we are able to test whether an environment where oil prices are increasing influences the relationships between oil and financial variables differently when compared to a period of decreasing oil prices. An auxiliary benefit of using this procedure is that it permits us to see which types of extreme oil market shocks dominate the historical bear phases in the crude oil market over the time period under investigation.

Phases in the Pagan and Sossounov (2003) algorithm are determined based on maxima and minima in real crude oil prices with the application of various rules. A peak (trough) is based on whether the oil price in month t is above (below) other months within the interval $t - \tau_{window}$ and $t + \tau_{window}$. Furthermore, the turning points which trigger a switch between phases are restricted with minimum duration rules. For instance, a cycle cannot be less than 16 months and a phase cannot be less than 4 months. Additionally, a censor (τ_{censor}) prevents extrema values towards the end of the interval from distorting the identification of market states. Moreover, the minimum duration rule is overruled if the real oil price increase or decrease is larger than 20%, which initiates a change in the market phase. We set $\tau_{window} = 8$ months and $\tau_{censor} = 6$ months, which are feasible combinations given in Pagan and Sossounov (2003). We subsequently acquire an oil price dummy variable where bear (bull) phases are coded as 1 (0).

5.2.2 Estimating Oil-Finance Dynamic Correlations

We specify a DCC model to obtain the three pairs of time-varying correlations between oil, exchange rate, and stock returns. The DCC model uses oil market data, as well as exchange rate and stock market indicators for Trinidad and Tobago. For crude oil prices, we again use European Brent crude oil prices in constant 2010 US dollars from the preceding section. For the exchange rate indicator we use the real effective exchange rate (REER),[5] where a rise (fall) in this index implies currency appreciation (depreciation). We also use real stock prices, which are represented by the Trinidad and Tobago Stock Exchange (TTSE) Composite Stock Price Index (CSPI) adjusted for inflation, with a 2010 base year, using the RPI.[6] These three variables are first expressed as returns.[7] In order to avoid the issue of omission of relevant variables (see, e.g., Rigobon, 2019), we pre-filter the return series before approaching the DCC model. Following Mahadeo et al. (2019), we work with residuals (ε_t) from Eqs. (5.4), (5.5), and (5.6), respectively, as our adjusted returns net of market fundamental. Our specifications for these regressions are motivated by the plausible assumption that a frontier market such as Trinidad and Tobago is a price-taker with respect to crude oil market, where

[5] Data are sourced from the International Monetary Fund (IMF) International Financial Statistics and retrieved via Thomson Reuters Eikon, accessed in November 2018.

[6] These data are calculated using data from the Central Bank of Trinidad and Tobago (CBTT), and are available from www.central-bank.org.tt/statistics/data-centre and accessed in November 2018.

[7] Returns are calculated as the first difference in the natural logarithm for each series, times 100.

prices are internationally determined. Hence, the single equation regression in Eq. (5.4) is used to obtain adjusted oil returns:

$$\Delta \ln BR_t = \gamma_0 + \gamma_1 \Delta \ln BR_{t-1} + \gamma_2 USIR_{t-1} + \varepsilon_t \tag{5.4}$$

where $\Delta \ln BR_t$ are real Brent crude oil returns, γ_0 is a constant, $\Delta \ln BR_{t-1}$ is the lag of the real Brent crude oil returns, and $USIR_{t-1}$ are interest rates for the US. SBIC suggests an optimal lag length of 1 month and the LM test shows no statistically significant serial correlation in the residuals.

A VAR model, which includes exogenous regressors, is used to adjust exchange rates and stock returns for Trinidad and Tobago in order to appropriately treat with domestic endogenous and foreign exogenous variables. Therefore, we work with the residuals from Eqs. (5.5) and (5.6) to take market fundamentals into account for these two series:

$$\begin{aligned}\Delta \ln REER_t =& \gamma_{10} + \gamma_{11} \Delta \ln REER_{t-1} + \gamma_{12} \Delta \ln TTSR_{t-1} + \gamma_{13} TTIR_{t-1} \\ &+ \gamma_{14} \Delta \ln BR_{t-1} + \gamma_{15} USIR_{t-1} + \varepsilon_{1t}\end{aligned} \tag{5.5}$$

$$\begin{aligned}\Delta \ln TTSR_t =& \gamma_{20} + \gamma_{21} \Delta \ln TTSR_{t-1} + \gamma_{22} \Delta \ln REER_{t-1} + \gamma_{23} TTIR_{t-1} \\ &+ \gamma_{24} \Delta \ln BR_{t-1} + \gamma_{25} USIR_{t-1} + \varepsilon_{2t}\end{aligned} \tag{5.6}$$

where $\Delta \ln REER_t$ is the REER returns, $\Delta \ln TTSR_t$ are Trinidad and Tobago stock market returns, $TTIR_{t-1}$ is a domestic interest rate variable for Trinidad and Tobago, along with exogenous variables for oil returns ($\Delta \ln BR_{t-1}$) and US interest rates ($USIR_{t-1}$). SBIC suggests a 1 month optimal lag length for the VAR system and a LM test shows no evidence of autocorrelation in the residuals.

In line with the contagion literature, interest rates are included in Eqs. (5.4), (5.5), and (5.6) to ensure returns are net of market fundamentals (see, inter alia, Forbes & Rigobon, 2002; Fry et al., 2010). To these ends, we use US shadow short rates as a foreign interest rate measure relevant to this small-island economy. US shadow short rates adjusts the conventional policy rate to accommodate for unconventional monetary authority actions characterising much of the post 2008/2009 global financial crisis era (see Krippner, 2016). The commercial banking median basic prime lending rate is used to account for activity from the real and financial sectors, as well as the policy environment in Trinidad and Tobago. Additionally, we allow exchange rate and stock returns to enter each other's regression functions endogenously to account for possible lead-lag effects.

The DCC estimation consists of a two-step process. Step 1 involves the estimation of univariate generalised autoregressive conditional heteroskedastic (GARCH) processes for all three adjusted returns. Step 2 uses the residuals from the first stage to estimate the three pairs of conditional correlations between these three variables.

In step 1, we aim to optimally estimate each individual return series. Due to the pre-filtering of the data, the mean equation for each return series (r_t) takes the form of a constant only, as no autoregressive terms are necessary, as defined in Eq. (5.7):

$$r_t = a_0 + \epsilon_t \tag{5.7}$$

To estimate the conditional variances, we commence with the parsimonious GARCH(1,1) process given by Eq. (5.8) for each series:

$$h_t = \omega_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5.8}$$

where ω_0 is the intercept of the variance, ϵ_t are ARCH innovations with a conditional distribution that has a time-dependent variance h_t, and h_{t-1} are lags of the conditional variance. Further, ϵ_t follows the Student's t-distribution and the solver used is a non-linear optimisation with augmented Lagrange method. The GARCH(1,1) models for all returns are stable in variance as the condition $\alpha + \beta < 1$ is met (see Table 5.2). Additionally, the Ljung-Box and ARCH Lagrange multiplier (LM) tests indicate no concerns regarding autocorrelation and ARCH effects, respectively, in the residuals of the GARCH(1,1) specification for all three returns. Moreover, Engle and Ng (1993) sign bias tests provide no substantive evidence of asymmetric responses to positive and negative news in the three financial returns.[8] Hence, the parsimonious univariate GARCH(1,1) process is an optimal representation of the conditional variance for each return series.

Step 2 of the DCC model follows Engle (2002). The k x k conditional covariance matrix of returns, H_t, is decomposed as:

$$H_t = D_t P_t D_t \tag{5.9}$$

where D_t are the standard deviation diagonal matrices derived from the GARCH(1,1) models suggested in Eq. (5.8) and P_t is the correlation evolution of the (possible) time-varying correlation matrix which takes the form:

$$P_t = diag\left(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}\right) Q_t diag\left(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}\right) \tag{5.10}$$

[8] We find no statistically significant asymmetric responses to positive and negative news for exchange rates and stock returns. However, in the case of oil returns, the asymmetric volatility tests show that the individual sign bias tests convey no asymmetric volatility in the standardised residuals, but the joint effects test is statistically significant. Therefore, we consider asymmetric GARCH variants for this particular series to accommodate for this artefact. Yet, an EGARCH(1,1) for oil returns, which we find to be the most suitable alternative GARCH specification for this series, shows that the leverage effects term is not significant. Further, the differences in dynamic correlations estimated from a model where oil returns follows either a GARCH(1,1) or an EGARCH(1,1) specification is negligible. As such, we revert to the parsimonious GARCH(1,1) model for oil returns.

where Q_t defined in Eq. (5.11) is a symmetric positive definite matrix whose elements follow the GARCH(1,1) specified in Eq. (5.8):

$$Q_t = S(1 - \lambda_1 - \lambda_2) + \lambda_1 \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \right)' + \lambda_2 Q_{t-1} \tag{5.11}$$

where S is the unconditional correlations matrix, and the adjustment parameters λ_1 and λ_2 are time-invariant non-negative scalar coefficients related to the exponential smoothing process that is used to construct the dynamic conditional correlations. The constraint $\lambda_1 + \lambda_2 < 1$ indicates that the process is stationary. Finally, the time-varying correlations are estimated by:

$$\rho_{i,j,t} = q_{i,j,t} / \sqrt{q_{i,i,t} q_{j,j,t}} \tag{5.12}$$

5.2.3 Comparing Dynamic Correlations by Oil Market Conditions

Using the discrete oil market conditions identified with the rule-based specifications and the time-varying correlations obtained from the DCC model, it becomes straightforward to perform oil market contagion analysis. We offer complementary qualitative and quantitative perspectives for this purpose. The qualitative approach involves a visual analysis of the extreme oil market shocks and bear phases in the oil market superimposed onto the dynamic correlations. Such graphics are useful for contagion analysis as they can reveal the oil market conditions that tend to characterise any potential marked increases in the correlations, fully embracing the time-varying feature of the relationships, without having to average the correlation values over extreme conditions as this can dilute a crisis.

For a quantitative contagion test, we use the Welch (1947) two-sample *t*-test to compare the equality of means for the three pairs of market correlations under the relatively calm periods versus extreme structural oil market shock conditions, and bullish versus bearish oil market phases. Welch's t-test has desirable properties over the Student's *t*-test when comparing the equality of means between two samples. In particular, the former is robust to unequal variances and unequal sample sizes relative to the latter, reducing the incidence of a Type I error (Fagerland & Sandvik, 2009).

5.3 Application to the International Crude Oil Market and a Small Oil-Exporter

5.3.1 Discrete Calm and Extreme Oil Market Conditions

In Fig. 5.1, the blue dots show the extreme positive shocks and red stars show the extreme negative shocks identified by our novel rule-based specification, described in Eq. (5.3), for classifying oil market shocks into discrete calm and extreme conditions. Graphs (A), (B), and (C) illustrate the result of this filtering process applied to each of the structural oil supply, global aggregate demand, and oil-specific demand shocks, respectively, obtained from the global oil SVAR model described in Eq. (5.2). With reference to Fig. 5.1 (A) and (C), extreme oil supply and oil-specific demand shocks, respectively, are seen to occur intermittently over the entire sample. On the other hand, when compared to the latter half of the 1990s, extreme global aggregate demand shocks in Fig. 5.1 (B) appear to increase in frequency from the 2000s and especially so in the 2008/2009 Global Financial Crisis (GFC) and post-GFC eras.

Bear phases in the real Brent crude oil prices are shown by grey vertical panels in Fig. 5.1. Graph (D) conveys that the contemporary oil slumps identified coincide with international crises such as the Asian financial crisis (1997), the internet bubble burst and the 9/11 terrorist attacks (2001) in the US, and the GFC (2008). Additionally, Baumeister and Kilian (2016a, 2016b) find that the stark oil decline between June 2014 and January 2015 can be explained partly due to a negative oil-specific demand shock from a slowdown in the global economy, and positive oil supply shocks coming from the US shale boom and other major oil producers.

5.3.2 Performance of Returns Under Alternative Oil Market Conditions

Table 5.1 shows simple summary statistics which captures the behaviour of the monthly returns (adjusted for market fundamentals) under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases. We provide results for two samples: a full sample and a sample where the GFC is censored.[9] The latter sample omits the main adverse events associated with GFC crisis in international markets, which incorporates the infamous collapse of Lehman Brothers in September 2008. In a study of nine episodes of turbulence in global financial markets, ranging from 1997 to 2013, Fry-McKibbin et al. (2014) find that the 2008 Great Recession is a true global financial crisis. As this is an unprecedented event in our study, we take care to account for the potential role of the GFC and understand how sensitive our results are to the effects of this global debacle.

The *relatively calm* oil market condition, in Table 5.1, is that time period in the international oil market where no extreme structural shock is identified by our consolidated non-linear rule-based specification. Such a common calm period can be used as a basis for comparing how financial returns from the oil, exchange rates, and stock markets and the relationships between them behave during comparatively

[9] The National Bureau of Economic Research defines the timespan of the Great Recession in the US from December 2007 to June 2009. The dating is obtained from www.nber.org/cycles, and accessed in November 2018.

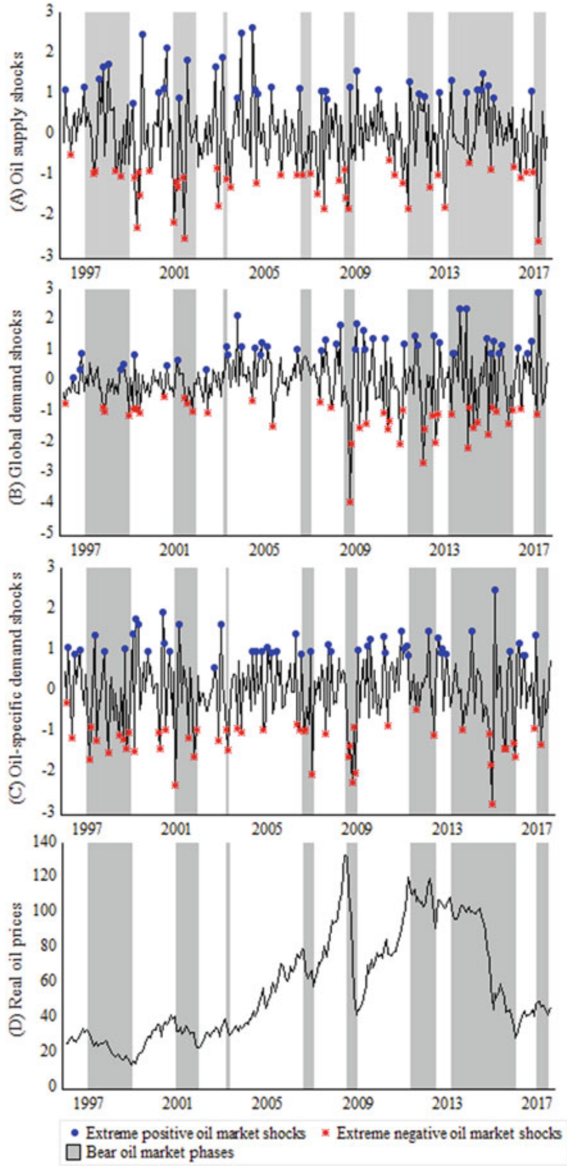


Fig. 5.1 Graphs (A), (B), and (C) shows the oil supply, global aggregate demand, and oil-specific demand shocks, respectively, from the international crude oil market which are derived from the SVAR model specified in Eq. (5.2). For each of these three graphs, the extreme positive (blue dots) and negative (red stars) conditions for a particular shock are identified by our novel rule-based specification in Eq. (5.3). To provide an illustrative perspective of our procedure for identifying discrete calm and extreme oil market conditions, consider that the extreme positive (negative) shocks in the three structural oil market shocks in graphs (A), (B), and (C) are either values greater (less) than the standard deviation band of +0.850 (−0.850) or the largest (smallest) value over the preceding 12 months. Bear oil market phases identified by the Pagan and Sossounov (2003) algorithm are shown in grey vertical panels in graphs (A) to (D). For reference, graph (D) shows real Brent crude oil prices in US dollars per barrel

calm oil market conditions versus periods when there are extreme oil supply, global aggregate demand, and oil-specific demand shocks. This relatively calm period is computed as the periods which are consistently identified as 0 in Eq. (5.3) across all three structural oil market shocks.

Table 5.1 Descriptive statistics of monthly adjusted returns under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, for the full and GFC-censored samples

Oil market condition	Obs	Adjusted returns														
		Oil					REER					Stock				
		Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max
Full sample																
Overall	260	−0.04	–	8.90	−26.54	24.39	0.01	–	0.96	−2.50	4.79	−0.05	–	2.82	−13.29	11.29
Structural shocks																
Relatively calm	85	0.60	–	4.88	−9.79	13.06	0.06	–	0.83	−2.22	2.61	0.07	–	2.76	−5.60	10.51
Extreme oil supply	83	−1.40	1.578	10.44	−26.54	19.18	0.17	−0.754	1.05	−2.50	4.79	−0.35	0.951	2.90	−13.29	7.72
Positive	39	−1.91	1.536	9.63	−26.54	15.74	0.26	−1.089	1.04	−1.47	4.79	−0.23	0.519	3.07	−13.29	6.12
Negative	44	−0.94	0.869	11.20	−24.89	19.18	0.08	−0.134	1.05	−2.50	2.52	−0.46	1.011	2.78	−5.28	7.72
Extreme global demand	88	−0.37	0.797	10.20	−26.54	24.39	−0.02	0.526	1.15	−2.50	4.79	−0.32	0.890	2.95	−13.29	7.72
Positive	46	1.70	−0.736	9.47	−24.55	19.18	−0.02	0.428	1.02	−2.17	2.80	0.02	0.092	2.75	−9.88	7.72
Negative	42	−2.63	1.875*	10.61	−26.54	24.39	−0.03	0.392	1.30	−2.50	4.79	−0.69	1.329	3.15	−13.29	4.69
Extreme oil demand	96	−1.47	1.484	12.62	−26.54	24.39	0.06	−0.067	1.01	−2.16	4.79	−0.40	1.039	3.26	−13.29	11.29
Positive	48	9.25	−8.621***	5.91	−1.03	24.39	−0.28**	2.123**	0.88	−2.16	1.33	−0.50	0.114	2.51	−9.88	5.75
Negative	48	−12.19***	10.903***	7.25	−26.54	1.11	0.41***	−2.024**	1.02	−1.37	4.79	−0.30	0.567	3.90	−13.29	11.29

(continued)

Table 5.1 (continued)

Oil market condition	Obs	Adjusted returns														
		Oil					REER					Stock				
		Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max
Oil market phases																
Bull	155	3.00***	–	7.34	−21.41	23.22	−0.11	–	0.94	−2.50	2.80	−0.09	–	2.49	−5.60	10.51
Bear	105	−4.52***	7.031***	9.14	−26.54	24.39	0.19**	−2.475**	0.96	−2.22	4.79	0.02	−0.290	3.27	−13.29	11.29
GFC-censored sample																
Overall	241	0.09	–	8.52	−24.89	24.39	−0.01	–	0.90	−2.50	2.80	0.05	–	2.68	−9.88	11.29
Structural shocks																
Relatively calm	81	0.47	–	4.94	−9.79	13.06	0.06	–	0.82	−2.22	2.61	0.18	–	2.75	−5.60	10.51
Extreme oil supply	77	−0.74	0.941	10.18	−24.89	19.18	0.06	0.020	0.88	−2.50	1.81	−0.12	0.724	2.37	−5.03	7.72
Positive	37	−1.25	1.089	8.98	−22.71	15.74	0.11	−0.289	0.71	−1.47	1.43	0.17	0.018	2.23	−4.51	6.12
Negative	40	−0.27	0.397	11.27	−24.89	19.18	0.02	0.242	1.02	−2.50	1.81	−0.38	1.126	2.48	−5.03	7.72
Extreme global demand	78	−0.51	0.810	9.53	−24.55	24.39	−0.08	0.976	1.04	−2.50	2.80	−0.23	0.945	2.68	−9.88	7.72
Positive	40	0.54	−0.046	9.37	−24.55	19.18	0.00	0.365	0.98	−2.17	2.80	−0.02	0.356	2.86	−9.88	7.72
Negative	38	−1.62	1.254	9.69	−22.71	24.39	−0.17	1.140	1.10	−2.50	2.43	−0.45	1.243	2.50	−8.33	4.69
Extreme oil demand	89	−0.75	0.879	12.00	−24.89	24.39	0.01	0.431	0.86	−2.16	2.80	−0.21	0.874	2.98	−9.88	11.29
Positive	46	9.05***	−8.312***	5.93	−1.03	24.39	−0.25*	1.930*	0.89	−2.16	1.33	−0.58	1.578	2.50	−9.88	5.75
Negative	43	−11.23***	9.945***	6.82	−24.89	1.11	0.28**	−1.470	0.75	−1.37	2.80	0.19	−0.021	3.40	−8.33	11.29

(continued)

Table 5.1 (continued)

Oil market condition	Obs	Adjusted returns														
		Oil					REER					Stock				
		Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max
Oil market phases																
Bull	142	2.76***	–	7.42	−21.41	23.22	−0.11	–	0.93	−2.50	2.80	−0.09	–	2.45	−5.60	10.51
Bear	99	−3.74***	6.107***	8.58	−24.89	24.39	0.13	−2.030**	0.83	−2.22	2.61	0.26	−0.958	2.98	−9.88	11.29

Notes ***, **, and * associated with the mean returns indicate where such mean returns are significantly different from zero at the 1, 5, and 10% levels, respectively, evaluated against the Student's t distribution. Test statistics and accompanying significance levels, where appropriate, from two-sample Welch's *t*-tests for Testing the Equality of Means (TEM) with unequal variances and sample sizes, for the average adjusted returns during calm v. extreme and bullish v. bearish oil market conditions, are noted as ***, **, and * for the 1, 5, and 10% levels of significance, respectively. The Welch's *t*-tests are evaluated against the Student's *t* distribution using Welch's degrees of freedom (see Welch, 1947). The descriptive statistics for the adjusted returns are based on the residuals of the regressions specified in Eqs. (5.4), (5.5), and (5.6), and can be interpreted as percentages. The relatively calm period is that time period which is consistently identified as 0 in Eq. (5.3) across all three structural oil market shocks and is the base sample in the tests for equality of the means. As there are months which can be characterised by more than one type of extreme oil market shock, the summation of the subsample observations for the alternative oil market conditions does not equate to the overall observation. Other abbreviations are obs. for observations, SD for standard deviation, Min for minimum, and Max for maximum

For the oil market, the highest (lowest) returns are observed under periods of extreme positive (negative) oil-specific demand shocks. Moreover, the highest market volatility occurs during extreme positive oil-specific demand shocks, while the lowest volatility is, as we might expect, in the calm oil market condition. Furthermore, we find that the mean oil returns are highly significantly different from zero under extreme positive and negative oil demand shocks, and under bearish and bullish oil market phases. Also, Welch's *t*-test for the equality of means shows that average oil returns under extreme negative global aggregate demand shocks, and positive and negative oil demand shocks are significantly different from the relatively calm period, and average returns in the bearish oil market phases are statistically different to bullish oil market conditions.

Turning to the returns of the exchange rate index for Trinidad and Tobago, there are two particularly surprising observations for this small oil-exporter. First, the mean REER appreciations (depreciations) of the greatest magnitude are exhibited under extreme negative (positive) oil demand shocks and the value is significantly different from zero. Secondly, REER depreciations are noted under bullish oil market phases and appreciations occur in bearish conditions, where the latter results are significantly different from zero. Both statistical artefacts contradict the Dutch disease and positive wealth effects propositions of real exchange rate appreciations in the presence of increasing oil prices, at least from a contemporaneous perspective. Moreover, the Welch's *t*-test for the equality of means conveys that there are statistically significant differences in the mean adjusted REER returns under extreme positive and negative oil demand shocks compared to relative calm periods, as well as bearish compared to bullish oil market conditions.

Considering stock returns behaviour in this frontier market, the mean returns are highest in the relatively calm period, while the lowest negative returns are in periods of extreme negative global demand shocks. However, these results are sensitive to the GFC. Once this period is censored, the highest returns are instead observed during bearish oil market phases, whereas the largest negative returns are observed under extreme positive oil demand shocks. Once again, these are results contradicting the expectations for a small intensive oil-exporter. Market volatility is highest in both the full and GFC-censored samples during conditions of extreme negative oil demand shocks. However, none of the mean adjusted stock returns are found to be statistically different from zero and the Welch's *t*-test for the equality of means shows that there are no statistically significant differences in the mean stock returns in calm versus extreme oil market conditions, or in bullish versus bearish oil market phases.

5.3.3 Oil-Finance Time-Varying Correlations Under Alternative Oil Market Conditions

The DCC parameters are shown in Table 5.2; while the evolution of the dynamic oil-REER, oil-stock market, and REER-stock market relationships over the sample period of January 1996 to August 2017 are graphed as the solid black lines in

Table 5.2 Crude oil, exchange rate, and stock market returns DCC(1,1) parameter estimates

	Coefficient	Std. error	t value	Prob.
a_0^{Oil}	0.1212	0.4896	0.2475	0.8045
ω_0^{Oil}	8.0666	7.9570	1.0138	0.3107
α_1^{Oil}	0.1832	0.0677	2.7082	0.0068
β_1^{Oil}	0.7246	0.1295	5.5944	0.0000
a_0^{REER}	−0.0187	0.0526	−0.3558	0.7220
ω_0^{REER}	0.0252	0.0194	1.3017	0.1930
α_1^{REER}	0.0874	0.0433	2.0172	0.0437
β_1^{REER}	0.8873	0.0497	17.8693	0.0000
a_0^{Stock}	−0.0832	0.1184	−0.7028	0.4822
ω_0^{Stock}	0.0000	0.0000	0.0044	0.9965
α_1^{Stock}	0.0467	0.0249	1.8752	0.0608
β_1^{Stock}	0.9523	0.0206	46.1906	0.0000
λ_1	0.0261	0.0154	1.6936	0.0903
λ_2	0.8980	0.0466	19.2627	0.0000

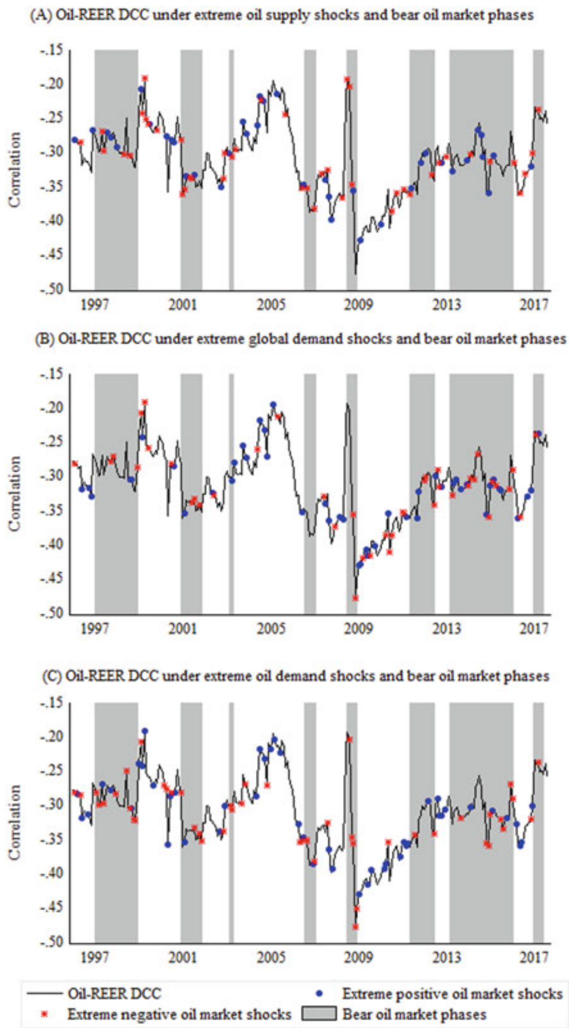
Notes The coefficients are from the mean and variance Eqs. (5.7) and (5.8), respectively, from the first step of the DCC model. The univariate GARCH models are stable as the condition $\alpha_1 + \beta_1 < 1$ is met. λ_1 and λ_2 are the scalars which take the same value for all the time series from the second step of the DCC model. The process is stationary as the condition $\lambda_1 + \lambda_2 < 1$ is satisfied

Figs. 5.2, 5.3, and 5.4, respectively.[10] These time-varying correlations are illustrated under extreme positive (blue dots) and negative (red stars) oil supply, global aggregate demand, and oil-specific demand shocks. Bearish oil market phases are superimposed, as grey vertical bars, for reference. All three pairs of dynamic correlations exhibit contagion effects during the GFC, as all relationships deepen in this period. The GFC is hallmarked by extreme negative global aggregate demand and oil-specific demand shocks, an artefact that is well-documented in the literature (see, e.g., Baumeister & Kilian, 2016a; Kim, 2018), and is a bear phase in the crude oil market.

Figures 5.2 and 5.4, which, respectively, show the time-varying correlations between oil and the REER of Trinidad and Tobago, as well as Trinidad and Tobago's REER and real stock returns, convey that these are both negative and relatively moderate associations across the two-decade sample period. Apart from the marked stronger negative relationship in these two DCCs during the GFC period, there is also additional observational evidence for oil market contagion as these relationships also deepen during the 2014/2015 oil market crash. In the 2014/2015 oil price plummet, the increase in the magnitude of the relationship for these pair

[10] The DCC model coefficients and dynamic correlations are estimated with the rmgarch package in R (see Ghalanos, 2019).

Fig. 5.2 Oil-REER DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between the real Brent crude oil returns and the REER returns of Trinidad and Tobago estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graphs (A), (B), and (C) show oil-REER DCC under periods of extreme oil supply, global aggregate demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (5.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (5.2). In graphs (A), (B), and (C) blue stars show the extreme positive episodes derived from each particular shock, while red stars show the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm



of DCCs can be seen to coincide with multiple shocks in the international crude oil market, i.e. extreme positive oil supply, negative global aggregate demand shocks, and negative oil-specific demand shocks, which are expected to adversely impact an oil-exporter. For Trinidad and Tobago, these relationships during crisis imply that as oil prices fell due to such disturbances in the crude oil market, the currency appreciated and appreciations are associated with negative stock returns.

Figure 5.3 shows that the oil-stock market association is typically weak with distinct punctuated phases where the correlation strengthens. The negative oil-stock market relationship prior to 1999 is reversed thereafter to a positive association, which is in line with the inferences of Miller and Ratti (2009) who examine a selection of OECD countries. They argue that the positive association

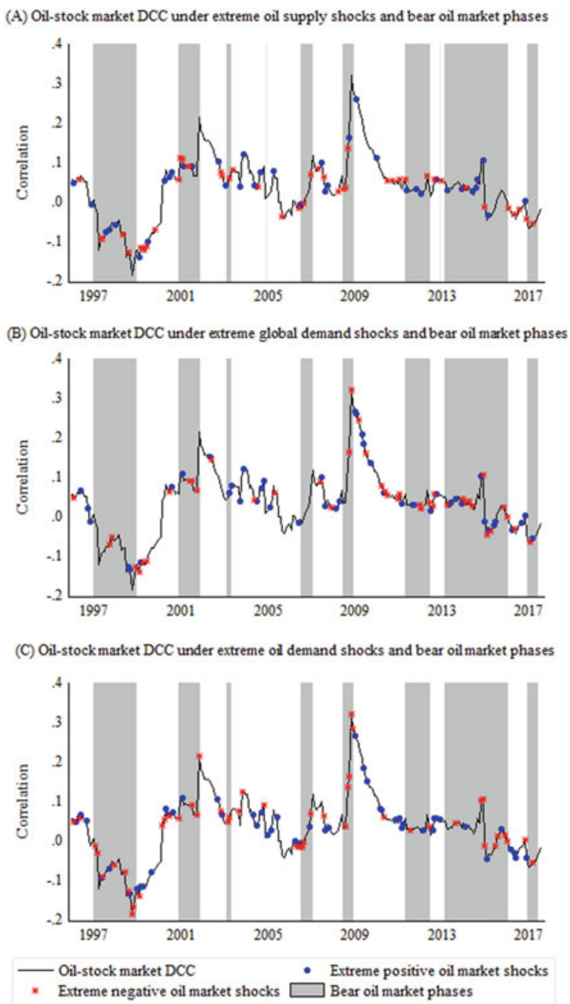


Fig. 5.3 Oil-stock market DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between the real Brent crude oil returns and the real composite stock returns of the Trinidad and Tobago Stock Exchange estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graphs (A), (B), and (C) show oil-stock market DCC under periods of extreme oil supply, global aggregate demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (5.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (5.2). In graphs (A), (B), and (C) blue stars show the extreme positive episodes derived from each particular shock, while red stars show the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm

is likely due to the existence of stock and oil market bubbles which have characterised twenty-first century financial markets. Indeed, we observe that there are three distinct periods where the time-varying oil-stock market correlations increase (in absolute value) over the sample period, which coincide with the Asian financial crisis, and the dot-com and sub-prime bubbles and crashes. Extreme negative oil demand shocks occur in all three periods of international financial turmoil, where we also see that the oil-stock market relationship strengthens.

Table 5.3 conveys the average financial correlations during relatively calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, in the full sample and a GFC-censored sample for robustness analysis. The relatively calm period in the crude oil market forms the sample which is used as basis for comparing each of the extreme structural shock periods. First,

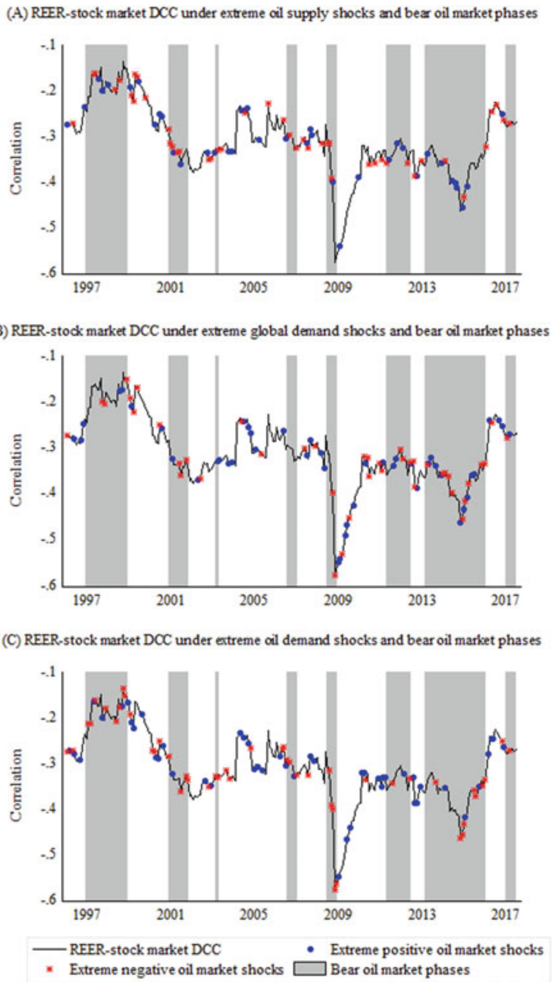


Fig. 5.4 REER-stock market DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between Trinidad and Tobago's REER index returns and the real composite stock returns of the Trinidad and Tobago Stock Exchange estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graphs (A), (B), and (C) show REER-stock market DCC under periods of extreme oil supply, global aggregate demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (5.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (5.2). In graphs (A), (B), and (C) blue stars imply the extreme positive episodes derived from each particular shock, while red stars imply the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm

Table 5.3 Dynamic conditional correlations under relatively calm and extreme oil market shocks, as well as under bull and bear oil market phases, in both the full and GFC-censored samples

Sample	Oil Market Condition	Obs	Dynamic conditional correlations								
			Oil-REER			Oil-stock			REER-stock		
			Mean	SD	TEM	Mean	SD	TEM	Mean	SD	TEM
Full	Overall	260	−0.31	0.05	–	0.03	0.08	–	−0.31	0.08	–
	Structural shocks										
	Relatively calm	85	−0.30	0.05	–	0.03	0.07	–	−0.31	0.07	–
	Extreme oil supply	83	−0.31	0.05	0.138	0.03	0.07	0.444	−0.30	0.08	−0.375
	Positive	39	−0.30	0.05	−0.020	0.04	0.07	−0.716	−0.31	0.08	0.457
	Negative	44	−0.31	0.05	0.234	0.01	0.07	1.350	−0.29	0.07	−1.087
	Extreme global demand	88	−0.32	0.06	2.047**	0.04	0.09	−0.850	−0.33	0.09	1.887*
	Positive	46	−0.32	0.05	1.876*	0.04	0.08	−0.937	−0.33	0.08	1.554
	Negative	42	−0.32	0.06	1.394	0.04	0.09	−0.412	−0.33	0.09	1.409
	Extreme oil demand	96	−0.32	0.05	1.444	0.03	0.09	0.018	−0.31	0.08	−0.012
	Positive	48	−0.31	0.06	1.030	0.03	0.08	0.210	−0.30	0.08	−0.257
	Negative	48	−0.32	0.05	1.313	0.03	0.10	−0.151	−0.31	0.09	0.203
	Oil market phases										
	Bull	155	−0.31	0.06	–	0.05	0.07	–	−0.31	0.07	–
	Bear	105	−0.31	0.04	0.140	0.01	0.08	3.502***	−0.31	0.09	0.406

(continued)

Table 5.3 (continued)

Sample	Oil Market Condition	Obs	Dynamic conditional correlations								
			Oil-REER			Oil-stock			REER-stock		
			Mean	SD	TEM	Mean	SD	TEM	Mean	SD	TEM
GFC-censored	Overall	241	−0.31	0.05	–	0.02	0.07	–	−0.30	0.07	–
	Structural shocks										
	Relatively calm	81	−0.30	0.05	–	0.03	0.07	–	−0.31	0.06	–
	Extreme oil supply	77	−0.30	0.05	0.277	0.02	0.07	0.807	−0.30	0.07	−0.743
	Positive	37	−0.30	0.05	−0.337	0.03	0.06	−0.258	−0.31	0.07	0.029
	Negative	40	−0.31	0.05	0.777	0.01	0.07	1.438	−0.29	0.07	−1.199
	Extreme global demand	78	−0.31	0.05	0.981	0.02	0.07	0.363	−0.31	0.07	0.793
	Positive	40	−0.31	0.04	0.859	0.03	0.07	0.107	−0.31	0.07	0.491
	Negative	38	−0.31	0.05	0.728	0.02	0.07	0.483	−0.32	0.07	0.776
	Extreme oil demand	89	−0.31	0.05	1.044	0.02	0.07	0.984	−0.30	0.07	−1.034
	Positive	46	−0.31	0.05	0.759	0.02	0.07	0.710	−0.30	0.06	−0.872
	Negative	43	−0.31	0.04	0.997	0.01	0.08	0.895	−0.30	0.08	−0.810
	Oil market phases										
	Bull	142	−0.30	0.05	–	0.04	0.07	–	−0.30	0.06	–
	Bear	99	−0.31	0.03	0.972	0.00	0.07	4.122***	−0.31	0.08	0.626

Notes Significant results from two-sample Welch's *t*-tests for Testing the Equality of Means (TEM) with unequal variances and sample sizes, for the monthly dynamic conditional correlations between calm v. extreme and bullish v. bearish oil market conditions, are noted as ***, **, and * for the 1, 5, and 10% levels of significance, respectively. The Welch's *t*-tests are evaluated against the Student's *t* distribution using Welch's degrees of freedom (see Welch, 1947). The abbreviations obs. is observations and SD is standard deviation. The relatively calm period is that time period where there are no atypical structural shocks in the international crude oil market as identified by discrete rule-based specification. This calm period is used as the comparison sample for testing the equality of means in the dynamic correlations. As there are months which can be characterised by more than one type of extreme oil market shock, the summation of the subsample observations for the alternative oil market conditions does not equate to the overall observation we observe a moderate and inverse oil-REER interdependence. This relationship suggests that oil price increases (decreases) are associated with exchange rate depreciations (appreciations), and is inconsistent with the Dutch disease conjecture and the positive wealth effect spillovers expected for an oil-exporter which implies the opposite outcome. As the US dollar is a vehicle currency and the energy sector in Trinidad and Tobago has traditionally been the main source of foreign currency for authorised dealers, the Central Bank of Trinidad and Tobago supports the local foreign exchange market with the sale of foreign reserves to authorised dealers. Such interventions maintain exchange rate stability when there is a shortfall in the inflows of foreign exchange or when the demand for foreign exchange is robust (CBTT FSR, 2019; CBTT MPR, 2019). In the full sample, we find statistically significant results that the oil-REER relationship marginally deepens during extreme global aggregate demand shocks when compared to the relatively calm period. This conforms with the findings of Atems et al. (2015) for the responses of exchange rate indexes to this demand-side shock. However, such evidence of oil market contagion in the oil-REER correlation is primarily associated with the GFC period.

Looking at the oil-stock market correlation in Table 5.3, this association is generally weak. Therefore, we find no evidence of either interdependence or contagion. We also observe that oil-stock returns correlation in bullish oil market phases becomes weaker under bearish conditions. These results can be linked to the relatively underdeveloped stock market of Trinidad and Tobago, and the fact that there is only one energy security listed on the stock exchange, which subdues the spillover effects from the international oil market. The minimal effect of the oil market on the stock market is consistent with evidence from other oil-exporting markets in the Global South such as the Gulf Cooperation Council countries (Al Janabi et al., 2010), Mexico (Basher et al., 2018), and Trinidad and Tobago (Mahadeo et al., 2019). Yet, this can be contrasted against the experience of other oil-exporters in the Global North such as Canada (Kang & Ratti, 2013), Norway (Bjørnland, 2009; Park & Ratti, 2008), and Russia (Ji et al., 2018), where a positive oil-stock market relationship is exhibited.

Turning to the REER-stock market association, the inverse interdependence suggests that an exchange rate appreciation (depreciation) is correlated with a downturn (uptick) in stock returns. This result is in contradiction with those of Delgado et al. (2018) for Mexico, also an emerging market and oil-exporter, who find that an appreciation of the exchange rate is related to an improvement in the stock market performance. It is plausible to pin down the differences in the findings to differences in exchange rate regimes between Mexico (free float) and Trinidad and Tobago (managed float). Moreover, there is also indication of the exchange rate and stock market dependence strengthening since the GFC, which is consistent with Caporale et al. (2014). It can be useful to consider this result in tandem with the aforementioned oil-REER relationship. Although the oil-stock returns relationship is weak, it is possible for crude oil to have indirect spillovers for the stock market performance through the exchange rate channel. We also find that the REER-stock returns relationship becomes somewhat stronger under the global aggregate demand shocks, but this result is sensitive to the omission of the GFC period. This is in line with Wei et al. (2019), who find that compared to other macroeconomic fundamentals, the exchange rate market plays the most significant role in transmitting the impacts of oil prices on the emerging Chinese stock market, especially in the GFC aftermath.

Altogether, Table 5.3 shows that there are some statistically significant results for differences in correlations derived from the equality of means tests. However, the average correlations generally do not convey a *marked* increase in cross-market linkages, to satisfy the operational definition of contagion used in this chapter, under extreme or bearish oil market conditions as these variations tend to be relatively small. Such findings, which are consistent with Mahadeo et al. (2019), might lead to an inference of no oil market contagion risk for this frontier market. Yet, the qualitative (graphical) analyses of Figs. 5.2, 5.3, and 5.4 underscore the potential consequences of overlooking the time-varying nature of correlation as we observe that the contagion phenomenon has a tendency to intermittently appear and vanish under certain extreme conditions.

In addition, correlations during the calm period versus periods of extreme oil supply shocks across all three dynamic relationships appear less sensitive when compared to correlations under demand-side shocks. This resonates with Atems et al. (2015) and Basher et al. (2016) who find limited evidence that oil supply shocks affect exchange rates, and with Filis et al. (2011) who find that supply-side oil price shocks do not influence the oil-stock market relationship. In fact, many studies are alluding to the notion that the role of oil supply shocks on the real and financial sectors is no longer consequential (see Broadstock & Filis, 2014 and references therein).

Our results also align with Antonakakis et al. (2017), who find that global aggregate demand innovations are the main source of shocks to stock market during economic turbulence, as well as Aloui and Aïssa (2016), who find that the dependence structure between oil, exchange rates, and stock returns are sensitive over the 2007–2009 GFC and Great Recession period. Indeed, we also find that shocks associated with the GFC appear to deepen cross-market linkages between these three returns more than oil market shocks outside of this period in Trinidad and Tobago.

5.4 Conclusion

We have put forward an original approach to trace the sources of contagion in three pairs of financial market relationships: the crude oil-exchange rate returns, crude oil-stock returns, and exchange rate-stock returns correlations. This is done by combining non-linear oil price measures to design a rule-based specification in order to filter supply and demand-side shocks originating from the international crude oil market into discrete typical and extreme episodes. Such identified episodes are then used in order to compare the time-varying financial market relationships (estimated with a dynamic conditional correlations model) under calm versus extreme, as well as bullish versus bearish, oil market conditions. Our methodology is particularly appropriate for financial stability analysis in economies vulnerable to disturbances from the international crude oil market.

Our empirical analysis is carried out on the Brent crude oil market and financial market indicators of the small petroleum intensive economy of Trinidad and Tobago. The results show a moderate interdependence in the oil-exchange rate and exchange rate-stock market linkages, as well as a generally weak oil-stock market relationship. We also find evidence of contagion in all three market relationships, the most pronounced occurring during the 2008/2009 global financial crisis. Additionally, the 2014/2015 oil crash is a source of contagion in the relationship between the exchange rate and stock market, whereas intermittent increases in correlations are observed in the oil-stock market relationship in the Asian financial crisis in the late 1990s and again in the dot-com crash in the early 2000s. By using a dynamic framework, as opposed to a static correlation approach, we have been able to detect further episodes of contagion during international financial crises. In general, we find that contagion in the nexus between the crude oil market and this frontier market tends to be driven more by extreme negative demand-side shocks in the international oil market rather than supply-side shocks.

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Volatility Contagion Between Crude Oil and G7 Stock Markets in the Light of Trade Wars and COVID-19: A TVP-VAR Extended Joint Connectedness Approach

6

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6.1 Introduction

The link between crude oil and financial markets is a well-researched topic in the relevant empirical literature. Over the years, researchers have focused on various aspects of this interaction considering the importance and the repercussions of developments in crude oil for financial markets. What is more, the examination of this interaction has become more crucial in the light of the increased financialisation of the market for crude oil which was initially reflected upon huge investment activity in commodity exchanges around 2004 (see Silvennoinen & Thorp, 2013).

Some of the most popular strands of the relevant literature include studies that investigate (i) whether stock market responses to developments in the market for crude oil depend on the nature of the economy under examination and more particularly, on whether the stock market response involves either a net oil exporting or a net oil importing country and (ii) whether stock market responses are triggered by either demand-side or supply-side developments in the market for crude oil. As far as the first strand is concerned, the basic argument is that net oil exporting countries enjoy increased revenue when oil prices rise—a fact that, mitigates the negative impact from higher oil prices on cost push inflation and could even be suggestive of a positive reaction from the stock market. Relevant studies in this line

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of research which considers the distinction between net oil importing and net oil exporting countries include, among others, Filis et al. (2011), Filis and Chatziantoniou (2014), Lee et al. (2017), Degiannakis and Filis (2018), Chkir et al. (2020), Jiang and Yoon (2020).

In turn, the basic argument of the second popular strand in existing relevant literature is that a shock in the price of oil may differ in its outcome depending on whether the shock originates in either the demand or the supply side. For example, it may be the case that hikes in the price of oil due to disruptions in oil production (i.e., supply-side shock) may indeed act as the bellwether for bad news in global financial markets. Nonetheless, an increase in the price of oil that occurs due to higher demand for oil in a period of rapid economic growth might actually be perceived as good news. For a more thorough analysis with regard to this strand, the reader is directed to the seminal work by Hamilton (2009a, 2009b) and Kilian (2009), but also to authors such as Antonakakis et al. (2014, 2017), Kang et al. (2017), as well as, Kwon (2020).

Following these two important strands that we mention above, another related strand in existing literature is the distinction between the effects of oil shocks on stock market volatility and the effects on stock market returns. The crucial point here is to highlight the inverse relation; that is, to note that when an oil price shock increases stock market volatility then it should have a diminishing impact on stock market returns and vice versa. Authors who have considered the difference between stock market returns and volatility include, among others, Degiannakis et al. (2014), Kang et al. (2015), and Antonakakis et al. (2017).

Nonetheless, there are factors that affect the volatility in the market for crude oil as well. In this regard, aspects that affect the latter have also been investigated in existing literature. Relevant studies include, among others, Efimova and Serletis (2014), Phan et al. (2016), Chatziantoniou et al. (2019). Among other factors, the impact from uncertainty in international financial markets has been stressed by authors such as Chatziantoniou et al. (2021a). Besides, the correlation between volatility in the market for oil and volatility in various stock markets has been investigated in the work by Boldanov et al. (2016) who document that the nature of the correlation is rather dynamic and depends on the ensuing events of each period. It follows that, there clearly is a link between the market for oil and the stock market and thus, the investigation of the potential for volatility contagion becomes crucial in order to better understand developments in these markets.

With these in mind, the objective of this study is to shed additional light upon the linkages between volatility in the market for crude oil and stock market volatility in G7 countries. Recent developments such as the decision by the US to revise tariffs—which affected bilateral trade with countries such as Canada or China, or the outbreak of the COVID-19 pandemic—which resulted in a remarkable drop in global demand (i.e., including demand for oil), make this topic particularly timely for the countries under investigation which are substantially exposed to international trade.

In this study we are particularly interested in the investigation of possible channels of volatility transmission across the markets of interest. To this end, we employ connectedness as the means to accomplish our research objective. More particularly, we focus on the time-varying parameter vector autoregressive (TVP-VAR) extended joint connectedness method (see Balcilar et al., 2021) which constitutes an augmented version of the standard TVP-VAR connectedness method (see Antonakakis et al., 2020; Chatziantoniou & Gabauer, 2021; Gabauer & Gupta, 2018). At this point, it should be noted that standard connectedness methods originate in the work of Diebold and Yılmaz (2009, 2012, 2014). In these studies, dynamic connectedness is obtained through the popular rolling-windows approach. Nonetheless, the development of the TVP-VAR presents certain advantages over the standard rolling-windows approach. More particularly, the TVP-VAR method ensures that (i) there is no arbitrary choice either of the forecast horizon or of the window-length, (ii) there is no distortion due to outlier values, and (iii) no observations are being left out (i.e., as is inevitably the case when we use rolling windows). In turn, the Balcilar et al. (2021) TVP-VAR extended joint connectedness approach further refines existing TVP-VAR methods by considering an alternative way of normalising connectedness measures (see also the description of the method in Sect. 6.3 of the present study). It would also be instructive at this point to note that in the interests of robustness, in this study we present results both for the standard TVP-VAR method (i.e., which predicates upon the initial normalisation approach by Diebold and Yılmaz (2014) and from the TVP-VAR extended joint connectedness approach which predicates on the normalisation approach by Lastrapes and Wiesen (2021). In this respect, the contribution of this study rests mainly with its empirical application. That is, we consider two closely related connectedness methods to the effect that we obtain robust results and be more confident in our conclusions about the underlying relations.

Turning to the main findings of the study, first and foremost, we should highlight that we obtain qualitatively similar results from both methods (i.e., considering the direction of connectedness and the distinction of the variables of the network between net transmitters and net recipients) with only minor differences associated with the magnitude of connectedness. This fact adds to the robustness of our approach and lends additional gravity to the relevant arguments. Findings further suggest that volatility connectedness in this network fluctuates around relatively high levels over time—which is indicative of the increased contagion potential across the variables of the network. What is more, total dynamic connectedness appears to be highly responsive to major events that affected international financial markets throughout the sample period. In addition, we find that some of the variables of the network may shift from dominant net transmitters to major net recipients of uncertainty shocks within the network. The market for crude oil is a striking example of this finding, considering that it assumes an important role as a net transmitter of spillover shocks around the time of the oil price collapse in 2014 while, it clearly receives shocks, on net terms, from capital markets between 2018 and 2019. In line with the discussion above, the period around 2019 was a very turbulent period for international financial markets reflecting to a great extent development on international trade. This is also a period when the French stock market switches into a net transmitting position. The stock markets of Germany, Italy, and Japan remain for the most part on the receiving end of spillover uncertainty shocks while the UK stock market assumes a considerable net transmitting role around the time of the EU referendum. The US stock market is a principal net transmitter of uncertainty in the system almost throughout the entire period of study until early 2018. From then on—during a period that was severely marked by trade rearrangements and the outbreak of the COVID pandemic, the Canadian stock market becomes the dominant net transmitter in this network; a fact that further highlights the importance of this major export economy for volatility in international financial markets.

Investigating the linkages and the contagion potential across a network of variables helps attain a better understanding of the relevant transmission channels through which uncertainty propagates a system and fuels reactions. By examining dynamic connectedness within this specific network, policymakers may draw additional information which could prove particularly useful when considering, for example, the negative effects of turbulent crude oil markets. Furthermore, in view of the recent financialisation of commodity markets, the investigation of the mechanisms through which volatility affects performance could further facilitate portfolio managers to develop appropriate diversification strategies especially during times of financial turmoil. In this regard, dynamic connectedness measures constitute a crucial tool for the arsenal of decision making.

The remainder of this chapter is organised as follows. In Sect. 6.2, we set out the data and the market proxies that we have included in the study. Then, in Sect. 6.3 we describe the employed methods highlighting the main difference between the standard TVP-VAR approach and the TVP-VAR approach which predicates upon the extended joint connectedness approach. In turn, we present the findings of the study and proceed with a relevant discussion of the main findings in Sect. 6.4. Finally, Sect. 6.5 concludes the chapter.

6.2 Data

This study employs a daily dataset retrieved from yahoo finance comprising crude oil and stock market indices of all G7 countries. In more details, we cover the American S&P 500, Canadian S&P/TSX, British FTSE 100, German DAX 30, French CAC 40, Italian FTSE MIB, and Japanese Nikkei 225 index. Our data spans over the period from 2nd January 2007 to 30th April 2021. We calculate daily annualised daily per cent standard deviation in the spirit of Parkinson (1980):

$$\sigma_{it} = 100 \cdot \sqrt{365 \cdot 0.361\left(\frac{x_{it}^{max} - x_{it}^{min}}{x_{it}^{min}}\right)} \tag{6.1}$$

where x_{it}^{max} and x_{it}^{min} are the highest and lowest price of variable i on day t, respectively. The transformed series are shown in Fig. 6.1.

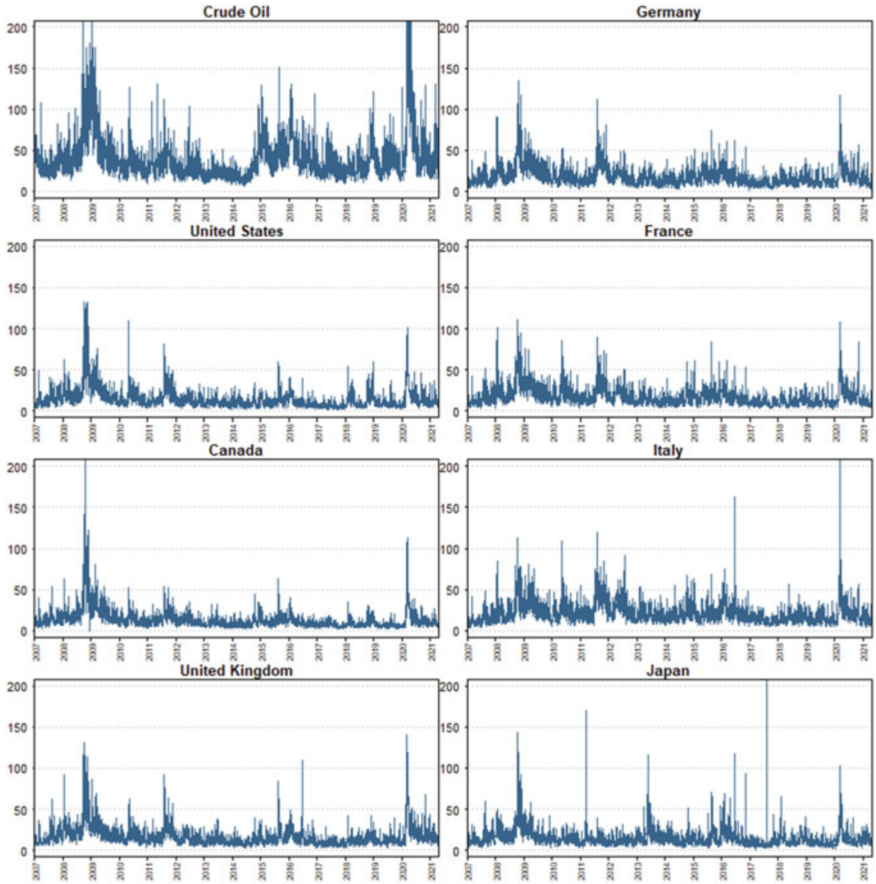

Fig. 6.1 Crude oil and stock market returns (*Notes* Series are calculated based on Parkinson [1980])

Table 6.1 shows that crude oil has by far the highest average variance among all series, followed by the Italian and German stock market indices. All transformed series are significantly non-normally distributed according to the Jarque and Bera (1980) normality test which is also supported by the fact that all series appear to be right skewed and leptokurtic distributed on the 1% significance level. Furthermore, all variables are significantly autocorrelated, exhibit ARCH errors, and are stationary according to the Elliott et al. (1996) unit-root test on the 1% significance level. Those results are suggestive that modeling the volatility transmission mechanism between crude oil and the G7 stock market indices applying a TVP-VAR model is appropriate.

Table 6.1 Summary statistics

	Crude Oil	United States	Canada	United Kingdom	Germany	France	Italy	Japan
Mean	41.07	15.08	13.69	16.75	18.26	18.00	21.72	15.10
Variance	3220.83	171.53	163.14	153.20	163.93	149.71	205.25	168.99
Skewness	23.15***	3.37***	4.65***	3.34***	2.79***	2.54***	3.34***	6.57***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Kurtosis	744.319***	17.52***	38.02***	18.22***	12.97***	10.12***	24.24***	92.48***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JB	74,825,941***	47,378***	206,093***	50,690***	26,835***	17,245***	85,037***	1,173,813***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ERS	−11.40***	−8.13***	−7.28***	−8.11***	−7.50***	−7.30***	−6.60***	−8.68***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q(20)$	4282.24***	12580.81***	13177.60***	10197.33***	9711.28***	9095.47***	6967.26***	4766.43***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

(continued)

Table 6.1 (continued)

	Crude Oil	United States	Canada	United Kingdom	Germany	France	Italy	Japan
$Q^2(20)$	936.07***	8717.88***	5973.61***	6180.68***	7369.05***	6391.60***	2933.18***	325.23***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Crude Oil	1.00	0.31	0.34	0.34	0.29	0.29	0.21	0.18
United States	0.31	1.00	0.57	0.52	0.49	0.49	0.38	0.30
Canada	0.34	0.57	1.00	0.46	0.43	0.45	0.35	0.27
United Kingdom	0.34	0.52	0.46	1.00	0.53	0.56	0.41	0.29
Germany	0.29	0.49	0.43	0.53	1.00	0.71	0.55	0.24
France	0.29	0.49	0.45	0.56	0.71	1.00	0.60	0.26
Italy	0.21	0.38	0.35	0.41	0.55	0.60	1.00	0.22
Japan	0.18	0.30	0.27	0.29	0.24	0.26	0.22	1.00

Notes ***, **, * denote significance at 1, 5, and 10% significance level; () denote *p*-values; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test

6.3 Methodology

The connectedness approach proposed by Diebold and Yılmaz (2009, 2012, 2014) allows to monitor and evaluate the transmission mechanism within a predetermined network. This supports in general policymakers to adequately adjust economic and political strategies in order to mitigate adverse effects that propagate from shocks in specific variables/sectors. Therefore, it is of essential importance that spillovers and the relative strength of shocks are accurately measured and investigated.

The relevance and applicability of this framework already led to multiple improvements and extensions overcoming two major shortcomings which are that (i) the original dynamic approach rests on a rolling-window VAR—that requires to choose a rolling-window size—and (ii) that the GFEVD normalization is sub-optimal (Caloia et al., 2019). The first issue has been tackled by Antonakakis et al. (2020) who propose a TVP-VAR based connectedness approach to (i) overcome the arbitrarily chosen VAR window size, (ii) be less sensitive to outliers, (iii) to monitor more accurately the parameter changes, and (iv) avoid the loss of observations. A solution for the second shortcoming has been suggested by Lastrapes and Wiesen (2021) who derived a normalization method based upon the goodness-of-fit measure R^2. Their so-called joint spillover index leads to a more natural interpretation of connectedness measures and also to a more accurate illustration of the propagation mechanism at hand. These two concepts have been combined and extended in Balcilar et al. (2021) who even allowed to examine the net pairwise directional connectedness measure in a joint connectedness setting which has previously not been possible. Additionally, the TVP-VAR based extended joint connectedness approach includes all aforementioned advantages over the original connectedness approach of Diebold and Yılmaz (2009, 2012, 2014).

To explore the volatility propagation mechanism between crude oil and the G7 stock market indices, we first estimate a TVP-VAR[1] —with a lag length of order one as suggested by the Bayesian information criterion (BIC)—which can be outlined as follows,

$$\boldsymbol{y}_t = \boldsymbol{B}_t \boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_t) \tag{6.2}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{6.3}$$

where $\boldsymbol{y}_t$, $\boldsymbol{y}_{t-1}$ and $\boldsymbol{\epsilon}_t$ are $K \times 1$ dimensional vector and $\boldsymbol{B}_t$ and $\boldsymbol{\Sigma}_t$ are $K \times K$ dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$ dimensional vectors whereas $\boldsymbol{R}_t$ is a $K^2 \times K^2$ dimensional matrix. Subsequently, the TVP-VAR is transformed to a TVP-VMA according to the Wold representation theorem: $\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{A}_{h,t} \boldsymbol{\epsilon}_{t-i}$ where $\boldsymbol{A}_0 = \boldsymbol{I}_K$.

[1] Since the detailed algorithm of the TVP-VAR model with heteroscedastic variance-covariances is beyond the scope of this study interested readers are referred to Antonakakis et al. (2020).

6.3.1 TVP-VAR Based Connectedness Approach

We start with the TVP-VAR based connectedness approach as some prior knowledge and definitions are required for better understanding the TVP-VAR extended joint connectedness approach. The TVP-VAR based connectedness approach (Antonakakis et al., 2020) is based upon the H-step ahead generalised forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran & Shin, 1998) which represents the effect a shock in series j has on series i. This can be mathematically formulated as follows:

$$\phi_{ij,t}^{gen}(H) = \frac{\sum_{h=0}^{H-1}(\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{e}_j)^2}{(\boldsymbol{e}_j' \boldsymbol{\Sigma}_t \boldsymbol{e}_j) \sum_{h=0}^{H-1}(\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{A}_{ht}' \boldsymbol{e}_i)} \tag{6.4}$$

$$gSOT_{ij,t} = \frac{\phi_{ij,t}^{gen}(H)}{\sum_{k=1}^{K} \phi_{ik,t}^{gen}(H)} \tag{6.5}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ zero selection vector with unity on its ith position and $\phi_{ij,t}^{gen}(H)$ is the unscaled GFEVD ($\sum_{j=1}^{K} \zeta_{ij,t}^{gen}(H) \neq 1$). Based upon the work of Diebold and Yılmaz (2009, 2012, 2014) the unscaled GFEVD is normalised to unity by dividing it by the row sum which leads to the scaled GFEVD, $gSOT_{ij,t}$.

The scaled GFEVD is the fundament on which all other connectedness measures can be calculated. The total directional connectedness from all others to series i and the total directional connectedness to all others from a shock in series i which represents by how much the network influences series i and how much series i influences the predetermined network, respectively, can be computed as follows:

$$S_{i \leftarrow \bullet,t}^{gen,from} = \sum_{j=1, i \neq j}^{K} gSOT_{ij,t} \tag{6.6}$$

$$S_{i \rightarrow \bullet,t}^{gen,to} = \sum_{j=1, i \neq j}^{K} gSOT_{ji,t} \tag{6.7}$$

Based upon the previous two measures the net total directional connectedness of series i can be calculated which can be interpreted as the net influence of series i on the network,

$$S_{i,t}^{gen,net} = S_{i \rightarrow \bullet,t}^{gen,to} - S_{i \leftarrow \bullet,t}^{gen,from} \tag{6.8}$$

If $S_{i,t}^{gen,net} > 0$ ($S_{i,t}^{gen,net} < 0$), series i is influencing (influenced by) all others more than being influenced by (influencing) them and thus is considered as a net transmitter (receiver) of shocks indicating that series i is driving (driven by) the network.

At the core of the connectedness approach is the total connectedness index (TCI) which highlights the degree of network interconnectedness and hence its market risk. The TCI is equal to the average total directional connectedness from (to) others and can be outlined by the following:

$$gSOI_t = \frac{1}{K}\sum_{i=1}^{K} S^{gen,from}_{i\leftarrow\bullet,t} = \frac{1}{K}\sum_{i=1}^{K} S^{gen,to}_{i\rightarrow\bullet,t}, \tag{6.9}$$

A high (low) value implies that the market risk is high (low).

Finally, the connectedness approach supplies also information on the bilateral level. The net pairwise directional connectedness illustrates the bilateral power between series i and j,

$$S^{gen,net}_{ij,t} = gSOT^{gen,to}_{ji,t} - gSOT^{gen,from}_{ij,t}. \tag{6.10}$$

If $S^{gen,net}_{ij,t} > 0$ ($S^{gen,net}_{ij,t} < 0$), series i dominates (is dominated) series j which means that series i influences (is influenced by) series j more than being influenced by it.

6.3.2 TVP-VAR Based Extended Joint Connectedness Approach

The main difference between the joint and the original connectedness approach is that the normalization method is not chosen arbitrarily but derived from the popular R^2 goodness-of-fit measure.[2] $S^{jnt,from}_{i\leftarrow\bullet,t}$ represents the impact all variables in the network have on variable i. This can be mathematically formulated by:

$$\boldsymbol{\xi}_t(H) = \boldsymbol{y}_{t+H} - E(\boldsymbol{y}_{t+H}|\boldsymbol{y}_t, \boldsymbol{y}_{t-1}, \ldots) = \sum_{h=0}^{H-1} \boldsymbol{A}_{h,t}\boldsymbol{\epsilon}_{t+H-h} \tag{6.11}$$

$$E(\boldsymbol{\xi}_t(H)\boldsymbol{\xi}'_t(H)) = \boldsymbol{A}_{h,t}\boldsymbol{\Sigma}_t\boldsymbol{A}'_{h,t} \tag{6.12}$$

$$S^{jnt,from}_{i\leftarrow\bullet,t} = \frac{E(\xi^2_{i,t}(H)) - E[\xi_{i,t}(H) - E(\xi_{i,t}(H))|\epsilon_{\forall\neq i,t+1}, \ldots, \epsilon_{\forall\neq i,t+H}]^2}{E(\xi^2_{it}(H))} \tag{6.13}$$

$$= \frac{\sum_{h=0}^{H-1} \boldsymbol{e}'_i\boldsymbol{A}_{ht}\boldsymbol{\Sigma}_t\boldsymbol{M}_i(\boldsymbol{M}'_i\boldsymbol{\Sigma}_t\boldsymbol{M}'_i)^{-1}\boldsymbol{M}'_i\boldsymbol{\Sigma}_t\boldsymbol{A}'_{ht}\boldsymbol{e}_i}{\sum_{h=0}^{H-1} \boldsymbol{e}'_i\boldsymbol{A}_{ht}\boldsymbol{\Sigma}_t\boldsymbol{A}'_{ht}\boldsymbol{e}_i} \tag{6.14}$$

[2] For the detailed mathematical derivations interested readers are referred to the technical appendix of original study of Lastrapes and Wiesen (2021).

where $\boldsymbol{M}_i$ is a $K \times K - 1$ rectangular matrix that equals the identity matrix with the ith column eliminated, and $\epsilon\forall \neq i, t+1$ denotes the $K-1$-dimensional vector of shocks at time $t+1$ for all variables except variable i. In the next step, the joint total connectedness index is calculated as follows,

$$jSOI_t = \tfrac{1}{K}\sum_{i=1}^{K} S^{jnt,from}_{i\leftarrow\bullet,t} \tag{6.15}$$

which is within zero and unity opposed to the TCI of the originally proposed approach as shown in Chatziantoniou and Gabauer (2021) and Gabauer (2021).

An important extension of Balcilar et al. (2021) is that multiple scaling factors are used to link $gSOT$ to $jSOT$:

$$\lambda_{it} = \frac{S^{jnt,from}_{i\leftarrow\bullet,t}}{S^{gen,from}_{i\leftarrow\bullet,t}} \tag{6.16}$$

$$jSOT_{ij,t} = \lambda_{it}\, gSOT_{ij,t} \tag{6.17}$$

Based upon this equality, the total directional connectedness from variable i to all others, the net total directional and the net pairwise directional connectedness measures can be calculated as well:

$$S^{jnt,to}_{i\rightarrow\bullet,t} = \sum_{j=1,i\neq j}^{K} jSOT_{ji,t} \tag{6.18}$$

$$S^{jnt,net}_{j,t} = S^{jnt,to}_{i\rightarrow\bullet,t} - S^{jnt,from}_{\bullet\rightarrow i,t} \tag{6.19}$$

$$S^{jnt,net}_{ij,t} = jSOT^{jnt,to}_{ji,t} - jSOT^{jnt,from}_{ij,t}. \tag{6.20}$$

6.4 Results and Discussion

In this section, we set out the main findings of the study based on extended joint connectedness and elaborate on the corresponding implications. In the interests of comparison, we also include the results from the standard TVP-VAR connectedness approach. Please be reminded that the TVP-VAR extended joint connectedness approach practically constitutes a refined version of the standard TVP-VAR connectedness approach. In this regard, we expect findings to be qualitatively similar across the two different approaches; with the joint connectedness method though, offering more adequately justified (and in this respect, more accurate) results.

Furthermore, in order to highlight the dynamic character of the study, we focus mainly on dynamic results; namely, total dynamic connectedness, net directional connectedness, as well as, pairwise connectedness.

6.4.1 Average Connectedness Results

We begin by considering average results; that are, results that emerge when we consider the entire sample period as a whole. These results are given by Table 6.2. Please note that the main diagonal element which corresponds to each variable in our network reflects each variable's idiosyncratic effect (i.e., own contribution to uncertainty) while, off diagonal elements represent the contribution of uncertainty to this variable from others.

Furthermore, according to the average value of the total connectedness index (TCI) for the period, 67.93% of the forecast error variance in each one of the variables of our network can be attributed to innovations in all other variables. This practically implies that average variable co-movement is rather moderate-to-high and therefore we should not neglect the potential for volatility contagion within the network.

A closer look at Table 6.2 further allows for a distinction (i.e., always on average net terms) of the variables of the network between net transmitters and net recipients of uncertainty shocks. In this regard, we note that Canada appears to be the major net transmitter in the network with an average net connectedness value of 16.67%, followed by the US (14.78%), and the UK (5.31%). By contrast, all other variables in our network assume a rather net receiving position with Japan (−14.64%) and Italy (−8.53%) being the main average net recipients of the network.

Although the averaged results do provide a generic picture of the interaction among the variables of the network, we should be able to draw safer conclusions by decomposing the sample period into shorter intervals and by considering a rather dynamic investigation of the interaction among the variables. The reason being that average results may mask major economic developments and events that transpired during the sample period and had a profound impact on the network under investigation. In this regard, in the sections that follow, we proceed with such a dynamic investigation of the results that we obtained from both alternative empirical methods.

6.4.2 Total Dynamic Connectedness

In turn, we consider total connectedness across time. Findings are given by Fig. 6.2 which illustrates the evolution of the total value of connectedness within the system/network under investigation. For illustration purposes, the black-shaded area corresponds to extended joint connectedness results while the red solid line represents the results from the standard TVP-VAR connectedness approach.

First, we notice that—as was in fact expected, results obtained from both of these methods remain qualitatively similar and differences are practically limited to the magnitude of connectedness across the sample period. Apparently, both methods are capable of identifying the relevant peaks and troughs of connectedness within this particular network of variables.

Table 6.2 Averaged connectedness table

	Crude oil	United States	Canada	United Kingdom	Germany	France	Italy	Japan	FROM others
Crude oil	64.63	7.19	8.04	6.65	3.79	4.18	3.17	2.35	35.37
United States	6.07	26.55	20.29	13.45	10.82	11.15	7.95	3.71	73.45
Canada	7.17	20.40	30.03	12.85	9.10	9.91	7.09	3.45	69.97
United Kingdom	6.22	15.88	14.55	22.68	12.62	14.20	9.82	4.03	77.32
Germany	4.72	13.36	12.50	14.78	14.14	21.72	15.15	3.63	85.86
France	4.46	14.09	13.36	16.31	20.97	10.20	17.38	3.23	89.80
Italy	3.27	10.05	9.91	12.18	16.18	18.91	26.44	3.06	73.56
Japan	3.33	7.27	8.00	6.42	4.34	4.28	4.46	61.91	38.09
TO others	35.25	88.24	86.64	82.63	77.81	84.36	65.03	23.45	TCI
NET spillovers	−0.11	14.78	16.67	5.31	−8.04	−5.44	−8.53	−14.64	67.93

Notes Results are based on a TVP-VAR model with lag length of order 1 (BIC) and a 20-step-ahead forecast

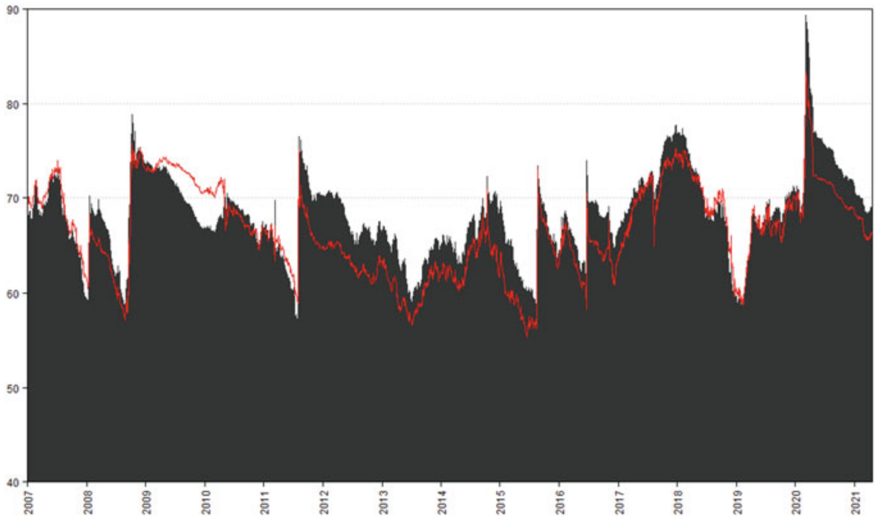

Fig. 6.2 Dynamic total connectedness (*Notes* Results are based on a TVP-VAR model with lag length of order 1 [BIC] and a 20-step-ahead forecast)

In turn, focusing primarily on the extended joint connectedness results, we note that, connectedness within this network of variables is relatively high; that is, connectedness is persistently greater than 55% and from time to time it reaches peaks greater than 75% and—more recently, as high as approximately 90%. These findings are indicative of the very strong association between the variables of this system. Findings also highlight the strong linkages across international financial markets and reflect—to some extent, the importance of the financialisation of the oil market. To give an example, a connectedness value in the region of 55% practically implies that for a particular point in time, 55% (on average) of the evolution within this particular system of variables can be attributed to developments within the network itself. To put differently, if connectedness is in this particular region, then approximately 55% of the forecast error variance in one of the constituents/variables of the network can be attributed to innovations that occur in all other constituents.

The practical implication is that, researchers by looking into connectedness have an additional source of information regarding the feedback that each variable receives within a specified network. In this regard, connectedness becomes a useful tool towards identifying potential sources of contagion within a given network. More importantly, under a dynamic framework of study, that is, a framework that investigates the extent of connectedness through time, researchers can effectively identify patterns of the responses of this network not only to major developments in financial markets and the broader economy but also to major crisis episodes that affect societies the world over.

It follows that increased levels of connectedness during specific points in time (e.g., in the light of major crisis episodes) suggest that the variables of the network move closely together. In fact, if such patterns of increased connectedness systematically occur during similar events then connectedness in the network rather is event-dependent. Being highly responsive to such events, practically causes connectedness to fluctuate across time (as evidenced in Fig. 6.2) exhibiting periodical peaks and troughs.

By contrast, lower levels of connectedness are suggestive of weak interrelations within the network. Weak connectedness could in some cases be associated with rather tranquil periods of time; or—particularly during turbulent periods, it could be suggestive of decoupling. The latter case would no doubt be very interesting (and useful) from the standpoint of investments and active portfolio management considering that differing behaviours during turbulent times could potentially offer opportunities for diversification. As we shall discuss later on in this section, distinguishing the constituents of the network between net transmitters and net receivers of shocks could provide additional information regarding the dynamic behaviour of the relevant variables.

In turn, results are suggestive of specific periods whereby connectedness in this network was rather pronounced. Apparently, connectedness reached very high levels in the beginning of 2009, 2012, and 2018 while its highest value can be located around the first quarter of 2020. In the section that follows we shed additional light on these relationships by considering net total connectedness.

6.4.3 Net Total Directional Connectedness

We now focus on Fig. 6.3 which illustrates the specific position of each variable of the network over time. To put differently, Fig. 6.3 depicts whether any variable of the particular network assumes either a net transmitting or net receiving role across the sample period. For the purposes of illustration, please note that values above zero suggest a net transmitter of shocks into the system while values below zero, a net recipient.

Understandably, during the sample period, it is not uncommon for a variable to switch between roles. Notice for example that oil is mostly a recipient of shocks with a notable exception around 2014. It follows that the adopted empirical method allows for making a distinction between variables which—for their most part, have acted as net transmitters and variables which—for their most part, have rather positioned themselves on the receiving end. The practical implication of distinguishing between net transmitters and net receivers in this particular network of variables which focuses on volatility is that it improves our understanding of potential sources of uncertainty within the network.

Furthermore, given that the empirical method allows for a dynamic analysis of the issue at hand, we are also able to isolate specific periods whereby a variable classifies as either a net transmitter or net receiver in the light of some specific event. For instance, following on from the point that we made earlier about the

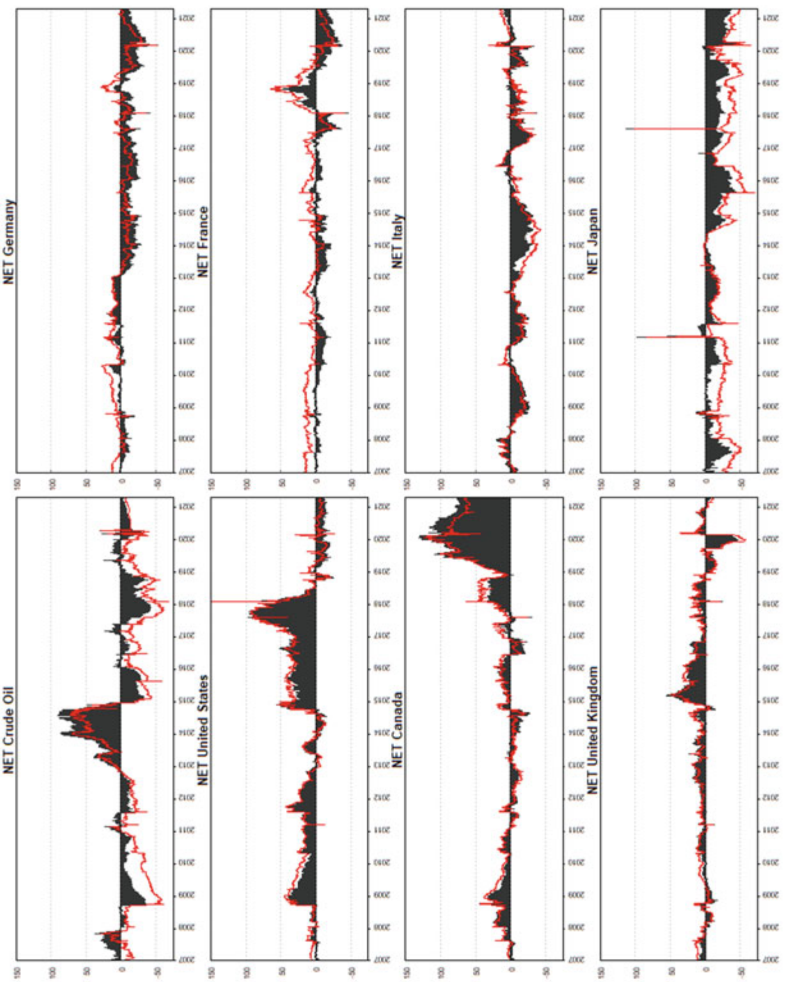

Fig. 6.3 Net total directional connectedness (*Notes* Results are based on a TVP-VAR model with lag length of order 1 [BIC] and a 20-step-ahead forecast)

position of oil around 2014, we could further acknowledge that this period largely coincides with the unprecedented collapse in the price of oil which was particularly evident between June and December 2014. Within the framework of our model, this could be interpreted as oil being an important source of uncertainty for the entire network during these specific months. In other words, during that period, oil—on net terms, was not so much a receiver of uncertainty shocks from other variables in the network as it was a transmitter of these shocks.

If we interpret the findings presented in Fig. 6.3 in this way then, we can draw some useful initial conclusions about the interaction among the variables of the network. More particularly, we note that most variables assume both roles across time with the exception perhaps of both the Italian and the Japanese stock market who both appear to be on the receiving end. Furthermore, the German stock market is also a rather persistent net receiver of uncertainty shocks, with only one or two exceptions throughout the period of study; nonetheless, the magnitude of transmission from the German stock market during these exceptional intervals was rather negligible.

Despite those findings in connection with the UK indicate that the extent of the transmission of this particular stock market is rather low, there clearly exists a period between the beginning of 2015 and the end of 2016 whereby the UK stock market appears to have a key role to play as a net transmitter of uncertainty shocks to the remaining variables of the network. It is perhaps no surprise that this particular interval coincides with developments associated with the EU membership referendum which eventually took place in the UK on the 23rd of June 2016.

The French stock market is mainly a net recipient of uncertainty shocks from all other variables of the network. Nonetheless, there is an interval between the beginning of 2018 and mid-2019 when the French stock market injects uncertainty into the system. This particular period was marked by high volatility in international financial markets following events such as the escalating trade war between China and the US and rising interest rates in the US. An interesting aspect that makes these developments pertinent for the French index and potentially justifies these findings is that stocks listed on CAC 40 are largely owned by multinational corporations and overseas investors who were greatly affected by these developments.

In turn, results suggest that the US stock market is a persistent net transmitter of uncertainty shocks, a fact that most likely underscores the importance of developments in the particular market for the global economy. Interestingly enough though, the US stock market switches to a net recipient role around the beginning of 2019, which is exactly the period in which the Canadian stock market becomes an important net transmitter. The latter begs the question of whether this finding is entirely random or not, suggesting that there may be a common story between the two markets that lies behind this particular development. To answer this question (and similar ones) we have to look into net pairwise spillovers—which is the focal point of the following section.

6.4.4 Net Pairwise Dynamic Connectedness

We turn to Fig. 6.4 which illustrates the pairwise dimension of the results. In line with previous analysis, positive values are indicative of net recipient variables in the network. In effect, the pairwise dimension verifies previously reported results and also offers a more complete picture with regard to uncertainty spillover shocks within this particular network.

Focusing on the findings presented in the first column of Fig. 6.4, we notice that in all cases, oil consistently contributes shocks to the system around the period of the oil price collapse. In point of fact, results remain qualitatively similar irrespectively of whether the country is a net oil importer (e.g., Germany) or a net oil exporter (e.g., Canada). The episode of the oil price collapse and its effect on financial markets has been well documented in existing literature (see Balli et al., 2019; Chatziantoniou et al., 2021a, 2021b; Degiannakis & Filis, 2018).

Furthermore, with the exception of Japan, it is also evident that the oil market receives considerable uncertainty shocks from all stock markets around 2018. As aforementioned, the period around 2018 was a very turbulent period for global stock markets. To be more explicit, 2018 was mostly marked by the escalation of the trade war between China and the US with the unprecedented measures of the period (e.g., increased tariffs) having a profound impact both on international trade, investments, and financial markets (see Egger & Zhu, 2020; He et al., 2020; Xu & Lien, 2020). It follows that the economic environment during 2018 was rather discouraging for investments (resulting for instance in a slowdown in demand for oil) and international tensions had a strong impact on the market for oil (see Bouoiyour et al., 2019; Li et al., 2020). At the same time, the rather uncertain economic environment of 2018 also affected the oil market through financial markets—considering the relatively recent financialisation of commodity markets (see Silvennoinen & Thorp, 2013; Zhang, 2017).

If we then turn our attention to the remaining panels in Fig. 6.4, we can find out more about the relevant bilateral relationships of the network. For example, looking down the results presented in the second column (with the exception of the last panel in that column), we can see the pairwise connectedness between the US stock market and all other G7 stock markets. Following on from our discussion above, it seems that the period around 2018 was a period when the US stock market assumed a dominant role as a net transmitter of uncertainty shocks in the system. There is indeed a strong link between the US economy and other economies around the globe and therefore developments affecting the US could cause a chain reaction to other countries. Apart from developments in relation to the recent US-China trade war that was previously discussed, evidence also suggests that contractionary monetary policy in the US (i.e., higher interest rates)—such as the one we experienced around 2018, could negatively affect GDP in other countries (see Iacoviello & Navarro, 2019).

Interestingly enough, findings with regard to the Canadian stock market reveal that volatility in this particular market greatly affected almost all other stock markets in the network, around the onset of the COVID-19 pandemic. This finding

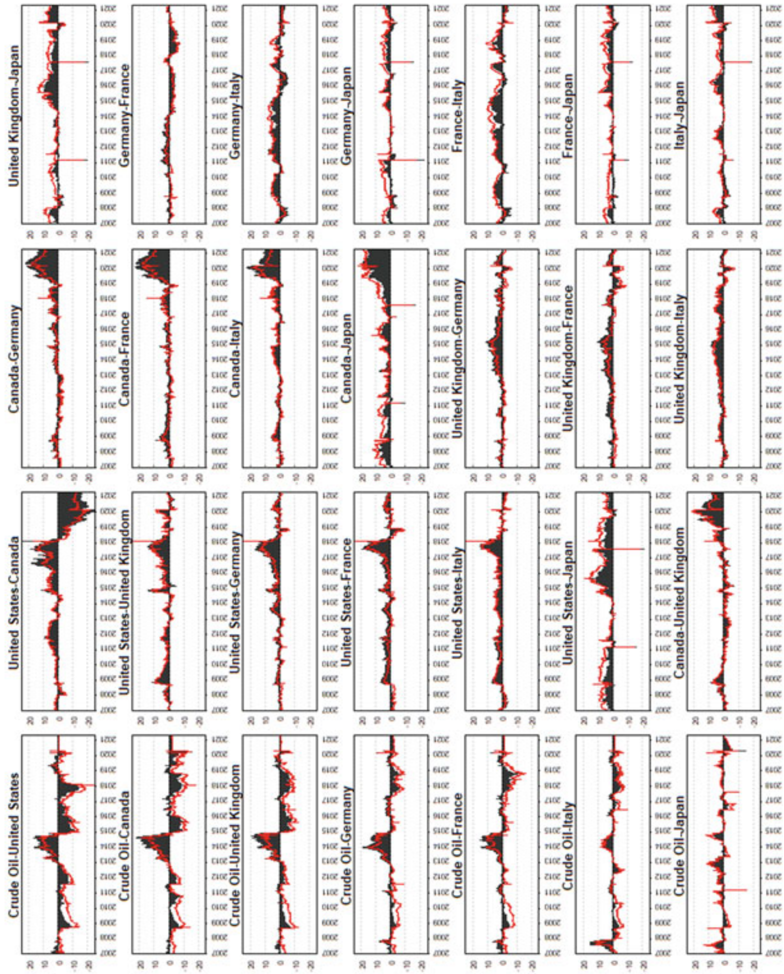

Fig. 6.4 Net pairwise dynamic connectedness (*Notes* Results are based on a TVP-VAR model with lag length of order 1 [BIC] and a 20-step-ahead forecast)

is closely linked to our discussion above relating to the slowdown of investment in recent years; however, in this case, results should be viewed from the standpoint of Canada being a major exporting country during a period when the prospects of manufacturing, energy, and the financial sector were rather gloomy and unfavourable. Given Canada's reliance on international trade, authors such as Talbot and Ordonez-Ponce (2020) stress that the COVID-19 pandemic affected the Canadian economy in a profound way. Considering these prospects, the Toronto Stock Exchange suffered its most severe decline between February and March 2020 subsequently affecting major stock markets in the world—including the US stock market; a fact which stands to reason considering that Canada and the US are very close trade partners. In this regard, the developments of the period affecting bilateral trade between Canada and the US; that is, particularly in connection with the increased tariffs of the period (see Cavallo et al., 2021) was also struck from developments associated with the COVID-19 pandemic. At the same time, authors such as Xu (2021) point out that uncertainty in connection with COVID-19 had a profound impact on the Canadian stock market relative to the US.

In retrospect, the main findings of this study indicate that, as far as this particular network of variables is concerned, volatility connectedness was mostly affected around three specific periods; that is, around 2014, during 2018, and in the beginning of 2020. All these periods could be linked with certain major events such as the oil price collapse, stock market unrest, as well as, the outbreak of the COVID-19 pandemic. Distinguishing the variables of the network into net transmitters and net receivers of spillover shocks improves our understanding of the underlying dynamics that propagate our system and determine the direction of contagion across the variables of interest. Understanding these dynamics could be useful to policy and decision-makers who—in order to restore tranquillity during periods of economic turbulence, require information on the interaction among several macroeconomic and financial variables.

6.5 Conclusion

In this study we focused on a specific network of variables in order to examine the interrelation between volatility in G7 stock markets and volatility in the market for crude oil. By looking into this network, we shed additional light into the potential sources of uncertainty contagion afflicting the relevant markets.

To this end, we collected monthly data for the period between 2007 and 2021 and utilised appropriate proxies. To the effect that we predicated results upon a robust empirical approach, we employed the extended joint TVP-VAR connectedness method (Balcilar et al., 2021) which augments the standard connectedness index initially developed by Diebold and Yılmaz (2009, 2012, 2014). For the purposes of illustration and in the interests of comparison we provided results from both methods. Results were qualitatively similar between the two, exhibiting mainly differences with regard to the magnitude of connectedness.

Overall, we found that total dynamic connectedness assumed large values over time which is indicative of the great extent of interrelation among the variables of the network. In fact, connectedness persistently remained above the 55% mark across time while, during the most recent months of the sample period, connectedness was as high as approximately 90%. In turn, findings regarding net total dynamic connectedness helped us distinguish between net transmitters and net receivers of uncertainty shocks within the network. In point of fact, we were able to identify specific periods when each variable assumed either role in the light of events that had a profound impact on international financial markets.

More particularly, we found that crude oil did have an important net transmitting role during the 2014 oil price collapse. In turn, crude oil rather assumed a noteworthy net receiving position around 2018 which admittedly was a very turbulent period for stock markets around the globe. What is more, the UK stock market also assumed a net transmitting role for a short period around the events of the EU referendum.

Furthermore, on net terms, the stock markets of Germany, Italy, and Japan rather remained on the receiving end of this network. The US stock market on the other hand constantly acted as a net transmitter of uncertainty shocks within the network with the exception of the more recent period starting in the beginning of 2019. With reference to this particular finding, net pairwise analysis suggested that the US stock market mainly received uncertainty from the Canadian stock market which—considering its role as a major exporting economy, apparently affected volatility in many stock markets around the world in a period marked by turbulence with regard to international terms of trade and the COVID-19 crisis.

To conclude, in this chapter we highlighted the importance for considering a variety of empirical approaches in order to reach more robust conclusions. We found that both the standard TVP-VAR connectedness approach and the TVP-VAR extended joint connectedness approach provided qualitatively similar results in relation to the direction of connectedness and the distinction between net transmitting and net receiving variables within the network. We maintained that findings are important for policymakers and decision-makers in general who wish to better understand the interactions across stock markets and the market for crude oil in order to formulate and implement the necessary policies.

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Part III

Energy, Climate Change and the Environment

7 The Impact of Market Uncertainty on the Systematic Risk of Clean Energy Stocks

Perry Sadorsky

7.1 Introduction

Addressing climate change and limiting global temperature increases to 2 degrees above pre-industrialization levels requires a major transition in energy structure from fossil fuels to renewable energy sources. Through technological innovation, the levelized cost of electricity is falling for renewables and onshore wind is now less costly than coal (*The Economist*, 2020). Technological innovation, clean energy policy, green consumers, and socially responsible investing are powerful forces spurring investment in clean energy companies. Investment in clean energy equities totaled \$6.6 billion in 2019. While this number was below the record high of \$19.7 billion in 2017, the compound annual growth rate between 2004 and 2019 of 24% was above that of private equity or venture capital funding (Frankfurt School-UNEP Centre/BNEF, 2020). In response to this interest in clean energy, there is a literature on clean energy equity dynamics (Bondia et al., 2016; Dutta, 2017; Dutta et al., 2018; Elie et al., 2019; Gupta, 2017; Henriques & Sadorsky, 2008; Kumar et al., 2012; Maghyereh et al., 2019; Managi & Okimoto, 2013; Reboredo, 2015; Reboredo & Ugolini, 2018; Reboredo et al., 2017; Uddin et al., 2019; Wen et al., 2014) and the hedging of clean energy equities (Ahmad, 2017; Ahmad et al., 2018; Ahmad & Rais, 2018; Sadorsky, 2012a).

We don't, however, know much about time variation in clean energy equity systematic risk (beta) or how market uncertainty affects the systematic risk of clean energy equities. Systematic risk is often estimated from a capital asset pricing model (CAPM) and used for measuring the risk premium of an asset. The risk premium of an asset is equal to the asset's exposure to market risk (beta) times the risk premium of the market. The CAPM is one of the cornerstones of modern

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finance theory and is widely used by investors and practitioners to estimate the cost of capital (Graham & Harvey, 2001) and to formulate investment strategies (Barber et al., 2016; Berk & van Binsbergen, 2016). Beta is defined as the product of the correlation between the stock return and the market return and the standard deviation of the stock return divided by the standard deviation of the market return. Uncertainty about each of these three components can affect beta. For example, Naeem et al. (2020) study the impact of energy commodity uncertainty on the systematic risk of US stock market industries. Energy commodity uncertainty is measured using returns on oil prices, heating oil, gasoline, and natural gas. A two-step approach is used where in the first step, GARCH models are used to estimate industry betas and then in the second step, betas are regressed on commodity uncertainty variables. There is evidence that energy price uncertainty has a positive impact on industry betas. Dutta (2017) uses the implied volatility of oil prices when estimating the impact of oil price uncertainty on clean energy stock volatility. He finds that realized volatility of the clean energy stock index (Wilder Hill Clean Energy Index) is positively affected by the implied volatility of oil prices. Implied volatility is a useful measure of market uncertainty and probably more reliable than returns or realized volatility because implied volatility is the market's forecast of a future movement in an asset's price. If implied volatility is high, then the market is forecasting large price swings. If implied volatility is low, then the market is forecasting small price swings. Implied volatility tends to increase during bear markets and decrease in bull markets. If implied volatility has a significant impact on clean energy systematic risk, then this will affect the forecasting of stock returns and the discounting of future cash flows. The extant literature on clean energy equities has found stock market prices, oil prices, and technology stock prices to have an important impact on clean energy stock prices. The uncertainty of these variables can be measured using implied volatility. As investing in clean energy equities grows, a better understanding of the impact of market uncertainty on clean energy systematic risk is required because the systematic risk is important for forecasting stock returns and discounting future cash flows. This is the gap in the literature that this paper addresses.

The purpose of this paper is to estimate time-varying betas for clean energy equities, measured using exchange traded funds (ETFs), and evaluate the impact of market uncertainty, measured using implied volatility, on systematic risk. This paper makes several important contributions to the literature. First, time-varying conditional betas for four popular clean energy ETFs are estimated using multivariate GARCH models. While many earlier studies estimate unconditional and static beta values, more recent research suggests that time-varying conditional betas are more relevant for decision making (Bali et al., 2016; Engle, 2018). Thus, conditional time-varying betas are estimated. For robustness two multivariate GARCH models, asymmetric dynamic conditional correlation (ADCC) (Cappiello et al., 2006) and generalized orthogonal GARCH (GO-GARCH) (Peter Boswijk & van der Weide, 2011; van der Weide, 2002), are used. The ADCC model builds on the well-known dynamic conditional correlation model developed by Engle (2002) while GO-GARCH is based on the concept of principle components. Second, the impact of market uncertainty on clean energy systematic risk is estimated where uncertainty is measured using implied volatility. Stock market uncertainty is measured by the CBOE implied volatility index (VIX) and crude oil price uncertainty is measured by the CBOE implied crude oil volatility index (OVX). Technology stock market uncertainty is measured by the CBOE implied technology volatility index (VXN). These volatility indexes measure their respective markets expectation of 30-day forward looking volatility. Third, following Naeem et al. (2020) further analysis is conducted for the shale oil revolution period (January 1, 2014 to December 31, 2016) which dramatically increased US domestic oil production. Greater domestic oil production lessens the reliance on imported oil and this could affect the systematic risk of clean energy stocks.

This paper reveals several important findings. First, conditional clean energy equity beta is time varying. Beta tends to rise during times of market uncertainty and fall in times of tranquility. A recent example of this occurred in 2020. At the beginning of 2020, beta values were low and then rose starting on Wednesday 11 March, 2020 when the World Health Organization declared COVID19 a pandemic. The beta values are highly persistent, and the first difference of the betas are mean reverting. Second, stock market, oil market, and technology market uncertainty, as measured by implied volatility, does have a significant impact on the changes in clean energy equity beta.

This paper is organized as follows. The next section sets out the literature review. The following sections of the paper present the methods, data, and results. The last section of the paper provides some conclusions and suggestions for future research.

7.2 Background Literature

The empirical literature on clean energy equities can be categorized according to methods that focus on multifactor models, correlation dynamics, and hedging. Multifactor models are used to determine how sensitive clean energy stock returns are to macroeconomic or company specific factors. Dynamic correlations between clean energy stocks and other variables has been studied using methods like vector autoregression, GARCH, copulas, and wavelets.

The use of multifactor models to estimate risk shows that clean energy systematic risk is mostly greater than unity indicating that clean energy stocks are riskier than the overall market. Most studies use data on clean energy sector indices. Henriques and Sadorsky (2008), using weekly data over the period 3 January, 2001 to 30 May, 2007 find that clean energy betas from the WilderHill Clean Energy Index are approximately 1.4. Broadstock et al. (2012) use multifactor models to study the impact of risk factors on energy-related stocks in China. Oil price increases are associated with an increase in new energy stock returns. After the global financial crisis risk sensitivity increased. New energy stocks are more resilient to oil price shocks than other energy stocks. Sadorsky (2012b) uses clean energy company specific data for the period 2001–2007 to estimate the impact of risk factors on stock returns. Market risk varies between 2 and 3. Bohl et al. (2013) use a four-factor model to study the common risk factors of German renewable energy stocks for the period 2004–2011. Between 2004 and 2007, German renewable energy stocks had a strong positive momentum factor and outperformed the market. However, between 2008 and 2011, the outperformance reversed, and German renewable energy stocks turned into laggards. They find a systematic risk factor of approximately 2. Between 2004 and 2011 there is evidence of speculative bubble behavior. Bohl et al. (2015) further study bubble behavior in renewable energy stocks and find European and global renewable stocks do exhibit evidence of bubbles while North American renewable stocks do not. Market betas are time varying but generally range between 2 and 3. Inchauspe et al. (2015) use a multifactor state-space model to study the impact of risk factors on the WilderHill New Energy Global Innovation Index. Market risk and technology risk factors are more important than oil price risk. Market betas vary between 0.8 and 1.4. Gupta (2017) uses a firm level data set from 26 countries to investigate the impact of economic and societal factors on the financial performance of alternative energy stocks. Country-level technology and innovation are important determinants of alternative energy stocks. National culture factors can help explain the cross-country differences in the financial performance of alternative energy stocks. Reboredo et al. (2017) use multifactor models and propensity score matching to study the financial performance of alternative energy mutual funds for the period 2010–2016. One of the important results from this research is that in terms of returns and downside risk protection, alternative energy funds underperformed corporate and socially responsible funds. These results are consistent with investors paying a premium to invest in alternative energy funds.

There are papers that investigate the dynamic correlations between clean energy stocks and other variables using methods like vector autoregression (VAR), GARCH, copulas, and wavelets. Henriques and Sadorsky (2008) use a VAR to study the dynamic interaction between clean energy stock prices, oil prices, interest rates, and a technology factor. They find that the technology factor has a larger impact on clean energy stock prices than oil prices. Kumar et al. (2012) build on Henriques and Sadorsky (2008) and include several different clean energy stock price indices and a variable for carbon prices. Results from VAR estimation show that while technology stock prices and oil prices affect clean energy stock prices, carbon prices have a limited effect. Managi and Okimoto (2013) use Markov-switching VAR to study the relationship between clean energy stock prices, technology stock prices, interest rates, and oil prices. They find evidence of a structural change in late 2007. The impact of technology shocks on clean energy stocks is larger than the impact of oil prices. Wen et al. (2014) use a BEKK model to study the return and volatility spillovers between Chinese fossil fuel and new energy stocks. There are return and volatility spillovers between the two asset classes. Negative news has a larger impact on stock returns than positive news. Fossil fuel stocks and new energy stocks can be viewed as competing assets. Reboredo (2015) uses copulas to study the dependence and systematic risk (measured using CoVaR) between oil and renewable energy stocks. One of the important findings is that oil price dynamics contributes about 30% to the downside and upside risk of renewable energy stocks. There is significant evidence of tail risk between oil prices and renewable energy stocks. Bondia et al. (2016) allow for endogenous structural breaks while testing for cointegration between the stock prices of alternative energy companies (measured using the WilderHill New Energy Global Innovation Index), technology stock prices, oil prices and interest rates. There is evidence of causality from oil prices, technology stock prices and interest rates to alternative energy stock prices in the short-run but not in the long-run. Dutta (2017) studies the impact of implied oil price volatility on the realized volatility of clean energy stock prices. The WilderHill Clean Energy Index is used to measure clean energy stock prices. Evidence is presented showing that implied volatility positively impacts the volatility of clean energy stock prices and the impact of implied oil price volatility is larger than that of oil prices volatility. Dutta et al. (2018) use a VAR-GARCH model to study return and volatility relationships between EU carbon dioxide prices and clean energy stock prices. Clean energy stock prices are measured using the European-based ERIX index and the US-based ECO index. Volatility linkages are present between EU carbon prices and European renewable energy stock prices, but EU carbon price volatility has little impact on US renewable energy stock price volatility. Reboredo and Ugolini (2018) use multivariate vine-copulas to study quantile price movements in oil, gas, coal, and electricity on clean energy stock returns. Oil and electricity were major contributors to the price dynamics of clean energy stock returns. The price dynamic relationship is symmetrical between upward and downward energy price movements. These results applied to both European clean energy stocks and US clean energy stocks. Elie et al. (2019) use copulas to study the role of gold and oil as a safe-haven (hedge) against clean energy stock prices. Gold and oil are weak safe-haven assets but oil is a better safe-haven in cases of extreme market movements. Maghyereh et al. (2019) use wavelets and DCC-GARCH models to investigate risk and return transfer from oil and technology stocks to clean energy stocks. There is evidence of significant bidirectional return and risk transfer between oil and technology stocks to clean energy stocks. These effects are more pronounced at longer time horizons. Uddin et al. (2019) study the cross-quantile dependence between renewable energy stock returns, market returns, oil prices, gold prices, and exchange rates. The relationship between oil prices and renewable stock prices is not symmetric across quantiles and the asymmetry is higher in the longer lags.

Research that focusses on hedging clean energy equities often does so by using multivariate GARCH models to estimate conditional variances. Since conditional variances vary considerably over the sample period, so too do hedge ratios. Sadorsky (2012a) finds that, on average, a $1 long position in clean energy stocks can be hedged for 24 cents in a short position in oil prices or a $1.01 short position in technology stocks. Ahmad (2017) finds that, on average, a $1 long position in clean energy stocks can be hedged for 32 cents in a short position in oil prices or a $1.29 short position in technology stocks. Ahmad et al. (2018) use three multivariable GARCH models (DCC, ADCC, GO-GARCH) to estimate clean equity hedge ratios. They find that VIX is the best hedging instrument followed by OVX and oil prices. Ahmad and Rais (2018) find that, on average, a \$1 long position in clean energy stocks can be hedged for 21 cents in a short position in WTI oil prices, or 25 cents in a short position in Brent oil prices, or a 73 cents short position in technology stocks.

The papers that come closest to this present study are the ones that focus on estimating clean energy betas (Bohl et al., 2013, 2015; Henriques & Sadorsky, 2008; Inchauspe et al., 2015; Sadorsky, 2012a). These papers differ in methodology and data but find that clean energy betas are usually greater than one. What we don't know, however, is how implied volatility affects clean energy systematic risk. This is the gap in the literature that this paper fills.

7.3 Methods

Asset returns are characterized by volatility clustering, leverage, and heavy tails in the distribution. To account for these issues this paper uses multivariable GARCH models to estimate conditional betas for clean energy equities. The first model is the ADCC model (Cappiello et al., 2006). The ADCC model is built on the DCC model (Engle, 2002). The DCC model can be described as follows:

$$r_t = \mu_t + \varepsilon_t \tag{7.1}$$

$$\varepsilon_t = H_t^{1/2} z_t \tag{7.2}$$

The variable, r_t, is an $n \times 1$ vector of log returns at time t, ε_t, is a random error term at time, and μ_t is the mean vector (which represent the unconditional means of the returns). Time is indexed by $t = 1, \ldots, T$. The variable H_t is a $n \times n$ matrix of conditional variances at time t, and z_t is a $n \times 1$ vector of independent and identically distributed (iid) error terms with mean zero and variance of unity. Different specifications of multivariate GARCH usually involve different specifications of H. The conditional covariance matrix is decomposed into conditional standard deviations (D) and a correlation matrix (R).

$$H_t = D_t R_t D_t \tag{7.3}$$

$$D_t = diag\left(h_{11t}^{\frac{1}{2}}, \ldots, h_{nnt}^{\frac{1}{2}}\right) \tag{7.4}$$

The conditional variance for a univariate GARCH(1,1) model are written as:

$$h_t = \omega + \alpha\varepsilon_t^2 + \beta h_t \tag{7.5}$$

The conditional correlation matrix, R_t, must be positive definite and inverted at each point in time. Engle (2002) proposes modeling a proxy process, Q_t, where a + b < 1 is used to satisfy stationarity and positive definiteness of Q_t.

$$Q_t = (1 - a - b)\bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1} \tag{7.6}$$

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t \, diag(Q_t)^{-\frac{1}{2}} \tag{7.7}$$

For the ADCC model, Cappiello et al. (2006) generalize the DCC model to include asymmetric terms in the conditional variance. The dynamics of Q_t are:

$$\begin{aligned} Q_t = & \left(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q}^{-}G\right) \\ & + A' z_{t-1} z'_{t-1} A + B' Q_{t-1} B + G' z_t^{-} z_t'^{-} G \end{aligned} \tag{7.8}$$

The variables A, B, and G are the n $\times$n parameter matrices, z_t^{-} are the zero-threshold standardized error that are equal to z_t when less than zero and zero elsewhere. $\bar{Q}$ and $\bar{Q}^{-}$ are the unconditional matrices of z_t and z_t^{-}, respectively. In practice, A, B, and G are estimated assuming they are scalar, diagonal, and symmetric.

The second model is the GO-GARCH model (Peter Boswijk & van der Weide, 2011; van der Weide, 2002). The GO-GARCH model maps a set of asset returns, r_t, onto a set of uncorrelated components, z_t, using a mapping Z.

$$r_t = Z y_t \tag{7.9}$$

The unobserved components, y_t, are normalized to have unit variance. Each component of y_t can be described by a GARCH process. For example, consider a standard GARCH(1,1) process with a normal distribution.

$$y_t \sim N(0, H_t) \tag{7.10}$$

$$H_t = diag\left(h_{1,t}, \ldots, h_{n,t}\right) \tag{7.11}$$

$$h_{i,t} = \omega_i + \alpha_i y_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{7.12}$$

The index i runs from 1 to n. The unconditional covariance matrix of y_t is $H_0 =$ I. The conditional covariance matrix of r_t is:

$$V_t = Z H_t Z' \tag{7.13}$$

The matrix Z maps the uncorrelated components y_t to the observed returns r_t. There exists an orthogonal matrix U such that:

$$Z = P \Lambda^{1/2} U' \tag{7.14}$$

The matrices P and Λ can be obtained from singular value decomposition on the unconditional variance matrix V. For example, P contains the orthonormal eigenvectors of $ZZ' = V$ and Λ contains the eigenvalues. The matrix U can be obtained from the conditional variance matrix V_t. Recent work on GO-GARCH is concentrated on finding different ways to parameterize and estimate the matrix U.

The GO-GARCH model assumes that the mapping matrix Z is time invariant, and the covariance matrix H_t is a diagonal matrix. An orthogonal GARCH (OGARCH) model is obtained when Z is restricted to be orthogonal. The OGARCH model can be estimated using principle components on the normalized data and GARCH models estimated on the principle components. This corresponds to U being an identity matrix. The original formation of the GO-GARCH model uses a 1-step maximum likelihood approach to jointly estimate the rotation matrix and the dynamics. This method, however, is impractical for many assets because the maximum likelihood estimation procedure may fail to converge. The matrix U can also be estimated using nonlinear least squares (Peter Boswijk & van der Weide, 2011). These approaches involve two step and three step estimation procedures. More recently, it has been proposed that U can be estimated by independent component analysis (ICA) and this is the method employed in this paper (Broda & Paolella, 2009; Zhang & Chan, 2009).[1]

Asset returns are characterized by autocorrelation, volatility clustering and distributions that have fat tails. An AR(1) term is added to the mean equation to account for possible autocorrelation and a leverage term is added to the volatility equation. The ADCC is estimated with multivariate Student t (MVT) distributions. The GO-GARCH is estimated with the multivariate affine normal inverse Gaussian (MANIG) distribution. These distributions are useful for modeling data with heavy tails. All estimation is done in R (Ghalanos, 2019; R Core Team, 2019).

The conditional beta between the return on asset r_i and the market return R_i are calculated as:

$$beta_{it} = cov(r_{it}, R_{it})/var(r_{it}) \tag{7.15}$$

Once the conditional beta values are calculated, the impact of implied volatility on the betas can be tested using a linear regression model.

$$\Delta\ln(beta_{it}) = d + \delta Z_{t-1} + \xi_t \tag{7.16}$$

In Eq. (7.16), Z is the explanatory variable (return of the implied volatility) and ξ is the random error term. As shown in the following sections of the paper, beta values tend to have high persistence and therefore Eq. (7.16) is estimated using the first difference of the natural logarithm of beta and the returns of the implied volatility variables. This ensures that both the dependent and independent variables in Eq. (7.16) are stationary.

[1] The rotation matrix U needs to be estimated. For all but a few factors, maximum likelihood is not feasible. For a larger number of factors alternative estimation methods must be used. ICA is a fast statistical technique for estimating hidden factors in relation to observable data.

7.4 Data

The clean energy exchange traded funds (ETFs) included in this study are the First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), iShares Global Clean Energy ETF (ICLN), Invesco WilderHill Clean Energy ETF (PBW), and Invesco Global Clean Energy ETF (PBD). These US listed ETFs are widely used to invest in the clean energy equity sector (clean energy production, and energy conservation) but there are some differences between them regarding the included companies. PBW, the longest trading clean energy ETF, tracks an index of US listed companies that specialize in the business of clean energy and energy conservation. PBD is similar to PBW but has more of a global focus in the selection of companies. PBW mirrors the popular ECO index while PBD mirrors the popular NEX global innovation energy index (https://nexindex.com/available_products.php). PBW is focused on US listed clean energy companies while PBD is focused on globally listed new energy innovation companies. PBW is composed of approximately 40 companies while PBD is composed of approximately 90 companies. PBD has a much higher weighting of electric utilities (14%) compared to PBW (4%). QCLN tracks an index of clean energy stocks listed in the US. ICLN tracks a global index of clean energy companies that specialize in the production of energy from wind, solar, and renewable sources. Other popular clean energy ETFs like TAN (solar companies) or FAN (wind companies) are not studied because the focus of this paper is the broad-based clean energy sector. The stock market index is measured using the iShares MSCI All Country World Index ETF (ACWI). Implied stock market volatility is measured using the CBOE volatility index (VIX) which measures the market expectation of 30-day forward looking volatility. The VIX is used to gage market risk and investors' sentiments. Implied oil price volatility is measured using the CBOE crude oil price volatility index (OVX). The OVX applies the VIX methodology to the United States Oil Fund ETF (USO) options for different strike prices. The VXN is the CBOE NASDAQ implied volatility index which is constructed based on the prices of NASDAQ 100 Index options with 30 days to expiration. Stock price ETF data, and data on the VIX, VXN, and OVX are available from Yahoo finance. The data set begins on 25 June 2008, which reflects the beginning of trading for the ICLN, and ends on 31 July 2020.

The VIX shows sharp spikes in 2008 (the global financial crisis) and March of 2020 (the COVID19 Pandemic). Like the VIX, the OVX and VXN also show a sharp spike in March of 2020. The World Health Organization declared the global outbreak of COVID19 a pandemic on 11 March 2020. The ACWI has mostly trended upwards across the sample period but experienced a sudden drop in March of 2020 due to the COVID19 pandemic. PBW, PBD, and ICLN show similar patterns of a large drop in 2009 and afterward a mostly flat pattern. QCLN has a positive trend over the time period. All the clean energy ETFs experienced a drop in March of 2020 (Fig. 7.1).

The largest daily average value is recorded for ACWI (0.022%) and the smallest value recorded for ICLN (−0.033%) (Table 7.1). The performance of the clean

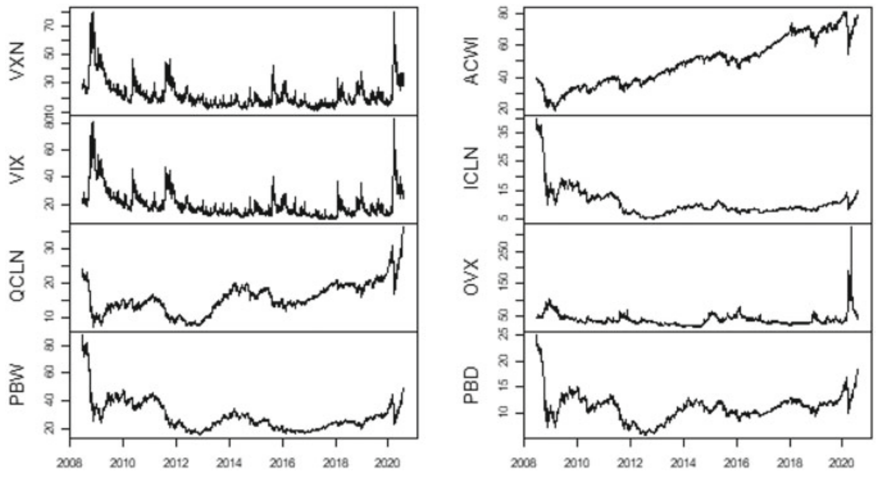

Fig. 7.1 Time series plot of the data

Table 7.1 Summary statistics for daily percentage returns

	VXN	VIX	QCLN	PBW	ACWI	ICLN	OVX	PBD
min	−31.305	−35.059	−15.483	−15.637	−11.896	−16.723	−62.225	−20.188
max	46.891	76.825	14.892	15.820	11.701	16.000	85.770	15.876
median	−0.525	−0.632	0.128	0.088	0.083	0.000	−0.362	0.088
mean	0.002	0.005	0.012	−0.021	0.022	−0.033	0.000	−0.010
std. dev.	6.733	7.798	2.110	2.211	1.391	2.155	5.632	1.920
skewness	0.876	1.090	−0.576	−0.620	−0.584	−0.741	1.617	−1.026
kurtosis	3.926	6.267	7.229	7.285	11.805	12.078	31.889	13.543
normtest.W	0.949	0.934	0.918	0.914	0.856	0.856	0.828	0.858
normtest.p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

There are 3046 daily observations. W is the Shapiro–Wilk test of normality

energy ETFs has been weak with none of them recording positive average daily values. The volatility indices (VIX, OVS, and VXN) have the largest standard deviations while ACWI has the lowest. For each data series, the mean and median deviate considerably indicating non-symmetric distributions. This is further verified by the skewness and kurtosis measures. The observed non-normality of asset returns, and volatility returns is consistent with stylized facts. Unit root tests, not reported, show that each return series is stationary.

The return correlations show that the clean energy ETFs correlate highly with each other and with the ACWI but show a negative correlation with the volatility indices (Fig. 7.2). Of the implied volatilities, OXV has the weakest correlation with

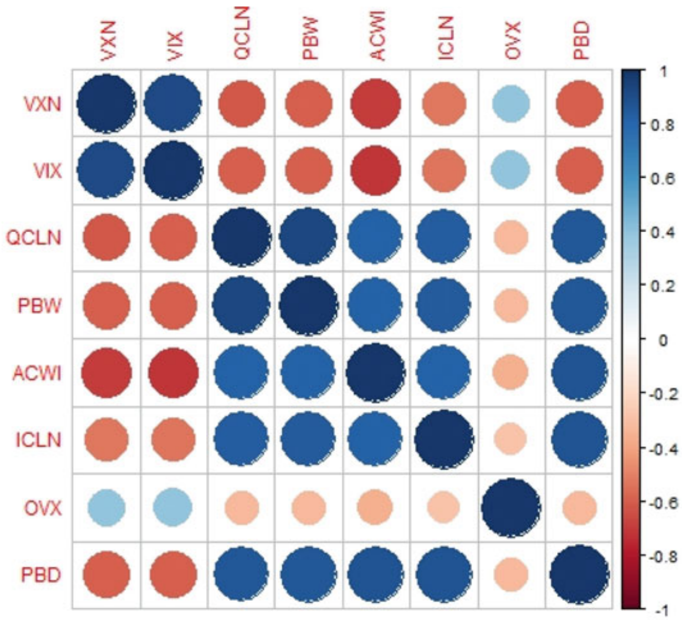

Fig. 7.2 Return correlations

Table 7.2 CAPM estimates

	QCLN	PBW	ICLN	PBD
α	−0.02	−0.05[b]	−0.06[a]	−0.04[b]
	(−0.77)	(−2.19)	(−2.79)	(−2.38)
β	1.24[a]	1.30[a]	1.26[a]	1.21[a]
	(43.16)	(43.01)	(28.62)	(50.68)
R sq	0.66	0.67	0.66	0.77

HAC robust t statistics shown in parentheses. The superscripts [a, b] denote a level of significance at 0.01 and 0.05 respectively. The estimation equation is: $r_t = \alpha + \beta\ MR_t + \xi_t$

the clean energy ETF returns. The implied volatilities have a positive correlation with each other but a negative correlation with the clean energy ETFs.

As a first look at systematic risk, a standard CAPM model is estimated for each clean energy ETF (Table 7.2). In Table 7.2, alpha represents the intercept term and beta is the systematic risk. The estimated beta values are greater than unity for each clean energy ETF indicating that clean energy stocks are riskier than the market. PBW is the riskiest while PBD is the least risky. The R squared values show that between 66 and 77% of the variation in clean energy stock returns are explained by the CAPM.

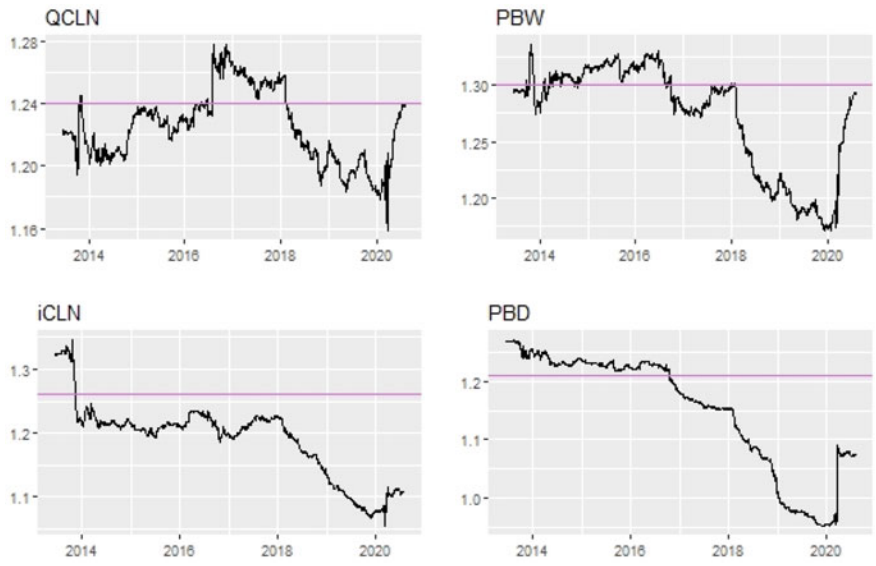

Fig. 7.3 Rolling beta values

As evident from Fig. 7.1, the period under study has experienced considerable volatility. Consequently, beta values calculated using the full data set may not be representative for all time periods. It is interesting to see how the beta values have evolved using a rolling window analysis. The window length was set at 1250 observations, which corresponds to approximately 5 years of daily trading days. Plots of the clean energy equity betas show considerably variability over the sample period (Fig. 7.3). The horizontal lines in Fig. 7.3 represent the static beta values. Each clean energy ETF recorded the lowest beta values in early 2020. Notice that PBD recorded a beta value less than unity in early 2020 indicating that at this time, an investment in PBD was less risky than the market. The sharp increase in beta resulting from COVID19 was most noticeable for PBW. While each of these ETFs is a measure of the clean energy sector, different sub-sector focus, geographical coverage, and firm choice contribute to the different time series patterns in the betas.

7.5 Results

Plots of the estimated time-varying conditional betas are reported in Figs. 7.4 and 7.5. The plots show evidence of considerable time variation. The betas for QCLN and PBW show similar patterns which are expected since these two assets display a high correlation with each other (Fig. 7.2). By comparison, the betas for ICLN

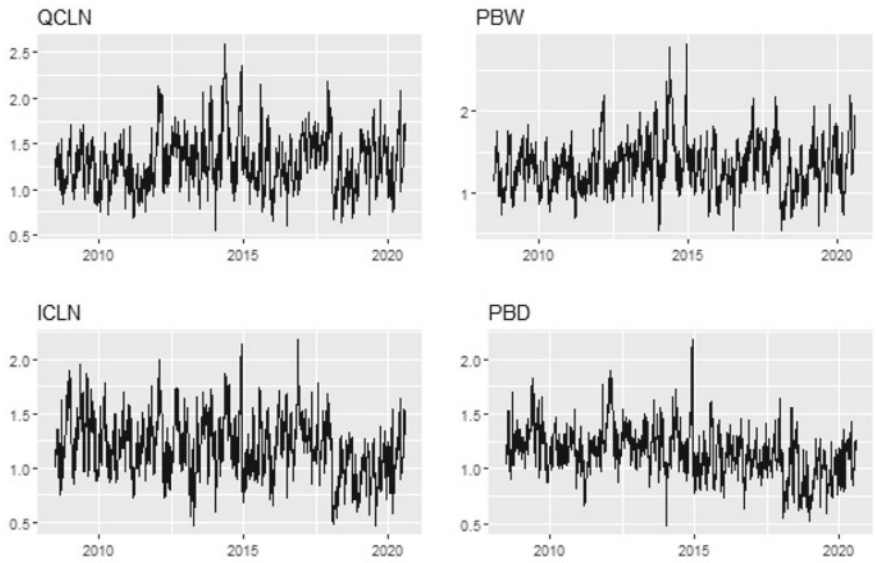

Fig. 7.4 Conditional betas from ADCC

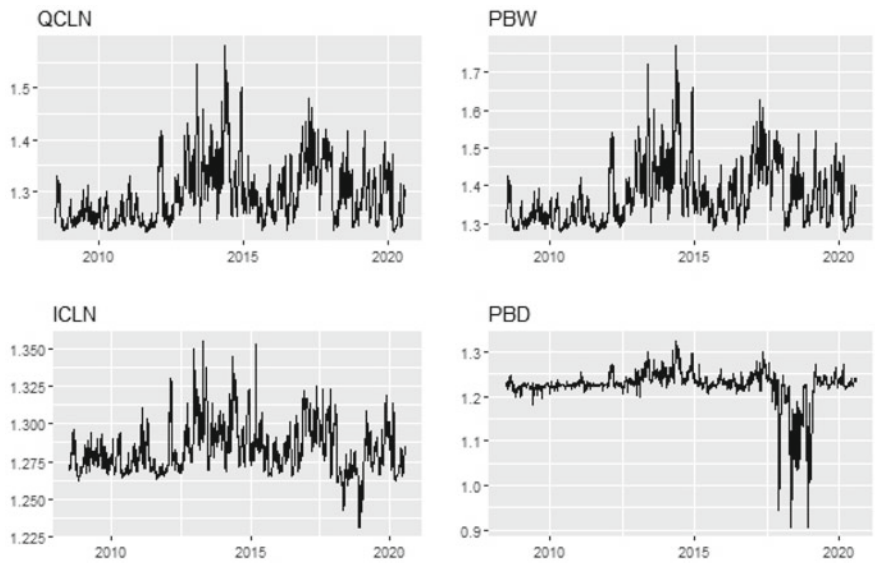

Fig. 7.5 Conditional betas from GO-GARCH

Table 7.3 Descriptive statistics for conditional systematic risk

	QCLN(A)	PBW(A)	ICLN(A)	PBD(A)	QCLN(G)	PBW(G)	ICLN(G)	PBD(G)
nbr. val.	3046	3046	3046	3046	3046	3046	3046	3046
min	0.549	0.537	0.466	0.477	1.220	1.277	1.231	0.905
max	2.584	2.818	2.176	2.170	1.581	1.768	1.355	1.323
range	2.036	2.281	1.711	1.693	0.361	0.492	0.124	0.418
median	1.286	1.318	1.179	1.158	1.280	1.356	1.280	1.229
mean	1.303	1.338	1.199	1.153	1.294	1.375	1.283	1.225
std. dev.	0.295	0.314	0.272	0.217	0.058	0.078	0.016	0.040
coef. var.	0.226	0.234	0.227	0.188	0.045	0.057	0.012	0.033
Acf(1)	0.943	0.943	0.936	0.936	0.968	0.968	0.957	0.964

Beta estimates from the ADCC model (A) and GO-GARCH model (G)

and PBD display different patterns which is consistent with their low correlation with each other and assets (Fig. 7.2). Beta tends to rise during times of market uncertainty and fall in times of tranquility. At the beginning of 2020, beta values were low and then rose starting on Wednesday 11 March 2020 when the World Health Organization declared COVID19 a pandemic.

For each clean energy equity, the mean values of ADCC and GO-GARCH are similar. The main difference between the ADCC estimates and the GO-GARCH estimates appears to be that GO-GARCH produces beta values with lower standard deviations than those from the ADCC model (Table 7.3). For each clean energy ETF, the coefficient of variation estimated from the GO-GARCH model is lower than the corresponding value from the ADCC model. It is also the case that for each clean energy ETF, the range estimated from the GO-GARCH model is lower than the corresponding value from the ADCC model. Notice also that ADCC beta values record minimum values below unity, indicating that these clean energy equity ETFs have at these values less risk than the overall stock market. Only one GO-GARCH beta, PBD, has a minimum value below one. The PBD ETF contains a higher proportion of utility companies compared to the other clean energy ETFs which may be the reason for the greater occurrence of low beta values. Each of the beta values has a high degree of persistence as indicated by the first lag of the autocorrelation function. Acf(1) values range between 0.968 and 0.936.

The correlations between beta values vary between estimation method (Table 7.4). Among the ADCC beta estimates QCLN and PBW correlate the highest while QCLN and ICLN correlate the least (Table 7.4). Among the GO-GARCH beta estimates, QCLN and PBW correlate the highest while QCLN and PBD correlate the least. For each ETF, correlations between ADCC beta estimates and GO-GARCH estimates are 0.64 (QCLN), 0.69 (PBW), 0.45 (ICLN), and 0.22 (PBD). The difference in correlations between ADCC and GO-GARCH estimated betas is probably

Table 7.4 Correlations of conditional systematic risk

	QCLN(A)	PBW(A)	ICLN(A)	PBD(A)	QCLN(G)	PBW(G)	ICLN(G)	PBD(G)
QCLN(A)	1.00	0.91	0.60	0.61	0.64	0.64	0.58	0.22
PBW(A)	0.91	1.00	0.65	0.62	0.69	0.69	0.64	0.30
ICLN(A)	0.60	0.65	1.00	0.71	0.39	0.39	0.45	0.21
PBD(A)	0.61	0.62	0.71	1.00	0.24	0.25	0.30	0.22
QCLN(G)	0.64	0.69	0.39	0.24	1.00	1.00	0.85	0.23
PBW(G)	0.64	0.69	0.39	0.25	1.00	1.00	0.85	0.25
ICLN(G)	0.58	0.64	0.45	0.30	0.85	0.85	1.00	0.56
PBD(G)	0.22	0.30	0.21	0.22	0.23	0.25	0.56	1.00

Beta estimates from the ADCC model (A) and GO-GARCH model (G)

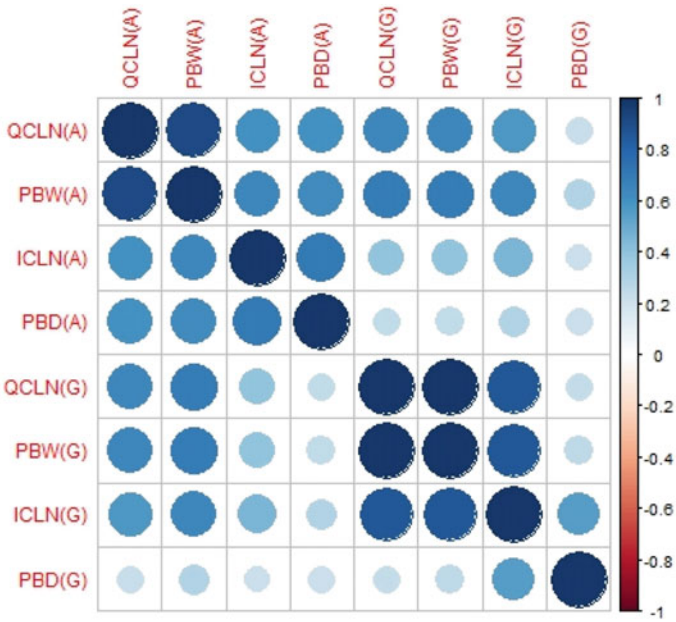

Fig. 7.6 Correlations of conditional systematic risk (full sample)

due to the fact that GO-GARCH beta estimates have lower standard deviation compared to their respective ADCC values.

The correlations reported in Table 7.4 are displayed graphically in Fig. 7.6. Figure 7.7 shows the graphical representation of the correlations for the betas over the shorter shale oil revolution period. Naeem et al. (2020) identify the period 1 January 2014 to 31 December 2016 as the shale oil revolution. Over this time

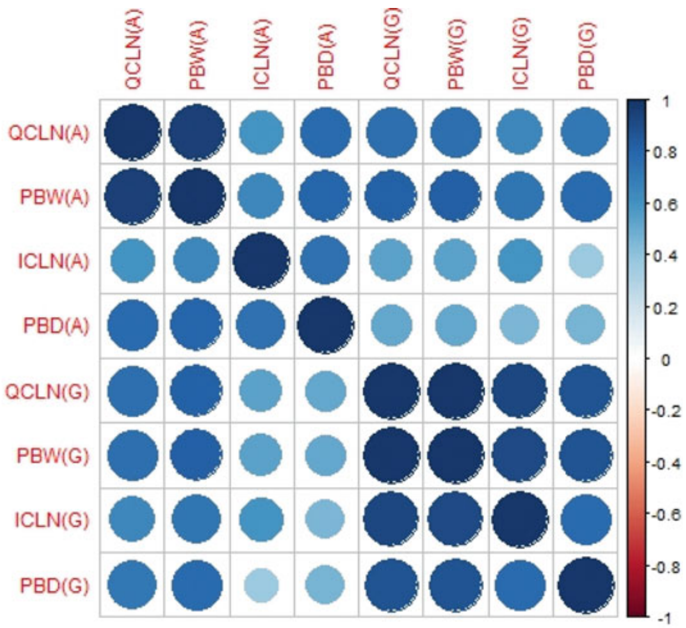

Fig. 7.7 Correlations of conditional systematic risk (January 1, 2014 to December 31, 2016)

period WTI crude oil prices dropped from \$98 per barrel to \$54 per barrel mostly in response to the large increase in shale oil production. The 11 February 2016 low of \$26 per barrel would not be broken until March of 2020 during the COVID19 pandemic. During the shale oil revolution period US shale oil production increased dramatically and turned the US from an oil importer to close to self-sufficiency. September of 2019 marked the first time since 1973 the US was a net oil exporter. More plentiful domestic oil supply reduces energy supply concerns and could affect the relationship between clean energy systematic risk and market uncertainty. The most notable difference between Figs. 7.6 and 7.7 is that in Fig. 7.7 the correlations between the beta for PBD and the other betas are higher. This is also the case for ICLN.

Since betas have a high degree of persistence (Table 7.3), the first difference of the natural log of beta was used as the dependent variable in estimating the results in Table 7.5. The Hurst exponent for the first difference of the natural log of the beta values ranges between 0.254 (ICLN(A)) to 0.343 (PBD(G)) indicating considerable mean reversion. The estimated coefficient on the lag value of the implied volatility variable is negative and significant for each case except one (PBD(G)) (Table 7.5). This result is consistent with a mean reversion response of beta to increases in market volatility. An increase in market uncertainty in one period is followed by a decrease in beta in the next period. This provides strong evidence

Table 7.5 Impact of implied volatility on conditional systematic risk

		VIX	OVX	VXN
QCLN(A)	d	0.0159	0.0130	0.0155
		(0.1394)	(0.1016)	(0.1304)
	δ	−0.4815[a]	−0.3055[a]	−0.4799[a]
		(−15.4524)	(−6.0571)	(−13.2736)
	R squared	0.2177	0.0457	0.1611
PBW(A)	d	0.0164	0.0134	0.0161
		(0.1423)	(0.1037)	(0.1344)
	δ	−0.4987[a]	−0.2995[a]	−0.5103[a]
		(−14.8584)	(−5.9175)	(−13.3868)
	R squared	0.2192	0.0412	0.1711
ICLN(A)	d	0.0099	0.0065	0.0096
		(0.0883)	(0.0514)	(0.0837)
	δ	−0.5536[a]	−0.3492[a]	−0.5901[a]
		(−14.4256)	(−5.3686)	(−14.051)
	R squared	0.2559	0.0531	0.2167
PBD(A)	d	0.0034	0.0013	0.0032
		(0.0345)	(0.0123)	(0.0318)
	δ	−0.3498[a]	−0.2115[a]	−0.3654[a]
		(−13.0217)	(−6.0209)	(−11.6516)
	R squared	0.1516	0.0289	0.1232
QCLN(G)	d	0.0016	0.0012	0.0016
		(0.0942)	(0.0649)	(0.0895)
	δ	−0.0618[a]	−0.0366[a]	−0.0645[a]
		(−12.0897)	(−5.7559)	(−11.4041)
	R squared	0.1941	0.0355	0.1576
PBW(G)	d	0.0020	0.0016	0.0020
		(0.0957)	(0.0665)	(0.0911)
	δ	−0.0770[a]	−0.0455[a]	−0.0805[a]
		(−12.0634)	(−5.7555)	(−11.3682)
	R squared	0.1929	0.0351	0.1568
ICLN(G)	d	0.0004	0.0003	0.0004
		(0.082)	(0.0565)	(0.0783)
	δ	−0.0174[a]	−0.0111[a]	−0.0182[a]
		(−10.1255)	(−4.8659)	(−9.8799)
	R squared	0.1463	0.0310	0.1196

(continued)

Table 7.5 (continued)

		VIX	**OVX**	**VXN**
PBD(G)	d	0.0004	0.0004	0.0004
		(0.0274)	(0.0289)	(0.0277)
	δ	0.0038	0.0026	0.0035
		(0.919)	(0.6403)	(0.8014)
	R squared	0.0009	0.0002	0.0006

Beta values are calculated from the ADCC model (A) and GO-GARCH model (G). HAC robust t statistics shown in parentheses. The superscript [a] denotes a level of significance at 0.01. The estimation equation is: $\Delta \ln(\text{beta}_t) = d + \delta Z_{t-1} + \xi_t$ where Z_{t-1} is the return on either VIX, OVX, or VXN

that market uncertainty, measured by implied volatility has a significant impact on clean energy beta. For each beta, the VIX equation produces the highest R squared value followed by the VXN and OVX equations respectively. This result is robust to the choice of GARCH model used to estimate beta, although R squared values from equations estimated using GO-GARCH betas tend to be less than their corresponding ADCC values. In the case of ICLN(A), the R squared from the VIX, VXN, and OVX equations are 0.2559, 0.2167, and 0.0531 respectively. For the ADCC estimated betas, the estimated coefficient on the market uncertainty variable ranges between −0.5536 and −0.3498. For the GO-GARCH estimated betas, the estimated coefficient on the market uncertainty variable, where significant, ranges between −0.0770 and −0.0174. Overall, there is strong evidence to show that market uncertainty affects beta. Omitting the impact of market uncertainty on clean energy equity beta may influence cost of equity calculations or investment decisions.

Table 7.6 reports the results from estimating the impact of market uncertainty on clean energy equity beta for the shorter shale oil revolution period. During this time period, the estimated coefficient on the lag value of the implied volatility variable is negative and significant for each case (Table 7.6). The biggest difference between the results reported in Table 7.6 and those reported in Table 7.5 are that in Table 7.6 all clean energy equity betas are significantly affected by implied volatility whereas in Table 7.5 all clean energy equity betas except PBD(G) are significantly affected by implied volatility.

7.6 Conclusions and Implications

Technological innovation, clean energy policy, green consumers, and socially responsible investing are powerful forces encouraging investment in clean energy equities. As investing in clean energy equities grows, a better understanding of the impact of market uncertainty on clean energy systematic risk is required because

Table 7.6 Impact of implied volatility on conditional systematic risk (January 1, 2014 to December 31, 2016)

		VIX	OVX	VXN
QCLN(A)	d	0.0210	0.0569	0.0236
		(0.0778)	(0.2043)	(0.0848)
	δ	−0.4635[a]	−0.4446[a]	−0.4937[a]
		(−7.9224)	(−4.4695)	(−6.5777)
	R squared	0.1865	0.0581	0.1521
PBW(A)	d	0.0074	0.0428	0.0103
		(0.028)	(0.1569)	(0.0378)
	δ	−0.5140[a]	−0.4372[a]	−0.5518[a]
		(−7.4477)	(−3.7966)	(−6.7804)
	R squared	0.1980	0.0486	0.1641
ICLN(A)	d	0.0046	0.0423	0.0077
		(0.0193)	(0.1662)	(0.0319)
	δ	−0.5588[a]	−0.4645[a]	−0.6114[a]
		(−9.1122)	(−4.2027)	(−8.1769)
	R squared	0.2511	0.0588	0.2161
PBD(A)	d	−0.0110	0.0135	−0.0090
		(−0.0485)	(0.0578)	(−0.0387)
	δ	−0.3659[a]	−0.3015[a]	−0.3862[a]
		(−7.689)	(−3.1135)	(−7)
	R squared	0.1517	0.0349	0.1215
QCLN(G)	d	0.0018	0.0071	0.0022
		(0.0464)	(0.1658)	(0.0557)
	δ	−0.0731[a]	−0.0647[a]	−0.0810[a]
		(−7.9564)	(−4.8405)	(−7.1543)
	R squared	0.2138	0.0568	0.1884
PBW(G)	d	0.0021	0.0087	0.0026
		(0.0421)	(0.161)	(0.0515)
	δ	−0.0917[a]	−0.0811[a]	−0.1016[a]
		(−7.9242)	(−4.8177)	(−7.1287)
	R squared	0.2127	0.0564	0.1879
ICLN(G)	d	0.0010	0.0027	0.0012
		(0.0983)	(0.232)	(0.1063)
	δ	−0.0214[a]	−0.0206[a]	−0.0236[a]
		(−8.3872)	(−5.0727)	(−7.7092)
	R squared	0.1982	0.0619	0.1722

(continued)

Table 7.6 (continued)

		VIX	OVX	VXN
PBD(G)	d	−0.0009	0.0002	−0.0008
		(−0.061)	(0.0169)	(−0.0569)
	δ	−0.0093[a]	−0.0142[a]	−0.0113[a]
		(−3.2281)	(−3.1862)	(−3.1278)
	R squared	0.0231	0.0182	0.0245

Beta values are calculated from the ADCC model (A) and GO-GARCH model (G). HAC robust t statistics shown in parentheses. The superscript [a] denotes a level of significance at 0.01. The estimation equation is: $\Delta\ln(\text{beta}_t) = d + \delta Z_{t-1} + \xi_t$ where Z_{t-1} is the return on either VIX, OVX, or VXN

the systematic risk is used to estimate the cost of capital and to formulate investment strategies. The focus of this paper is to use multivariate GARCH models to calculate time-varying conditional clean energy equity betas and to study the impact that market uncertainty, measured using implied volatility, has on clean energy equity betas.

Clean energy stock prices are measured using several popular ETFs (QCLN, PBW, ICLN, and PBD). Time-varying conditional clean energy equity betas are calculated using multivariable GARCH models. For robustness two multivariate GARCH models, asymmetric dynamic conditional correlation (ADCC) (Cappiello et al., 2006) and generalized orthogonal GARCH (GO-GARCH) (Peter Boswijk & van der Weide, 2011; van der Weide, 2002), are used. Conditional time-varying betas show considerable variation and time series patterns that are different from the unconditional static betas. Clean energy equity betas show persistence. Persistence in clean energy equity betas suggests that a random walk forecasting model for beta is difficult to beat. The change in beta is mean reverting. The impact of market uncertainty on clean energy equity beta is investigated where stock market uncertainty is measured using implied stock market volatility (VIX), oil market uncertainty is measured using implied oil market volatility (OVX), and technology stock market uncertainty is measured using implied technology stock market volatility (VXN). Implied volatility has a statistically significant impact on clean energy equity beta. In regressions where the percentage change in beta is the dependent variable and the one period lag of the percentage change in implied volatility is the explanatory variable, the average value of the estimated coefficient on the VIX is −0.4709 for the ADCC estimated betas and −0.0381 for the GO-GARCH estimated betas. In comparison, the average estimated coefficient on the OVX is −0.2914 for the ADCC estimated betas and −0.0227 for the GO-GARCH estimated betas while the average estimated coefficient on the VXN is −0.4864 for the ADCC estimated betas and −0.0399 for the GO-GARCH estimated betas. These results are similar to those obtained using a shorter time period that represents the shale oil revolution indicating that the relationship between beta and implied volatility over the shale oil revolution period was similar to that for the full sample period. The findings in this paper are consistent with a mean reversion response of clean energy equity beta to increases in market volatility and is robust to the choice of GARCH model used to estimate beta. For each beta, the VIX equation produces the highest R squared value followed by the VXN and OVX equations, respectively. These results are important in establishing that stock market uncertainty, oil market uncertainty and technology stock market uncertainty have significant impacts on clean energy equity beta.

The research in this paper provides some ideas for future research. One possible direction for future research is to see how important implied volatility is for forecasting clean energy equity betas. Forecasting analysis could compare models that include implied volatility as an explanatory variable to models that do not include implied volatility. Analysis could be conducted both in-sample and out-of-sample. Another possible avenue for future research is to broaden the analysis to include clean energy ETFs that focus on specific clean energy sectors like solar or wind. A further possible direction for future research would be to look at the impact of implied volatility on firm specific clean energy company betas.

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Climate-Finance

8

Panagiotis Tzouvanas

8.1 Introduction

The late twentieth and the early twenty-first centuries are characterised by significant changes in weather patterns. A growing number of environmental initiatives have been activated to harmonise this phenomenon, which has taken monstrous magnitude mainly thanks to the continuing increase in carbon dioxide emitted by firms. Social and regulatory forces push firms to adopt a friendly, towards the environment, behaviour. In turn, firms have to be prepared with adequate tools and knowledge about the potential climate change effects on their financial performance (FP). These effects can be direct, such as extreme weather events and indirect such as environmental regulations. This Chapter presents an empirical investigation on how climate change has affected financial performance. Particularly, the main research question is whether "green" performing firms gain any financial benefits.

Human activities are estimated to have caused approximately 1 °C of global warming above pre-industrial levels (IPCC, 2018). The increasing consumption of goods, that our modern civilisation demands, has raised atmospheric carbon dioxide levels from 280 parts per million to 409 parts per million in the last 150 years. Given that the current rate of anthropogenic CO2 emissions continues, global warming is likely to reach 2 °C in the next 50 years (IPCC, 2014). The main challenge is to maintain global warming below the threshold of 1.5 °C. Beyond this level, extreme weather events will be more frequent and as a result the macroeconomic and financial conditions will be deteriorated significantly (Dell et al., 2012; Stern, 2007; Tzouvanas et al., 2019).

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Keeping global warming below 1.5 °C demands firms to adopt an environmental approach towards the natural environment. However, this proactive approach might be opposed with the main objective of firms (e.g., maximise shareholders' value). Therefore, firms will agree to comply with the social and regulatory actions against climate change only if the net benefit from environmental actions out-weights the compliance costs (Hatakeda et al., 2012). Besides, global warming has multidimensional characteristics that could potentially affect the financial performance of firms. For instance, firms can be influenced by the environmental regulations such as environmental reporting, carbon tax or carbon trading as well as by the perception of the market participants whose behaviour deviates from the traditional theory of finance and they might extract utility by turning into environmentally sensitive stocks (Fama & French, 2007; Tzouvanas et al., 2020b). On top of that, the contemporaneous topic of climate change in a micro-economic level is a rather unexplored field of study and for this reason, there is an uprising stream of scholars, managers and policymakers who attempt to make an inference between the firm and the environment (Bebbington & Larrinaga-Gonzalez, 2008). Therefore, the aim of this chapter is to answer, "if it is pays to be green".

In existing literature, environmental firms are considered firms with low Greenhouse Gas (GHG) emissions (Albertini, 2013; Dixon-Fowler et al., 2013; Endrikat et al., 2014). Also, the profitability of these firms is measured with accounting profitability ratios (e.g., ROA, ROE, ROS and Tobin's Q). The majority of the literature (around 60%) between GHG and profitability supports that reducing GHG increases profits; however, 20% shows that greater reducing GHG is costly, while the remaining while 20% argues that the relationship is unrelated (Busch & Lewandowski, 2018; Horvathova, 2010). These inconsistent research findings have encouraged scholars to delve deeper into this relationship. For example, Horvathova (2012) shows that GHG reduction has a time-varying effect on profitability; in the short term the direction of the effect is negative due to the additional costs, while in the long-term firms gain a competitive advantage. Also, Barnett and Salomon (2012), Misani and Pogutz (2015) examine the possibility that the relationship might be curvilinear, depending upon the magnitude of GHG reduction. On a different note, Hatakeda et al. (2012) underline that the relationship between GHG and profitability might be affected by the sample used, the variables employed and the econometric technique.

But why GHG affects firm's performance? There are two main channels through which GHG can affect the profitability of the firms. In a nutshell, Fig. 8.1 shows the two-way relationship between firms and climate change. Firms produce goods. The production process demands firms to use fossil fuels and other materials, which emit GHG emissions in the atmosphere. In turn, GHG emissions increase global temperatures and generate the so-called Greenhouse effect or otherwise climate change. Amid climate change, firms should decrease their GHG emissions, if not, these firms might be penalised by their stakeholders. The second reason how climate change can affect the firms is via the behavioural factor channel. Investors, influenced by the climate change movements, might be very precautious before

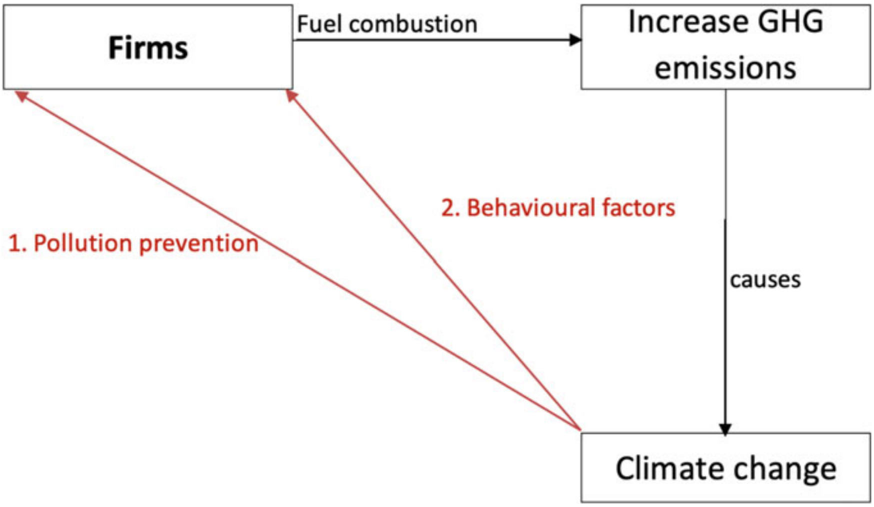

Fig. 8.1 Conceptualising climate-finance

acquiring a new stock into their portfolio; as Fama and French (2007) argue, some investors might extract utility by holding social stocks.

In this regard, this chapter investigates if firms, which prevent their own pollution, also enjoy higher price evaluations. We also explore how such an empirical research can be conducted, while we discuss various theoretical frameworks. Thus, the structure of this chapter has three main parts: (1) to investigate the channel between GHG and firm performance, (2) to empirically test this relationship and (3) to interpret our findings. In the empirical application, we use a large panel of firms from around the world and we regress their profitability on their relative GHG performance. We use full sample analysis, as well as we split the sample among firms from North America, Europe and Asian-Pacific regions. It is important to distinguish among regions because of (i) the differences in financial development, (ii) regulations and (iii) cultural and behaviour characteristics.

Indicatively, Fig. 8.2 shows the GHG emissions from three main markets for the period 1990–2017. Note that these are country/union data, while our investigation refers to firm-specific data. Nevertheless, it is useful to investigate the trend across different areas. Clearly, EU follows a decreasing trend, US is rather constant, while China has sharply increase their GHG emissions. Hence, it is important to understand how investors react to polluting firms across different regions.

This chapter has several contributions. First, we engage in the long-standing debate between carbon emissions and firm performance by showing that lower GHG emissions are highly appreciated by investors. Second, we present the theoretical framework of the relationship and we show that the *stakeholder theory* can well explain this relationship (Tzouvanas et al., 2020a). Third, we provide guidance on how to conduct such an empirical research. We estimate panel data models

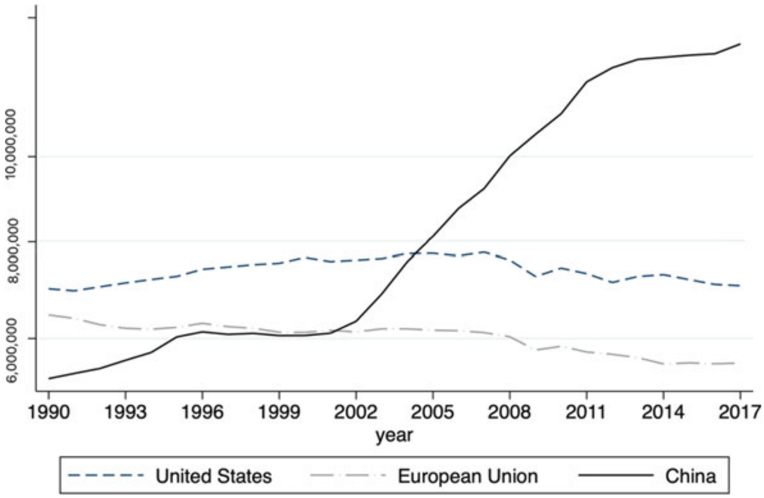

Fig. 8.2 GHG metric tonnes (*Source* Author's graph. Data retrieved from: https://stats.oecd.org/Index.aspx?DataSetCode=AIR_GHG and https://climateactiontracker.org/countries/china/)

as well as we treat for endogeneity with 2SLS regressions. Endogeneity is not a minor issue, if our model suffers from omitted variable bias or causality, then our results are not reliable. Fourth, we distinguish between firms from NA, EU and AP and we show that firms in EU are the ones highly rewarded when decreasing their GHG emissions. Finally, based on our findings, we provide some important implications.

The remainder of this chapter is organised as follows. In Sect. 8.2, we present the theoretical framework and discuss the relevant hypothesis. In Sect. 8.3, we describe the data and present the methods of the study. The empirical results are reported in Sect. 8.4. Finally, in Sect. 8.5, we discuss the main results of the study and reach a conclusion.

8.2 Theoretical Framework

GHG emissions play an essential role in promoting stakeholders' interests and influencing the profitability of firms. The connection between GHG and FP is based on a multitude of theoretical predictions which have been summarised in Fig. 8.3. The overriding objective of all these theories was to respond to the following question: "How is FP affected if we decrease firm pollution?" In order to achieve this objective, we provide a broad overview of the existing framework and further examine under what circumstances GHG emissions affect FP.

The first theoretical prediction suggests that GHG decreases the value of the firm. This negative link between GHG and FP, as proposed by the instrumental

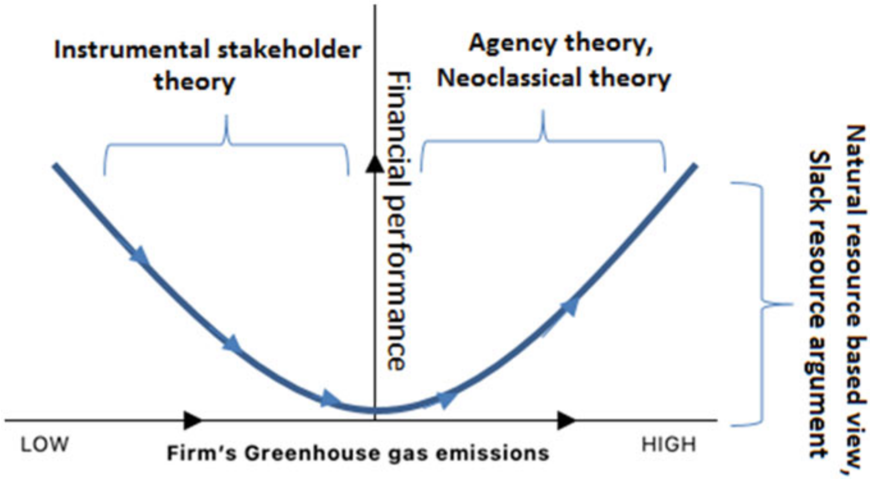

Fig. 8.3 Theoretical framework between GHG and FP (Modified graph retrieved by: Tzouvanas et al. [2020a]. https://doi.org/10.1016/j.bar.2019.100863)

stakeholder theory (Jones, 1995), presumes that long-term environmental objectives establish a consistent strategy that reduces the uncertainty of environmental issues and develops dynamic capabilities that in turn attract shareholders. The theory is a combination of the legitimacy and the agency theories. It focuses on the contracts between managers and stakeholders and claims that trust and cooperation within any company help to create a competitive advantage (Jones, 1995). For example, by satisfying stakeholder demands concerning climate change, firms may acquire better reputation, improve customers' loyalty and, overall, respond more effectively to external demands (Endrikat et al., 2014).

The second theoretical prediction is the positive link between GHG and FP, which is supported by the trade-off view (Jensen & Meckling, 1976), indicating that decreasing firm's GHG emissions merely reduce firms' profits. The positive relationship between GHG and FP can be attributed to the higher cost that firms have to bear. The neoclassical theory suggests that some industries experience high environmental compliance costs because they operate under green management policies and therefore face a competitive disadvantage (Wagner et al., 2002). This is particularly the case for manufacturing firms since the cost of decreasing their emissions is relatively high and results in an increase in the marginal cost of production. Similarly, the agency theory argues that GHG reductions might be in conflict with the main objective of the firm (e.g., maximise shareholder value) and thus would only decrease shareholders' satisfaction (Jensen & Meckling, 1976).

Finally, there is a third theoretical prediction according to which GHG might have a non-linear impact on FP (Misani & Pogutz, 2015). What is more, this argument has largely been supported by empirical research which provides evidence of a U-shaped relationship (Lewandowski, 2017; Nollet et al., 2016; Trumpp & Guenther, 2017). Initially, reductions in GHG are expected to diminish profits, (i.e., in line with the trade-off view); however, in time, a continued decrease beyond a certain level would bring benefits that would potentially offset costs, giving rise to the U-shape. In fact, the U-shaped relationship is also implied by the natural resource-based view of the firm. In particular, Hart (1995) opines that firms should develop new technologies in order to manage their resources efficiently. The implication is that corporate governance has a keen interest in investing in EP, expecting that this investment will help improving the future position of the corporation (Hart & Ahuja, 1996). Apparently, firms that reduce their emissions, gradually improve their stakeholders' satisfaction. In turn, gradually increasing stakeholders' satisfaction results in benefits outweighing the costs (i.e., the turning point in the GHG-FP relationship). The threshold at which this turning point occurs varies considerably, depending mainly on firm-specific characteristics (Broadstock et al., 2019) (Fig. 8.3).

Similar to the natural resource-based view, the slack resource argument underlines that decreasing emissions would not directly increase the FP of firms, but this depends on various aspects (Symeou et al., 2019). The theory is referred to the resource endowments in social and human capital and source constraints that can influence the performance of a firm in a competitive market. GHG emissions are inevitably connected with the source constrains (Busch & Hoffmann, 2007; George, 2005). For example, low resources firms have limited available financial funds to invest in GHG reductions, while, at the same time, pressure from stakeholders for profit maximisation remains the same. Thus, it is challenging for managers to increase their profitability while dealing with climate change issues. By contrast, firms with superior resources may utilise their available income in order to invest in eco-friendly technologies (Li et al., 2018). At the same time, high resources firms, are more likely to accomplish effective environmental investments.

On a final note, GHG emissions policies show considerable variability from one country to another. Governments have differently set greenhouse gas emissions targets due to variability in environmental regulations (Clarkson et al., 2015), also in light that to this date there is not a universal agreement on greenhouse emissions. For example, Clarkson et al. (2015) argue that the creation of the ETS in EU impacts upon the market valuation of GHG vis a vis other countries. Clarkson et al. (2015) find that highly GHG emissions firms receive higher negative market valuation in EU ETS. GHG emissions do not come cheap for firms as they entail financial costs related to changing their underlying operations and production process. Higher costs would increase future liabilities and reduce future cash flow and earnings. To this end, it is interesting to investigate whether there is variability across the regions. In particular, we would like to investigate the differences between three sizable stock markets, North America, EU and Asian-Pacific. For example, the US neglects, while the EU highly values climate change issues. Also, it is interesting to ask the same question for the Asia–Pacific region. In this regard, the hypothesis postulates that:

Hypothesis The association between GHG and FP varies across US, EU and Asia-Pacific regions.

The expectation is that EU firms should be awarded the most when decreasing their emissions. It is because the EU has paid a lot of attention to climate change issues, following by the Asian-pacific region. US firms should be the last.

8.2.1 Environmental-Climate Policy

We now turn to consider the regulatory regime against climate change. This further motivates the reason to investigate the GHG effects across different regions. Stabilising carbon emissions is a complicated task. According to Stern (2007), tackling climate change considers four main actions; (a) regulating the emissions, (b) incentivise the green investments, (c) minimising asymmetric information and transaction costs and (d) building informative network to the society. Different climate change policies are listed below.

The first policy is the Intergovernmental Panel on Climate Change (https://www.ipcc.ch/about/) which was set up in 1988 and is an international body for assessing climate change. The IPCC presents scientific, technical and socio-economic information in order to understand the future risk arising from the human-induced climate change. Its main contribution is to inform about potential impacts and provides with options for adaptation and mitigation. Furthermore, the United Nations Framework Convention on Climate Change (UNFCCC, http://newsroom.unfccc.int/about/) is a treaty which was signed in 1992 and having as a main target to stabilise the GHG in a harmless level to the environment. UNFCCC is probably the most serious attempt made against climate change and it is a treaty supporting posterior actions such as the Kyoto protocol, Clean Development Mechanism (CDM) and Paris Agreement. Regarding the Kyoto Protocol (http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php), it is an agreement made by UNFCCC with its main objective being to regulate a permissible limit of GHG. The Protocol had been negotiated since 1997 and was set in action in 2008. It requires ratification and signed members ought to decrease their emissions at a level of 5% below that in 1990. Similar to the Kyoto Protocol, Asia–Pacific Partnership (APP, http://www.asiapacificpartnership.org/) has attempted to meet goals for national air pollution reduction and climate change in a way that will not harm the growth and the sustainability of countries and firms. APP partners are Australia, Canada, China, India, Japan, Korea, and the United States. Additionally, the Clean Development Mechanism (CDM, http://cdm.unfccc.int/about/index.html) is a mechanism that promotes the low emission technologies in developing countries. Moreover, it motivates sustainable development emission reductions by giving developed countries some flexibility in how they meet their emission reduction limitation target under the Kyoto Protocol. Meeting the demands of CDM will cause an earning on certified emission reduction credit (CER) each equivalent to a tone of CO2

Accordingly, CDM supports the green investment and gives incentives for emission reductions. The most recent and prominent attempt against climate change took place in Paris in December of 2015. Paris agreement (http://unfccc.int/paris_agreement/items/9444.php) is being ratified by 189 out of 197 countries and was taken into force on November 2016. The agreement incorporates three main targets, (a) holding the world temperature increase below 2 °C (after the industrial revolution the temperature has increased by almost 1 °C), (b) facilitating the adaptation of low GHG technologies in respect to the food production and (c) making finance flows consistent and continuous to low climate-resilient development.

8.3 Data and Methods

8.3.1 Sample

The sample consists of 1800 European firms that are included in the STOXX Index, covering large, mid and small capitalisation companies around the world. Particularly, we considered 600 firms from North America (https://www.stoxx.com/index-details?symbol=SXA1E), 600 firms from the EU (https://www.stoxx.com/index-details?symbol=SXXP) and 600 firms from the Asian-Pacific region (https://www.stoxx.com/index-details?symbol=SXP1E). The sample period spans from 2005 to 2018. We choose to start in 2005, a period when not only talks against climate change escalated, but also when the first phase of the EU emissions trading scheme was activated. Also, investigating the period before 2005 is difficult as ESG data are not available. Data have been obtained from Thomson Reuters Datastream.

8.3.2 Variables

The main dependent variable is the Tobin's Q. Tobin's Q has been used by many previous studies as it is both conceptually and theoretically valid in the examination between profitability and GHG (Elsayed & Paton, 2005; King & Lenox, 2001; Konar & Cohen, 2001; Nakao et al., 2007). Particularly, it measures the profitability of firms by controlling for the intangibility. GHG emissions are considered as an intangible asset (Lins et al., 2017) and thus we expect that GHG directly influences the Tobin's Q. We follow Konar and Cohen (2001) to construct our dependent variable. The author stated that the valuation of the firm is based on its future profitability. Tobin's Q can be calculated as in Eq. 8.1:

$$Tobin's\ Q = \frac{Market\ Value\ (Equity + Debt + Preferred\ Stock)}{Replacement\ Value(Property,\ Plant\ and\ Equipment + Inventory + Short\ term\ Assets)} \tag{8.1}$$

This is defined as the value of the firm over its replacement cost. If the value of the firm is exactly equal to its replacement cost, then the ratio is a unity. If firms have substantial intangible assets such as patents, brand names, R&D etc., then the ratio is over the unity, signifying the future prospects of this firm.

Therefore, it is widely believed that investing in green technologies is considered as an intangible capital, which is ameliorate the future position of the firms (Lins et al., 2017). GHG emissions can serve as a good proxy for the environmental engagement of firms. GHG should be adjusted to firm's size, using the sales (some studies have used total assets or market values as well), and then it is measured as a logarithm in order to account for potential outliers. Following Misani and Pogutz (2015), the main independent variable is:

$$lnGHGS = LN\left(\frac{GHG}{Sales}\right) \tag{8.2}$$

The lnGHGS is our carbon intensity indicator, Higher values correspond to "bad" carbon performance, the variable avoids high skewness and captures the relative carbon performance scaled by sales.

Also, leverage (Lev) is used as a proxy of financial risk; it represents the level of debt to equity. It can be measured by summing the short- and long-term liabilities divided by the market value $\left(\frac{Debt}{Equity}\right)$. It is imperative to include risk proxies in the analysis (Busch & Hoffmann, 2011; Hatakeda et al., 2012; Matsumura et al., 2014). Tangible assets (Tang) can be a proxy for the collateral and shows the size of the firm. An ambiguous relationship between FP and tangibility is expected because creditors can liquidate assets easily and thus, they face less risk (Konar & Cohen, 2001); however, funds lying idle tend to increase the marginal costs. Future prosperity can be represented by intangible assets (Inta). They cannot be easily collateralised, but they can add value to the firm (Psillaki et al., 2010). Inta also have attributes of research and development (R&D) of the firm (Elsayed & Paton, 2005). Both Tang and Inta are entering the equation in logarithm form in order to capture for outliers.

8.3.3 Panel Data Model

Having discussed about how GHG and FP are connected, we now proceed to estimate their relationship. Following previous studies (Delmas et al., 2015; Nollet et al., 2016; Tzouvanas et al., 2020b) we employ panel data methodology, and we stress GHG in our regressions as shown below:

$$Tobin's\ Q_{i,t} = a_0 + a_1 lnGHGS_{i,t} + \boldsymbol{X}'_{i,t}B + \sum_{t=2}^{T} \delta_t Year_t + e_{i,t} \tag{8.3}$$

where the subscripts i and t correspond to firm and year, respectively, i = 1, 2, …, N and t = 1, 2, …, T and e the error term. Tobin's Q denotes the dependent variable and X' is a vector that contains control variables (Lev, Tang and Inta).

We also control for year fixed effects, so α_0 intercept is referred to the base year (2005). In other words, in our 14-year period of our investigation we drop the first year (2005) to avoid multicollinearity. Thus, summation sigma and delta refer to the remaining 13 coefficients (2006–2018); year coefficients are not reported in our results for brevity. Particular attention should be placed on the variable of interest which is lnGHGS and the coefficient we should observe is α_1. According to our main hypothesis, we perform two-tailed test, so the null hypothesis is $H_0 : \alpha_1 = 0$.

The results are presented under fixed effects and random effects models. For all different specifications, we use robust standard errors. The fixed effects model is appropriate when we focus on a specific firm characteristic (c_i) and therefore $e_{i,t} = v_{i,t} + c_i$ with $v_{i,t}$ being a time-varying error component. The random effects model represents random draws from the population so that (c_i) allows for individual effects. In contrast with the previous models, a simple OLS estimates constant coefficients ($c_i = c$). Finally, we report Hausman test results in order to identify if the individual effects (c_i) are unobserved and correlated with the explanatory variables (Baltagi, 2008; Wooldridge, 2010).

All estimations have been done in STATA 16.1. In the appendix of the Chapter, you may find the STATA codes.

8.3.4 Descriptive Statistics

Before moving to econometrically test the relationship, it is worth exploring the descriptive statistics of the variables. Table 8.1 displays these descriptive statistics for the variables employed in this study. Tobin's Q is the main dependent variable, and it has a mean of 1.94; higher Tobin's Q indicates higher evaluation of the firms. The main dependent variable is lnGHGS, which has a mean of −3.08. Because this variable is expressed in logarithmic form, it does not have direct interpretation,

Table 8.1 Descriptive statistics

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Tobin's Q	1.936187	2.941973	0.235582	322.6255	61.56267	6262.915
lnGHGS	−3.079089	2.105597	−13.14249	10.45109	0.1095257	3.617527
ROA	11.25171	27.91454	−3811.875	335.3424	−110.4951	15,161.22
Leverage	0.9124476	10.3609	−779.2174	491.8462	−29.35681	2237.55
Tangible	15.02573	1.463239	6.77079	19.31605	−0.3492295	4.008937
Intangible	13.34805	2.378086	0	19.55272	−0.7193577	4.37019
Board size	11.11649	3.691236	1	44	1.119114	6.113888
ESG disclosure	58.3311	17.56495	4.77	97.92	−0.2822279	2.3128
Employees	9.358011	1.733109	0	14.64842	−0.6184464	3.984802
Carbon trading	0.1648099	0.3710184	0	1	1.806911	4.264929

Notes Tangible, Intangible and Employees are measured in logarithmic terms but higher values correspond to firms that pollute, while low values for firms with very low emissions. We, next, present the control variables as well as some other variables that will be used for robustness checks and in the 2SLS regressions. As far as the distribution of the variables is concerned, lnGHGS, Tang, Inta Employees are very close to satisfy the normality conditions (Skewness = 0 and Kurtosis = 3). We now move to discuss our main results.

8.4 Results

8.4.1 Main Results

Table 8.2 displays the main results of this Chapter. Columns 1–4 contain results for the full sample, North America (NA) sample, European (EU) sample and Asian-Pacific (AP) sample, respectively. Columns "a" and "b" indicate that fixed effects models and random effects models are used, respectively. Following the principles of the Hausman test, fixed effects should be considered for the full, NA and EU samples, while random effects for the AP sample. Nevertheless, the results are identical between the two estimation methods. Starting with the control variables, *Leverage* appears weakly negative, this indicates that risky firms have lower firm values. *Tangible* assets have a negative coefficient, this is in line with the previous literature (e.g., Konar & Cohen, 2001). Tangibles indicate the size of the firms; large firms have lower profitability than small sized firms. *Intangible* assets have also a negative sign. Intangibles show the R&D of firms and hence an explanation is that R&D might deduct profits in the short run, while such an investment needs time to pay off. Overall, the effects of our control variables on Tobin's Q are in agreement with the previous literature (see, for example, Konar & Cohen, 2001; Elsayed & Paton, 2005; Nollet et al., 2016; Tzouvanas et al., 2020a).

Turning to the main hypothesis, *lnGHGS* has always a negative sign and it is significant at 5% level. Particularly, the full sample reports a coefficient of −0.1814 at 1% level of significance (column 1a). This indicates that a decrease of 1% of firm's relative emissions, will increase firm's performance by 0.1814%. When we split the sample, this coefficient varies in magnitude. Although, the sign remains negative, the EU sample documents the most negative sign. For example, comparing the coefficients for the fixed effects model, EU reports a coefficient of −0.2845, then the NA sample follows with −0.0532 and finally, the AP sample with −0.0274. Based on this, we can confirm the generic hypothesis that high GHG emissions are detrimental for the firm' performance. Also, our findings mirror the *instrumental stakeholder theory*, while these results are in line with the largest part of the empirical literature (Albertini, 2013; Busch & Lewandowski, 2018; Endrikat et al., 2014; Horvathova, 2010). Finally, our results show important variability among the three sub-samples. However, this variability should be tested for its statistical significance. We, next, continue with some sensitivity tests in Table 8.3, while in Table 8.4, we will statistically validate the difference among the three regions.

Table 8.2 Panel regressions with Tobin's Q as dependent variable

Sample:	Full		NA		EU		AP	
	(1a) FE	(1b) RE	(2a) FE	(2b) RE	(3a) FE	(3b) RE	(4a) FE	(4b) RE
lnGHGS	−0.1814***	−0.1131***	−0.0532**	−0.0859***	−0.2845**	−0.1420**	−0.0274*	−0.0366***
	(0.0648)	(0.0277)	(0.0224)	(0.0163)	(0.1342)	(0.0607)	(0.0146)	(0.0118)
Leverage	0.0009	−0.0101*	−0.0024**	−0.0032***	−0.0116	−0.0517	−0.0040	−0.0071**
	(0.0064)	(0.0058)	(0.0011)	(0.0011)	(0.0413)	(0.0341)	(0.0030)	(0.0030)
Tangible	0.0544	−0.4396***	−0.2171***	−0.2495***	0.5459**	−0.4951***	−0.0768***	−0.1641***
	(0.1076)	(0.0519)	(0.0271)	(0.0237)	(0.2640)	(0.1140)	(0.0265)	(0.0220)
Intangible	−0.3792***	−0.0574*	−0.1144***	−0.0959***	−0.9373***	−0.2529***	−0.0269***	−0.0243***
	(0.0552)	(0.0305)	(0.0177)	(0.0159)	(0.1387)	(0.0750)	(0.0099)	(0.0091)
Constant	5.5413***	8.9847***	7.0422***	7.1645***	5.6231	12.4933***	2.8589***	4.1698***
	(1.5658)	(0.7122)	(0.4108)	(0.3523)	(3.6516)	(1.4867)	(0.3985)	(0.3236)
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Hausman Test (Chi^2)	81.70***		29.41**		52.19***		23.29	
R^2	0.0105	0.0064	0.1954	0.1941	0.0173	0.0108	0.1185	0.1157
Observations	11,434	11,434	2959	2959	4901	4901	3574	3574

Notes Robust standard errors in parentheses. ***, ** and * denote the level of significance at 1, 5 and 10%, respectively. In case of significant Hausman test, fixed effects is the preferred model, random effects otherwise

Table 8.3 Panel regressions with ROA as dependent variable

	(1)	(2)	(3)	(4)
Sample:	Full	NA	EU	AP
Dependent:	ROA	ROA	ROA	ROA
lnGHGS	−0.5074***	−0.3678**	−0.5553***	−0.1875*
	(0.0828)	(0.1484)	(0.1261)	(0.1110)
Leverage	−0.0170*	−0.0064	−0.1998***	−0.0670*
	(0.0099)	(0.0118)	(0.0422)	(0.0357)
Tangible	0.1825	−0.0450	0.0297	0.3968*
	(0.1429)	(0.2361)	(0.2422)	(0.2158)
Intangible	−0.9190***	−0.7293***	−1.4521***	−0.5341***
	(0.0773)	(0.1623)	(0.1353)	(0.0993)
Constant	21.4942***	25.0203***	31.6533***	11.8462***
	(2.0385)	(3.4625)	(3.3165)	(3.0804)
Year Dummies	YES	YES	YES	YES
R^2	0.0614	0.0463	0.0869	0.0774
Observations	11,300	2944	4840	3516

Notes Robust standard errors in parentheses. ***, ** and * denote the level of significance at 1, 5 and 10%, respectively. Results are based on fixed effects model

8.4.2 Robustness Tests

In order to test the sensitivity of our results we substitute Tobin's Q in Eq. 8.3 with return on assets (ROA). Indeed, ROA has been used by many previous studies in the literature (Misani & Pogutz, 2015; Tzouvanas et al., 2020a). Table 8.3 reports the results with ROA as a dependent variable. These results are exactly in line with our previous estimations. Thus, using a different firm performance indicator does not alter our results. We should also underline that the most negative coefficient appears in EU sample, following by the NA and then AP. However, we should underline that comparing coefficients from different samples is not entirely correct. Instead, we should check their statistical differences among these coefficients.

In order to confidently answer our hypothesis, we should compare the coefficients across different estimations. This can be done with many different ways. The simplest one would be to run a t-test among the coefficients. However, we employ a slightly different approach. We use the full sample and interact lnGHGS with each region. Since, we have 3 regions we can create 3 different interactions. Each time, we drop one interaction to avoid multicollinearity. The first interaction variable is the $lnGHGS \times NA$, this variable denotes that if firms are from the NA then the interaction takes a value equal to the lnGHGS. By contrast, if firms are from different regions when the interaction has a value of zero. We repeat this for $lnGHG \times EU$ and $lnGHGS \times AP$. This approach will give an answer about the region where GHG emissions reductions are appreciated the most by investors.

Table 8.4 Panel regressions with region interactions in the full sample

	(1)	(2)	(3)
	Tobin's Q	Tobin's Q	Tobin's Q
$lnGHGS \times NA$	−0.1272	−0.1238	
	(0.1431)	(0.1432)	
$lnGHGS \times EU$	−0.2493***		−0.2489***
	(0.0881)		(0.0881)
$lnGHGS \times AP$		−0.0817	−0.0837
		(0.1266)	(0.1265)
Leverage	0.0009	0.0010	0.0009
	(0.0064)	(0.0064)	(0.0064)
Tangible	0.0587	0.0576	0.0571
	(0.1076)	(0.1076)	(0.1076)
Intangible	−0.3772***	−0.3722***	−0.3765***
	(0.0552)	(0.0552)	(0.0552)
Constant	5.5409***	5.7827***	5.5754***
	(1.5657)	(1.5639)	(1.5648)
Year dummies	YES	YES	YES
R^2	0.0106	0.0099	0.0106
Observations	11,434	11,434	11,434

Notes Robust Standard errors in parentheses. ***, ** and * denote the level of significance at 1, 5 and 10%, respectively. Results are based on fixed effects model. We drop one interaction term every time to avoid multicollinearity

For example, in Table 8.4 column (1), the coefficient on the interactions $lnGHGS \times NA$ is insignificant, while the opposite is true for $lnGHGS \times EU$. In the EU area, the coefficient is statistically significant and negative, while in NA the coefficient is not statistically different from zero. This indicates that in the EU, firms are rewarded more than firms in North America, when firms decrease their GHG emissions. In other words, column (1) considers as a benchmark the situation in the AP region and thus it compares AP vs. NA and then AP vs. EU. In column (2), the interactions between NA and AP are not significant, thus these two regions have homogeneous investors' reactions when firms decrease their emissions. Another interpretation is that EU, which is the benchmark in column (2), has a stricter reaction to GHG reductions than NA and AP; that is why their coefficients appear insignificant. Finally, in column (3), the EU has more negative interaction than the AP region. Overall, EU is ranked number one in rewarding GHG reductions, then in the second place, we rank both NA and AP firms together. Note that insignificant interactions do not contradicting our previous findings, but it only ranks the regions with the most rewarding behaviour towards GHG reductions.

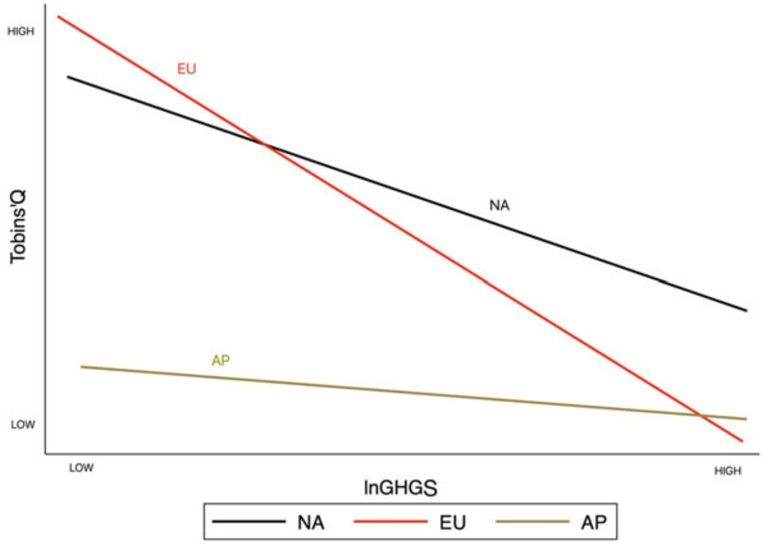

Fig. 8.4 Line plots between lnGHGS and Tobin's Q for different regions (*Source* Author's graph)

We can also graphically illustrate these coefficients. Figure 8.4 shows three lines, all of them have a negative slope, in line with our previous results. The most negative coefficient appears for the EU sample, then NA and last AP. Even though, NA's slope seems more negative than AP's, there is no statistical difference between them, as shown in the results of column (2) Table 8.4.

8.4.3 Endogeneity Test

As a final set of robustness checks, we consider endogeneity in our estimations. Endogeneity occurs because of simultaneity, causality, or omitted variable bias, and it should be carefully considered in the examination of the relationship between GHG and firm performance (see Albertini, 2013; Busch & Lewandowski, 2018; Papavasileiou & Tzouvanas, 2020). In other words, the independent variable (i.e., lnGHGS) may correlate with the error term (e), and thus the estimations might be biassed. A panel two-stage least squares (2SLS) regression is used to further solidify the results against possible endogeneity concerns. The estimation of this model is also a two-stage process. The first stage estimates the GHG model by considering the lagged values of GHG, firm's board size, ESG disclosure, number of employees and dummy if firms participate in carbon trading as instruments. These instruments are not randomly selected but should satisfy the exogeneity conditions as well as should be theoretically valid. Also, similar instruments have been chosen in previous empirical works (see Broadstock et al., 2018; Tzouvanas et al., 2020a; Papavasileiou & Tzouvanas, 2020). In the second stage, the fitted values of lnGHGS from Eq. 8.4 are used as an independent variable. Particularly, the first-stage equation is as follows:

$$lnGHGS_{i,t} = b_0 + b_1 lnGHGS_{i,t-1} + b_2 Board\ Size_{i,t} + b_3 ESG_{i,t} + b_4 Emp_{i,t} + b_5 Trading_{i,t} + X'_{i,t}B + \sum_{t=2}^{T} \delta_t Year_t + e_{i,t} \quad (8.4)$$

where X' remains the same as in Eq. 8.3 and b1–b5 are the coefficients of the instruments. In Table 8.5, results from the first stage are reported. Particularly, today's GHG is determined by the last year's GHG, as the coefficient is always significant and close to the unity. Board size appears insignificant, while ESG, number of employees and carbon trading seem to be significant determinants of GHG, especially for the full sample (column, 1).

Table 8.5 IV regressions: first stage results

	(1)	(2)	(3)	(4)
Sample:	Full	NA	EU	AP
Dependent:	lnGHGS	lnGHGS	lnGHGS	lnGHGS
$lnGHGS_{t-1}$	0.975***	0.983***	0.967***	0.977***
	(0.002)	(0.004)	(0.004)	(0.004)
Board size	0.001	0.002	0.000	0.002
	(0.001)	(0.003)	(0.002)	(0.002)
ESG disclosure	−0.001***	−0.000	−0.001*	−0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Employees	0.008**	0.004	0.011	−0.000
	(0.004)	(0.006)	(0.007)	(0.007)
Carbon trading	0.035***	0.024	0.063***	0.004
	(0.010)	(0.017)	(0.018)	(0.018)
Leverage	0.000	0.000	−0.002	0.002
	(0.001)	(0.001)	(0.003)	(0.002)
Tangible	0.007	0.005	0.001	0.009
	(0.005)	(0.007)	(0.008)	(0.009)
Intangible	−0.010***	−0.012**	−0.002	−0.005
	(0.003)	(0.005)	(0.006)	(0.005)
Constant	−0.143**	−0.069	−0.214**	−0.103
	(0.058)	(0.100)	(0.092)	(0.113)
Year dummies	YES	YES	YES	YES
R^2	0.960	0.973	0.953	0.958
Observations	9780	2514	4307	2959

Notes Standard errors in parentheses. ***, ** and * denote the level of significance at 1, 5 and 10%, respectively

Table 8.6 IV regressions: second stage results

	(1)	(2)	(3)	(4)
Sample:	Full	NA	EU	AP
Dependent:	Tobin's Q	Tobin's Q	Tobin's Q	Tobin's Q
$\widehat{lnGHGS}$	−0.088***	−0.109***	−0.115***	−0.028***
	(0.019)	(0.010)	(0.040)	(0.006)
Leverage	−0.014**	−0.008***	−0.064**	−0.015***
	(0.006)	(0.002)	(0.031)	(0.004)
Tangible	−0.489***	−0.352***	−0.546***	−0.176***
	(0.036)	(0.018)	(0.079)	(0.013)
Intangible	0.073***	0.012	−0.052	0.037***
	(0.022)	(0.014)	(0.056)	(0.007)
Constant	8.292***	7.324***	10.990***	3.787***
	(0.507)	(0.279)	(1.042)	(0.180)
Year dummies	YES	YES	YES	YES
R^2	0.028	0.213	0.032	0.105
Observations	9774	2514	4303	2957

Notes Standard errors in parentheses. ***, ** and * denote the level of significance at 1, 5 and 10%, respectively

Moving to the second stage regressions, we now use the fitted values ($\widehat{lnGHGS}$) from Eq. 8.4 as our main independent variable. 2SLS results are reported in Table 8.6. In line with our previous estimations, higher GHG deteriorates the firm's value. In fact, across our 4 different specifications, GHG has a negative sign and significant coefficient at 1% level, while once again, the most negative coefficient appears for the EU firms.

8.5 Conclusion

Our paper examined the effect of GHG on FP using data from a sample of 1800 global firms for the period 2005–2018. We employed panel data regressions such as fixed and random effects models. We also controlled for endogeneity with an instrumental variable approach. This gave us an opportunity to account for potential endogeneity between GHG and FP.

The main findings that emerge from this paper are that (i) GHG has a negative effect on FP across all regions, and (ii) firms in EU are rewarded (penalized) the most for decreasing (increasing) their pollution compared to firms in North America and Asian-Pacific. Taken together, the findings support theories that predict the negative association between GHG and FP (i.e. *instrumental stakeholder theory*).

Additionally, our findings should be seen in the light of recent stricter regulations on GHG emissions across all three examined regions. High GHG emissions should be connected with high environmental fines, which in turn could directly increase firms' costs. High costs might change firms' strategy towards GHG emissions. In close relation to this, regulators should consider developing cheap access to finance GHG reductions. Despite the increasing volume and complexity of environmental regulations, mitigation policies to address climate change provide insufficient incentives for adaptation. Besides, addressing stricter GHG targets could potentially increase profits, as documented in our results, it will eventually create a competitive advantage for firms (Porter, 1991). Our results also highlight the importance of GHG reductions for managers, financial analysts and investors. Particularly, from the investors point of view, firms' emissions have been monitored closely by large mutual and hedge funds, which aim to include low carbon stocks in their portfolios. Hence, there is a move of funds from polluting firms to non-polluting ones (see for example, BlackRock's strategy[1]). This explains why "greener" firms enjoy higher evaluations. At the same time, financial analysts should consider the climate risk—the risk related to a climate change—when evaluate portfolios. From a managerial point of view, our results are straightforward. Since *instrumental stakeholder theory* dominates this examination, managers should try to comply with the social demands against climate change. This can be a sustainable approach to attract new investors and decrease the cost of capital.

Concluding this paper, we would like to offer some potential avenues for future research. First, it could be interesting to examine the GHG effects on FP for different industries and countries separately. Second, we can enrich the methodology. For example, we may use dynamic panel models and non-parametric regressions to test the robustness of our results. Third, we can substitute GHG variable with other environmental variables, such as scope 1, scope 2 and scope 3 emissions. Finally, more research should be devoted to the risk associated with when decreasing emissions. For example, emission reductions might increase the firm risk, and in turn, higher risk is followed by higher returns. Using risk adjusted performance might be more accurate measure of FP.

Appendix: Stata Codes

Below, you may find the STATA codes. By changing the variable names according to your dataset, you can replicate the estimations of this study:

[1] https://www.ft.com/content/57db9dc2-3690-11ea-a6d3-9a26f8c3cba4.

. xtset ***id year*** // where *id* is the firm's id number and *year* corresponds to the time
. xtreg ***tobinsq lnghgs lev tang inta i.year*****, fe r** //xtreg is the command to run panel regressions, *tobinsq* is the dependent variable following by the control variables, *i.year* shows that we have included year dummies, *fe* indicates that we run fixed effects and *r* shows that we used robust standard errors (see Table 8.2, column 1a). If you change *tobinsq with roa,* Table 8.3 column (1) will be produced
. xtreg ***tobinsq lnghgs lev tang inta i.year*****, re r** // *re* shows that this is a random effects regression (see Table 8.2, column 1b)
. xtreg ***tobinsq lnghgs lev tang inta i.year if region = = 1,*** **fe r** // You need to create another variable named *region*; in our case this variable takes 1 if firms are in the NA, 2 if firms are in the EU and 3 if firms are in the AP region, "if region = = 1" means that we run the fixed effects regression just for the NA firms. Thus, if we would like to run the same regression for EU, we simply need to type the following:. xtreg *tobinsq lnghgs lev tang inta i.year if region = = 2,* fe r (see Tables 8.2 and 8.3, columns 2–4)
. xtreg tobinsq lnghgs lev tang inta i.year, fe **. estimates store fe** **. xtreg tobinsq lnghgs lev tang inta i.year, re** **. estimates store re** **. hausman fe re** //Finally, this code gives us the Haumsan test, if this is significant fixed effects should be used; if not, random effects is the correct model (see Table 8.2)
. xtreg ***tobinsq c.lnghgs#c.region1 c.lnghgs#c.region2 lev tang inta i.year,*** **fe r** // in this regression we interact *lnghgs* with *region1* (NA) and *lnghgs* with *region2* (EU), *region1* is a dummy that takes 1 if firms are in the NA, 0 otherwise; *region2* is a dummy that takes 1 if firms are in the EU, 0 otherwise and *region3* is a dummy that takes 1 if firms are in the AP, 0 otherwise (see Table 8.4, column 1)
. ivreg2 ***tobinsq lev tang inta i.year (lnghgs = l.lnghgs boardsize esg employes trading i.year*****), first** // we now run a 2SLS regression with the *ivreg2* command, in the parenthesis we instrumented lnghgs with exogenous variables. The command *first* reports the first stage results (see Tables 8.5 and 8.6, column 1)
. twoway (lfit tobinsq lnghgs if region = = 1, lcolor(black)) (lfit tobinsq lnghgs if region = = 2, lcolor(red)) (lfit tobinsq lnghgs if region = = 3, lcolor(brown)) // see Fig. 8.4

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Minimum Connectedness Portfolios and the Market for Green Bonds: Advocating Socially Responsible Investment (SRI) Activity

9

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9.1 Introduction

In recent years, the fixed-income investment market has evolved in a number of ways. Among the more noteworthy innovations has been the introduction of 'green bonds'. Green bonds have been a simple yet fundamental, and highly progressive, market innovation. Their simplicity can be gleaned from their definition: the Green Bond Principles define a green bond as '*any type of bond instrument where the proceeds will be exclusively applied to finance or re-finance, in part or in full, new and/or existing eligible Green Projects and which are aligned with the four core components of the GBP*' (ICMA, 2018). Complementary to the explicit 'green' orientation on the use of proceeds, it is also the case that a green bond must be both self-declared as a green bond by the issuer, and verified by an external 'second-opinion' provider, i.e. claiming green credentials is a pre-requisite, and a due-diligence requirement. Beyond these defining features, green bonds are otherwise equivalent to conventional (sometimes also known as 'black') bonds.

It is, arguably, the overlap in definition between green and black bonds, that has catalyzed market interest and adoption. Investors and issuers alike do not face a gap in understanding how they can be used, only in demarcating projects and project expenditures as being legitimately 'green'. Admittedly this introduces some additional cost to issuers, but against the backdrop of modern corporations, and

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the broad diffusion of corporate social responsibility (CSR) practices, these incremental costs are either already sunk within CSR reporting costs, or incrementally nominal relative to them. Green bonds are part of a wider suite of investment products aimed at supporting 'socially responsible investment' (SRI) activity which has become the dominant vehicle to operationalize corporate social responsibility, and make material/tangible progress towards achieving sustainable development goals.

Mainstream acceptability of SRI has gradually emerged following the report 'Who Cares Wins' published by the U.N. Global Compact,[1] and subsequently became popular after the launch of UN PRI (Principles for Responsible Investment) in 2006.[2] Thus, both CSR and ESG originate from the United Nations. To maintain momentum for SRI, and specifically the market for green bonds there is a need to promote secondary market liquidity (Fender et al., 2019). Liquidity is a defining feature of market efficiency, playing a critical role in the price discovery process and ensuring investments are fairly priced, and in a timely fashion. Promoting liquidity is nonetheless a challenging task for new financial instruments. Working against interest in green bonds are at least two features (i) a general unfamiliarity with the product and (ii) somewhat lapse rules on the disclosure, monitoring and enforcement of the use of proceeds criteria for the capital raised. But in the green bonds favour is the fact that as a financial product it is extremely similar to a regular bond, making it easy for investors to understand. Furthermore, green bonds are firmly in line with principles for responsible investment and efforts to support global climate action and deliver on SDGs (McInerney & Johannsdottir, 2016; Tolliver et al., 2019, 2020a, 2020b), and lastly the mechanisms required to enforce transparent use of proceeds consistent with the claims in the bond prospectus, are not new mechanisms and hence also easy to establish more rigor behind.

Green bonds already enjoy a global market, as discussed in Tang and Zhang (2020). Demand is international and often from institutional investors, supply however has been quite highly regionalized. The initial market position was established in Europe, and the Eurobond market remains extremely mature, coupled alongside strong internationally focused financial institutions—this means that the regional market maintains a strong influence over global market dynamics. The US market has emerged with arguably a different green bond offering than in some of the other global regions. There has been a strong interest among corporates to raise green debt, either as a means to legitimately fund green projects, or for greenwashing/marketing related purposes (Szabo & Webster, 2020). This introduces a new market dimension, opening the door not only to a new class of issuers but also opening up the doors to an inflow of funds from a different cluster of investors with pro-environmental preferences (Zerbib, 2019). Lastly the Greater China region has in recent years established a dominant position in the overall green bond market.

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[1] See: https://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf.

[2] See: https://www.unpri.org/pri/about-the-pri.

Evidence of this is manifest in both the value and number of green bond issuances in the region, which in recent years have constituted around 50% of the global market.

As will be discussed more thoroughly in Sect. 9.2, the volume of academic research on the market for green bonds is thin to say the least. One can postulate that this follows immediately from the relative age and maturity of the market. With the green bond initiating in 2007, and not achieving scale until nearer 2014, the availability (or lack thereof) of a sufficiently rich benchmark of empirical experience, and hence data available for research, has simply not been amenable to rigorous econometric inquiry. The papers closest to ours include an early study by Pham (2016) highlighting a material connection between green and black bond markets, and a suite of studies on the relation between green bonds and other asset classes as discussed in Reboredo (2018), Reboredo and Ugolini (2020) and Reboredo et al. (2020). These latter three studies are quite broad in their focus, trying to establish a comprehensive overview of the multitude of interactions between multiple asset classes. What sets this present paper apart from the above mentioned studies, aside from the fully dynamic econometric strategy and data sampling frame, is the explicit attention given to the three major geographies of the bond market and their interplay. Few existing studies focus on green bonds in China. Exceptions to this include Wang et al. (2020) who deploy an event-study to illustrate that (i) firm-specific stock returns are positively reacting to news about green bond issuance–relative to a matched sample of '*synthetic conventional bonds*'–and furthermore that (ii) the effect is strengthened for firms with strong corporate social responsibility profiles. Their findings overlap somewhat with Tang and Zhang (2020) who suggest, in an international sample including China, that benefits to green bond issuance include enhanced stock returns and improved stock liquidity.

We direct our attention towards the following fundamental investment question:

- Do green bonds have a (value enhancing) role to play in a balanced fixed-income investment portfolio?

The answer to such a question is of interest to at least three audiences. Firstly, the investment community is constantly looking for renewed guidance on innovative investment opportunities, and clarity as to whether a new instrument can complement existing ones in creating value. Second is the group of regulators, policy makers and compliance specialists, who wish to understand whether the overall financial performance of bonds of different classes does indeed differ? If it does not, then these groups need to consider if the existing policies are fit-for-purpose. Conversely, if performance differentials are extreme then again there is a need to review the efficacy of existing regulatory and policy frameworks. Lastly, the third audience with an interest in our findings would be the bond issuers themselves. Given the relative infancy of green bond markets, individual issuers have few personal benchmarks. We propose (hypothesize) that individual issuers would be able to benefit from (i) the consistent comparison of green versus conventional ('black') bond benchmarks and moreover that (ii) the differentials between geographic regions reveal information of incremental value with regard to the market characteristics that underlay successful green bond issuance.

However, there is a possible tension to our hypothesis, which predicates the need for formal empirical inquiry. For instance the existence of any 'green premium' of sorts is contingent on investors agreeing that green and black bonds with common financial characteristics, e.g. tenure, coupon rate, bond rating etc., still contain intangible value that will manifest in secondary market trade and liquidity, i.e. a pricing differential between green and black bonds. While it would be nice to assume that all investors are responsible investors in the SRI sense, it is more reasonable to assume that many, if not still most, of today's universe of investors are more pragmatic and do not value an intangible green premium over pure financial returns. Worded differently, the difference in premiums between green and black bonds appeals to an investor's altruistic behavioural orientation, which need not and may not exist. We do not investigate these behavioural aspects here, but recognize they rationalize a plausible tension in our hypothesis, hence justifying the need for our empirical investigation.

To develop testable hypotheses around our research question, we adopt the following framework. First, we estimate a time-varying parameter vector-autoregression, from which we obtain time-varying variance/co-variance matrices in a similar fashion to Antonakakis et al. (2020b), which are a vital ingredient for subsequent portfolio construction. In turn, we exploit variance decomposition analysis akin to Diebold and Yilmaz (2012, 2014), allowing for a detailed examination of the connectedness and spillovers between the various bond index benchmarks. For the third step of analysis, four multivariate portfolio construction methods are applied, including the time-varying (i) minimum variance, (ii) minimum correlation and (iii), minimum connectedness and (iv) the risk-parity portfolio, each of which drawing on the estimated time-varying variance-covariance matrix. In the last step, we use hedge effectiveness and Sharpe ratios to verify the role and importance of green bonds within a balanced fixed-income investment portfolio.

Main results indicate that, the outbreak of the COVID-19 had a noticeable, though rather short-lived, impact on connectedness among the variables of our network. More particularly, we note that there are two distinguishable peaks in total connectedness across the sample period. In both instances, the period around these peaks is characterized by unique and important events that affected international financial markets. Furthermore, we note that during the first quarter of 2020, black US bonds shift from being net recipients to being net transmitters of pricing shocks. In fact, this shift is the only considerable shift that takes place during this time interval. At the same time, both green and black Chinese bonds intensify their role as net transmitters in the network. The same is true for green US bonds. By contrast, green and black EU bonds, both strong net transmitters up to that point, appear to exert a rather moderate impact during this first quarter.

Furthermore, our analysis contributes unique evidence to the literature on the role of SRI practices as a complement to mainstream investment. Specifically, our results further indicate that green bonds assume a non-trivial role to a fixed-income investment portfolio. Portfolio weights for green bonds range on average from approximately 2% of the portfolio allocation, up to as much as 35% depending on the time and portfolio construction choice. There are some nuanced characteristics among portfolio techniques. We find that the minimum variance portfolio approach is rather selective and focuses mainly on EU black bonds while the risk-parity portfolio tries to weigh all assets more or less equally. The minimum correlation and minimum connectedness approach balance those two approaches. All multivariate portfolios have shown that they are meaningful when it comes to the reduction of investment risk as all hedging effectiveness scores have been significant on at least the 10% significance level. Depending on the asset under investigation 9–69% of the volatility of a single asset has been reduced. Finally, our empirical results suggest that the minimum connectedness portfolio outperforms all others as it reaches the highest Sharpe ratio and significantly reduces the risk in all assets.

The order of the paper is as follows: Sect. 9.2 provides a synopsis of the existing literature on green bonds; Sect. 9.3 introduces the data used in the paper; Sect. 9.4 describes the econometric framework; Sect. 9.5 reports the results; and Sect. 9.6 concludes.

9.2 Literature on Green Bonds

In this section of the paper we offer a brief summary of the literature on green bonds. The brevity of the review is preconditioned by the depth of the extant literature. As discussed in the introduction, academic research on this subject is thin. Here we qualify this. We omit discussion of literature focused purely on conventional bonds, and instead position our review of the literature in terms of providing a focused understanding of the preliminary research findings that have emerged from the literature on green bonds.

We begin the literature review by making reference initially to the Scopus academic literature corpus, which contains an expanse of bibliometric data for academic research published among leading international research outlets, not limited purely to journal publications, but also various other books, monographs, conference publications and so forth.[3] As broadly discussed and intimated in Aria et al. (2020), Corbet et al. (2019) among others, examination of bibliographic data and metadata can be highly revealing as to the depth, breadth, scope and general intellectual structure of research within a theme. Often these are larger reviews aimed at summarizing a burgeoning corpus of studies, but there are no constraints per se that inhibit their application to emerging bodies of literature such as ours. Nonetheless we do recognize their usefulness grows with sample

[3] Scopus is regarded as the most expansive source of academic bibliometric data, serving as an indispensable tool for thorough literature review. Details on the coverage, and history of Scopus are available at: https://www.elsevier.com/solutions/scopus/how-scopus-works/content.

Table 9.1 Summary statistics of Scopus search

Measure	Value	Measure	Value
Documents	93	Papers 0 citations	38
Sources (Journals, Books, etc.)	57	Papers 0 citations %	40.86
Timespan	2010:2020	Author's Keywords (unique)	303
Avg. Papers per year	9.30	Authors	189
Avg. Papers per year (post 2018)	27	Author Appearances	204
Citations	338	sole-authored papers	31
Average citations per documents	3.634	sole-authored papers %	33.33
h-index	11	Multiple-authored papers	62
Papers >100 citations	0	Multiple-authored papers %	66.67
Papers >100 citations %	0		

Notes For research with the term 'green bond', appearing in either of the title, abstract or keyword of a paper. Moreover, to ensure we do not contaminate our search results with literature from chemistry, biological or other natural sciences where green bonds take a very different meaning, we additional restrict the subject areas to be within either 'Economics', 'Business' or 'Social sciences'

size and time, and to this end, we only provide a brief focus on bibliometric summaries, before offering a more 'conventional' discursive summary of key research themes. For this part of our work, a search is conducted over the Scopus corpus for research with the term 'green bond', appearing in either of the title, abstract or keyword of a paper. Moreover, to ensure we do not contaminate our search results with literature from chemistry, biological or other natural sciences where green bonds take a very different meaning, we additionally restrict the subject areas to be within either 'Economics', 'Business' or 'Social sciences'—noting that finance falls within these areas.[4]

The search results will be summarized in several tables and plots, to reveal the core characteristics of the research corpus. First, some outline summary statistics are given in Table 9.1. The first point to note is that there are a grand total of 94 papers emerging using the specified search criteria. It is intuitive to question if the search term itself is somehow erroneous, but in our case this is highly unlike, as we do not require convoluted or multi-term appearances, or impose any constraints other than to literature within related disciplines. As such our previous assertions that the literature is thin is not an understatement or to be taken lightly. These publications cover the period 2010–2020, which is plausible since the first green bond only came to market in 2007. The literature is growing: across all years the average number of papers per year is 9.3, whereas the average number of papers per year in 2019/20 is 27, noting at the time of writing this will understate the true

[4] The specific Scopus search term was: `'TITLE-ABS-KEY ("green bond") AND (LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "SOCI"))'`.

average for this period, since it only covers until July 2020. What this additionally indicates is that the research is unlikely to have stimulated a large citation profile as yet, which is verified by the fact that more than 40% of the existing research fails to have generated citations as yet, though this number should decline substantially as the area of literature continues to grow. It is also worth noting that no papers have yet generated 100+ citations, suggesting the absence of a seminal study in this area as yet.

An important aspect of summarizing the literature is to appreciate the degree of coherence and consistency in themes of prior work. We will return to this again later, but some preliminary insights can be taken from Table 9.1. Specifically, it can be seen that with just 93 papers, some 303 unique keywords have been generated, thus on average each new paper brings more than 3 unique keywords, that do not appear in other papers. In total, and not reported in the table, there are 426 keywords, hence in the overall universe of keywords for these papers there are also some overlaps, nonetheless these are far fewer than non-overlapping keywords. This is highly indicative that the current corpus of research is disparate with loosely connected themes under the wider umbrella of green bonds. Further evidence indicating the same possible feature of the literature is that the 94 papers are published across 57 different journals, monograph/book series or other outlets. Accordingly, few journals have more than one paper on the topic. This is consistent with the view that the research is disparate or spread over a number of loosely connected research topics.

Notwithstanding the relative thinness of the literature, corpus analytics tools permit a structured visualization of the article metadata, which proves to be insightful as to the nature of connected topics. In Fig. 9.1 a network plot is used to show which keywords are connected with each other. Given the number of unique keywords, the number of observed permutations or pairs of keywords is prohibitively large to visualize, however a simple constraint brings the number down to a manageable set. The constraint applied is simply that the same connected pair of keywords must have appeared more than once. In so doing, the graph indicates which connected keywords are more likely to emerge as themes. The results are intuitively plausible. Unsurprisingly, the most connected term is 'green bonds', and this connects with a range of expected terms such as 'climate change', 'climate finance', 'corporate debt'. It is interesting to note that terms such as 'renewable energy' are not directly connected with 'green bonds', but instead are indirectly connected via 'green finance'. Considering this plot from the lens of our own work, while we do see that 'spillovers' (an alternative term for connectedness) are linked with 'green bonds', we do not see the appearance of either 'conventional bonds' or 'portfolios', though admittedly the references to 'municipal bonds' and 'corporate debt' do potentially cover wider fixed-income instruments than green bonds.

Risk is the foundation of financial markets, and the path to financial success when suitably mastered. To understand the notions of risk being discussed in the literature on green bonds, Fig. 9.2 plots the words which precede risk within the abstracts of the 93 identified studies. No constraints are required to de-noise this

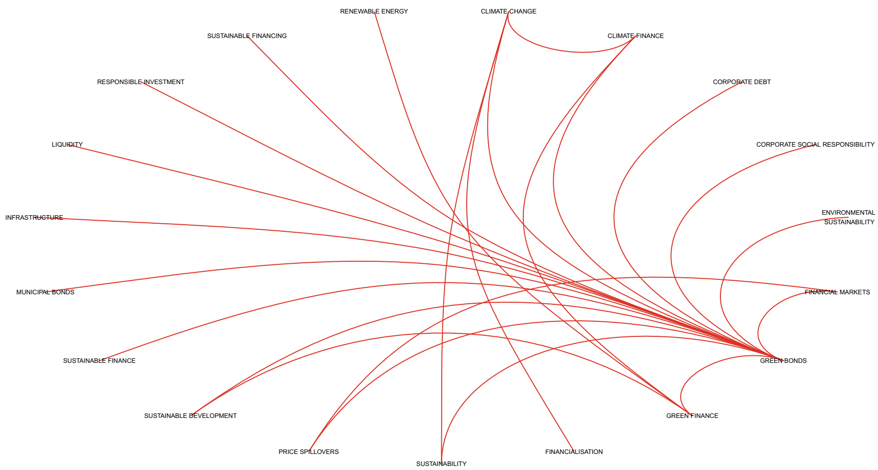

Fig. 9.1 Network plot of common ($n > 1$) connected keywords (*Notes* This plot takes the author provided keywords from the 93 papers contained in the Scopus corpus, to illustrate the nature of connected topics. To enable 'meaningful' visualisation, we only show keyword combinations that appear more than once)

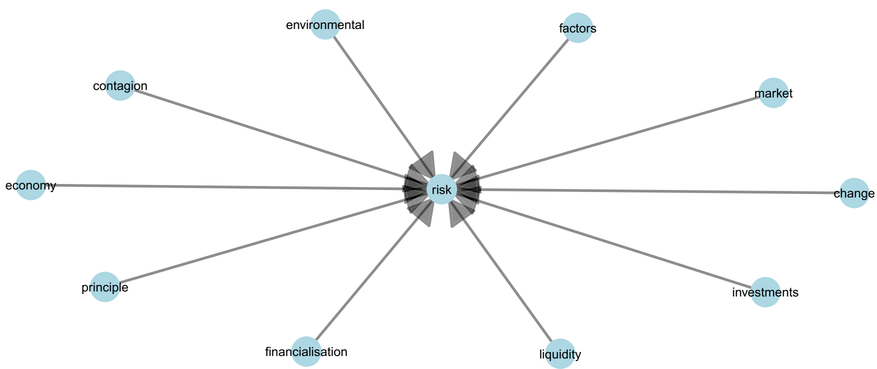

Fig. 9.2 Words preceding 'risk' (*Notes* This plot summarizes the term which appear before the word 'risk' within the abstracts of the 93 papers contained in the Scopus corpus. The objective of this graph is to indicate the aspects of risk which have been prioritized in existing research on green bonds)

plot to permit useful visualization. Ten terms precede risk, the majority of which making sense. The most intuitive these are: market-risk; change-risk; investments-risk; liquidity-risk; financialization-risk; principle-risk; economy-risk; contagion-risk and environmental-risk. The term factors-risk does not make immediate sense, though stopwords, such as the word 'at' are removed prior to producing the graph, and this might for example have originally been factors-at-risk. Taken together these keyterms support the range of issues outlined in the introduction, namely that risk to our environment stimulates a need for responsible investment, but the risk of innovation and change creates an associated investment risk which may align with poor liquidity. Moreover, being a new and untested financial instrument, green bonds are likely exposed more heavily to wider economic, financialization or contagion risk, which in term may jeopardize the invested principle. Of course this is a little bit of a word-play stringing together the terms appearing in the figure, yet not an inconceivable string of connections against the known market context.

The last point we will discuss from the Scopus corpus metadata concerns the geographic distribution of research, and the structure of the author collaboration network. Figure 9.3 presents a heatmap of research activity for the 93 papers on green bonds. The countries of the map shaded in white have no research output, and from this it is especially clear that Africa, and Southeast Asia are lacking any basic research. Research output increase as the colour graduates from yellow to red. From this it can be seen that there are three clusters: North America (which includes Alaska on definitional grounds); Europe, with UK, France and Italy being dominant; and China. This is consistent with our proposed geographic focus of study. It is worth noting that Australia has an emerging research presence, yet its orange tone indicates only around 7 studies or so. The blue lines overlaid on the plot indicate the countries which are paired through research collaborations. For example the line connecting China and the US indicates a paper co-authored by scholars from Chinese-based institutions with scholars from US-based institutions and so forth. Consistent with the number of papers, the number of co-author connections between countries is light. It would be remiss to try and attach too much importance to the geographical coverage and connectivity displayed in this figure, one can at the same time take some solace from the fact that research does bear the hallmarks of international collaboration. This implies that regional experiences will not remain in silos, which is a positive pre-condition for the diffusion of international best practices.

While the brief bibliometric review above uncovers several salient features and concepts being addressed within the literature, giving a broad oversight of the intellectual structure of research on green bonds. In the following text we turn attention to several of the more prominent emergent themes in the research.

9.2.1 Green Bond Policy and Regulatory Framework Development

The development of domestic and international standards for green bonds, and green finance, track closely alongside the wider efforts for capacity building and institutional readiness for financial markets and instruments that more readily support progress towards climate change and sustainable development goals. Green bonds and climate bonds have been shown, both theoretically and empirically, to be a viable part of the toolkit for financing climate policies and activities towards avoiding deep and irreversible climate change (Flaherty et al., 2017).

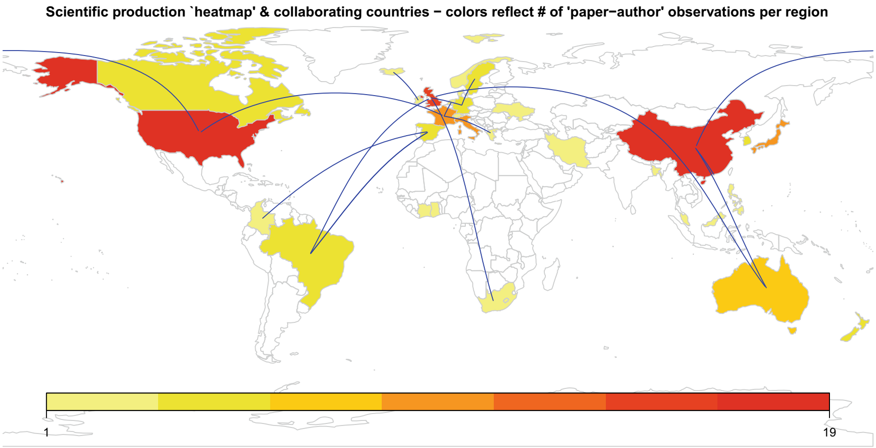

Fig. 9.3 Global production, and collaborative networks for research on green bonds (*Notes* This plot summarizes the geographic distribution of research on green bonds as captured within the Scopus database. The color of countries highlights the intensity of scientific production (publications) whereas the blue lines link countries where research collaborations exist)

However, where the theory and early evidence clarifies a viable role for green bonds, progress in expanding adoption and use of green bonds is hampered by incomplete and/or immature institutional environments.[5] Ng (2018) directly addresses the institutional framework for green bonds, in the context of the Hong Kong market, which in 2020 became the largest exchange by market cap, globally. Part of the discussion centers around the importance of institutional legitimacy which is initiated by top-down policy at the national level, and maintained through market-based activity and engagement. Tolliver et al. (2020a) similarly emphasize the importance of the national policy environment, highlight that existing domestic policy objectives such as commitments to the Paris Climate Accord act as a determinant of catalyst of growth in the market for green bonds.

Among the wider issues warranting additional attention is the post issuance monitoring and due diligence Tolliver et al. (2019). Whereas the definitions for classifying a bond are (i) quite clearly defined and (ii) subject to both self-declaration by an issuer, and external verification by a second party, in the early phase of the market less focus has been placed on post issuance monitoring, reporting and appraisal of use of proceeds. While efforts to enhance post issuance monitoring are being made, slow progress to agreed domestic and international standards remains a hurdle to providing investor confidence. Questions around the green credentials of green bonds remain a point of contention for researchers,

[5] In this regard we especially note the incremental challenges facing developing countries, as discussed in Banga (2019).

although recent evidence tends to support the view that green bond markets, and leading market benchmarks embed ‘greenness’ and reflect a legitimate sense of green value Kanamura (2020).[6]

9.2.2 Green Bonds and Financial Markets

While there is something of a lag in development of the green bond market and regulatory environment, investment activity has been forthcoming. This has allowed researchers to gain access to data on market activity and begin to raise questions as to whether and how green bonds may be impacting and potentially even disrupting wider financial market activity.

Perhaps the earliest study to examine the various interactions in financial markets is Pham (2016), who provided an examination of the correlations between green bonds, and black bonds for the US market. This paper introduces several empirical insights, yet perhaps the most interesting insight concerns the changing nature in correlation that emerged in 2013/2014, where dynamic correlations moved from being on average negative, to on average positive. Broadstock and Cheng (2019) more closely examined this, and recognized this switch aligned in time quite closely with the dates in which corporate green bond issuers entered the market. Broadstock and Cheng (2019) proceeded to examine whether the correlation between green and black bond markets was sensitive to a range of financial market features and market sentiment extracted from news media, and drew the conclusion that observable empirical connections were consistent with evidence of a maturing green bond market. Pham and Huynh (2020) build on this line of reasoning, showing the green bond market returns move in tandem with Google search activity trends, adding evidence to support that (i) market sentiment aligns with market performance as might be expected in an efficient market and (ii) that these movements cannot be solely due to coincident movement in black bond market returns.

A number of studies take a broader approach, not only looking at alternative classes of bonds, but aiming to develop a clearer picture of the interaction between green bonds and wider financial asset classes. Reboredo (2018) using a related methodology to that which we use in this study, examines the co-movement, connectedness and spillovers between green bonds and other benchmarks including a global stock index benchmark, and an energy index benchmark among others. The main findings of the study are that there is clear dependence between green bonds and conventional corporate and treasury bonds, which result in green bonds offering but ‘*...no diversification effects for investors in the corporate and treasury bond markets...*’, and that dependence with stock markets might only be classified

[6] It is worth noting that some earlier literature casts a different view on the legitimacy of green bonds, see for example Bracking (2015). Such literature remains valid reading as a means to appreciate the importance of robust, comparable and defensible use of proceeds monitoring, reporting and related due-diligence mechanisms.

as weak. Reboredo et al. (2020) examine a similar set of questions with an updated dataset and more flexible econometric model. They identify strong connectedness (wavelet dependence) between various bond classes in the short run, and long run for both the EU and US, while connectedness with the stock markets and energy assets are weaker. Reboredo and Ugolini (2020) also report similar results using more standard vector auto-regressions. Both Reboredo and Ugolini (2020) and Reboredo et al. (2020) allude to the portfolio investment implications of their findings, but fall short of constructing any portfolios to very the empirical nature of the implications. In a related study Jin et al. (2020) explore the relation between green bond market outcomes and carbon market (futures) outcomes—in addition to stock market, energy sub-index and volatility index (VIX) series—using a suite of dynamic conditional correlation (DCC) model variants. Jin et al. (2020) not only establish connectedness of a form, but moreover do proceed to examine portfolios and hedge ratios. They conclude that the '*...green bond index is the best hedge for carbon futures...*', and additionally highlight the role green bonds play in shielding carbon market risk during times of crisis.

9.2.3 Green Bonds and Corporate Social Responsibility

A number of studies are seeking to understand more clearly how green bond interacts with firm activities under the auspices of corporate social responsibility (CSR). Yet the growing consensus, aligning partly with the increase in empirical evidence, is that doing good things for the environment does not need to come at the expense of corporate performance, and firms can in fact 'do well by doing good' as discussed broadly in Bénabou and Tirole (2010). A view shared also more recently by Albuquerque et al. (2020) who argue that stocks with an environmental orientation display stronger resilience against uncertainty and negative market events.

In one recent study Tang and Zhang (2020) argue that '*Green bond issuance can be viewed as a proxy for firms to make environmentally friendly investments and change their ESG profiles*'. Noting that ESG refers to Environmental, Social and Governance reporting and scoring, and where ESG scores are often used as a measure of firm-specific CSR activity and performance. Their conclusion is that '*...existing shareholders derive net benefits from green bond issuance*', and in this regard green bonds play valuable role in symbolizing value enhancing ESG activity. Conversely there are emerging studies which take a more nuanced view of the role between green bonds and existing ESG practices.

From a more pure financing perspective, several authors including Zerbib (2019) are active in attempting to quantify the financial value of investors' pro-environmental preferences. Zerbib (2019) arrives at the conclusion that the premium is relatively small, at 2 basis points, and that '*...[this] does not represent, at this stage, a disincentive for investors to support the expansion of the green bond market*'. Gianfrate and Peri (2019) suggest that green bonds are more 'convenient' for corporate bond issuers, whereby the '*...the relative convenience of green* *bonds [is assessed] in terms of returns to be paid to investors...*' and that the relative decrease in repayment costs for a green bond is 0.18% of the bond value (or 18 basis points), relative to the repayment cost for a conventional or black bond. Similar questions about whether investors into the green bond market pay a premium include Nanayakkara and Colombage (2019), and conclude from an international market study that investors are willing to pay a premium of 63 basis points. Hachenberg and Schiereck (2018) examine the nature of the costs versus premium trade off, along the spectrum of bond ratings from AA to BBB, and find broadly similar conclusions i.e. that issuance costs may be higher, but lower interests rates are obtained due to the investor premium, and which can make the net costs lower relative to a conventional bond. Notwithstanding the above findings, there remains an open question as to what the true premium is, highlighted here even through the wide range of suggested premium values. It is additionally worth noting that studies such as Karpf and Mandel (2018) cannot exclude the possibility that the premium is '*...explained by the fundamental properties of the bonds*'. In a somewhat related study on bond yield spreads between green and black bonds, Febi et al. (2018) indicated that liquidity differentials may explain the yield spread, but also that the empirical importance of liquidity may have become negligible in recent years.

9.3 Data

This study is based on a daily dataset consisting of 6 bond market index benchmarks: US Green Bonds, US Black Bonds, EU Green Bonds, EU Black Bonds, Chinese Green Bonds and Chinese Black Bonds, with all data having been retrieved from *Datastream*. Our data spans the period from 1st July 2016 to 31st December 2020 based on data availability at the time of collection. The specific series are as follows:

- US.GB: S&P Green Bond Index Total Return
- EU.GB: Bloomberg Barclays MSCI Euro Green Bond Index Total Return Index Value Unhedged
- CH.GB: FTSE Chinese (Onshore CNY) Green Bond Index
- US.BB: S&P U.S. Aggregate Bond Total Return Index
- EU.BB: Bloomberg Barclays EuroAgg Total Return Index Value Unhedged EUR
- CH.BB: Bloomberg Barclays China Aggregate TR Index

Figure 9.4 illustrates the dynamics of these series through time, with each series standardized to ease visual interpretation. Strong geographical co-movements are evident, especially in the case of the US and EU. Furthermore, we can observe that Chinese Green Bonds are almost linearly increasing and clearly have different underlying dynamics than the other series under study. Since all those series

Fig. 9.4 Green and Black Bond Series (*Notes* This plot shows the index history for the 6 bond index benchmarks included in our study. The data sample covers 1st July 2016 to 31st December 2020. Additional description on the individual series is given in Sect. 9.3. To aid visualization, each series is standardized before plotting, noting that the series used in our econometric estimation work are *not* scaled)

are considered to be unit root processes according to the unit root test of Elliott et al. (1996)–not reported for brevity–we apply a log-difference transformation to each series prior to estimation e.g. $\ln(x_{it}) - \ln(x_{it-1})$ which has the added benefit of being naturally interpreted as index returns. The returns series are shown in Fig. 9.5, from which we can again see evidence that the Chinese Green Bond series behaves considerably differently than other index benchmarks. We would note that the series is nonetheless stationary, but with notable variation from one period to the next, and does not introduce any specific concerns prior to estimation.

Table 9.2 introduces a range of summary statistics for the returns series that will be used for our estimation work. The US Green Bond, EU Black Bond and CN Green Bond are all negatively skewed. In addition, all series are platykurtic except for the Chinese Green Bond which display significantly leptokurtic. These findings precede the findings of the Jarque and Bera (1980) normality test which confirms that all series are non-normally distributed. All series are confirmed to be stationary at the 10% significance level according to the Elliott et al. (1996) unit root test. Other important information includes that all time series, except the EU Green Bonds, exhibit ARCH/GARCH type effects. Finally, the unconditional correlations verify points raised from eye-balling the data (‘eye-conometrics’) including high geographical correlations in the US and EU whereas the correlation across

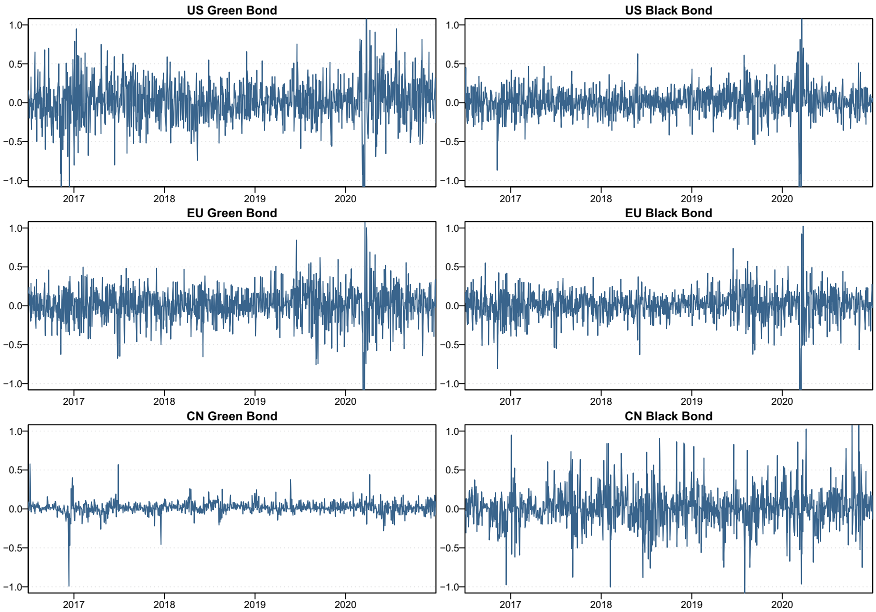

Fig. 9.5 Bond index returns. This plot shows the returns history for each of the 6 bond index benchmarks included in our study. Returns are calculated using a log-difference transformation e.g. the first difference of the natural logarithm of the original index values. The data sample covers 1st July 2016 to 31st December 2020. Additional description on the individual series is given in Sect. 9.3

EU bonds is highest with 0.91. Conversely, the correlation between Chinese bonds is only 0.114 indicating a low positive correlation. However, an interesting observation is the fact that the correlations between the Chinese green bonds and the US and EU bonds, are close to zero or even slightly negative. This is indicative of unique investment/hedging opportunities when creating investment portfolios.

9.4 Empirical Framework

Here we outline our modelling framework. In the introduction it was noted that our analysis involves four steps, which is accurate, yet here we precis this into two stages of methodological analysis. First involving the econometric modelling and immediate interpretation of the connectedness measures. The second concerning portfolio construction and evaluation.

Table 9.2 Summary statistics

	US Green bond	US Black bond	EU Green bond	EU Black bond	CN Green bond	CN Black bond
Mean	0.017	0.013	0.011	0.008	0.015	0.015
Variance	0.086	0.036	0.053	0.036	0.006	0.061
Skewness	−0.895***	−0.808***	−1.092***	−0.824***	−1.271***	0.168**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
Kurtosis	10.586***	10.003***	8.911***	6.645***	29.503***	3.442***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	5628.833***	5013.559***	4110.425***	2288.532***	42822.697***	584.175***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−6.918***	−11.142***	−4.706***	−8.878***	−3.464***	−9.102***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$Q(10)$	59.454***	21.132***	20.279***	18.196***	85.552***	13.575**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.012)
$Q^2(10)$	348.661***	1066.086***	655.605***	622.163***	32.096***	20.925***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unconditional correlations						
US Green Bond	1.000	0.541	0.480	0.475	0.010	0.313
US Black Bond	0.541	1.000	0.566	0.517	0.027	0.025
EU Green Bond	0.480	0.566	1.000	0.941	0.013	0.049
EU Black Bond	0.475	0.517	0.941	1.000	0.003	0.055
CN Green Bond	0.010	0.027	0.013	0.003	1.000	0.082
CN Black Bond	0.313	0.025	0.049	0.055	0.082	1.000

Notes ***, **, * denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit root test; $Q^2(5)$: Fisher and Gallagher (2012) weighted portmanteau test

9.4.1 Modelling Time-Varying Connectedness Using a TVP-VAR

In this section, we briefly outline the methodology we apply in order to model connectedness in a formal time-varying parameter (TVP) econometric framework. We begin with implementing the multivariate Kalman filter TVP-VAR algorithm as described in Antonakakis et al. (2020a). The method not only permits parameters of the VAR model to vary over time, but additionally introduces multivariate exponentially weighted moving average models to allow the error variance and the parameter variance matrix to vary over time. As such the model contains considerable flexibility to capture dynamics.[7]

Here we outline the key econometric structure of the TVP-VAR. For simplicity we present this in terms of a first-order VAR, noting that in our later empirical work Bayesian information criterion also indicates this to be the appropriate lag order for our exercise.[8] The TVP-VAR model can hence be written as follows:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_t \boldsymbol{y}_{t-1} + \boldsymbol{e}_t, \qquad \boldsymbol{e}_t | \boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{H}_t) \tag{9.1}$$

$$vec(\boldsymbol{\Phi}_t) = vec(\boldsymbol{\Phi}_{t-1}) + \boldsymbol{\zeta}_t, \qquad \boldsymbol{\zeta}_t | \boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{\Xi}_t) \tag{9.2}$$

where $\boldsymbol{F}_{t-1}$ represents all information available up to $t-1$, $\boldsymbol{y}_t$ and $\boldsymbol{e}_t$ represent $m \times 1$ dimensional vectors and $\boldsymbol{\Phi}_t$ and $\boldsymbol{H}_t$ are $m \times m$ dimensional matrices. In addition, $\boldsymbol{\zeta}_t$ and $vec(\boldsymbol{\Phi}_t)$ are $m^2 \times 1$ dimensional vectors and $\boldsymbol{\Xi}_t$ is an $m^2 \times m^2$ dimensional matrix. As such, the time-varying parameter transition equation adopts a random walk structure, which has been shown to be highly effective in capturing time-varying parameters accurately.[9] Financial time series, especially for daily or higher frequency data, are widely acknowledged to contain time-conditional heteroskedasticity and the matrices $\boldsymbol{H}_t$ and $\boldsymbol{\Xi}_t$ play an important role in handling this by permitting time-varying variance terms in the model.

The time-varying parameters and time-varying error variances are the basic ingredients for the generalized impulse response functions (GIRF), and generalized forecast error variance decompositions (GFEVD), developed by Koop et al. (1996) and Pesaran and Shin (1998), and on which the connectedness approach of Diebold and Yilmaz (2012), Diebold and Yılmaz (2014) rests. To obtain the GIRF and GFEVD, we first need to convert the TVP-VAR into its TVP-VMA representation by applying the Wold representation theorem, which states that $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{e}_t = \sum_{j=1}^{\infty} \boldsymbol{\Lambda}_{jt} \boldsymbol{e}_{t-j} + \boldsymbol{e}_t$.

GIRFs $\left(\boldsymbol{\Psi}_{ij,t}(K)\right)$, where K is the forecast horizon, do not assume or depend on the structure/order of the errors, and therefore provide a more robust approach to interpreting VAR models than standard IRFs, which have been known to be sensitive to the order of variables entering into the econometric system. The GIRF

[7] We note also that the Kalman gain makes the model resilient to outliers, which makes the algorithm well suited to the application at hand, since high frequency financial time series are known to often contain outlier observations.

[8] Similar to Antonakakis et al. (2020a), the lag order, as well as the prior means (coefficient values) and prior variances used to initialize the Kalman filtering, are obtained from a static VAR(1) on the first 200 observations.

[9] In an extensive Monte-Carlo simulation exercise Alptekin et al. (2019) explore the relative accuracy of random walk transition functions for time-varying parameters in a univariate model setting. Their results indicate that the random walk to be effective/accurate in a variety of different scenarios. Given the underlying mechanics of univariate and multivariate Kalman filters are the same, it is reasonable to expect similar results may generalize to the multivariate TVP-VAR context.

approach captures the difference of the dynamics among and between all variables j. Mathematically, this can be formalized as:

$$GIRF_t\left(K, \sqrt{H_{jj,t}}, \boldsymbol{F}_{t-1}\right) = E\left(\boldsymbol{y}_{t+K} | \boldsymbol{\epsilon}_{j,t} = \sqrt{H_{jj,t}}, \boldsymbol{F}_{t-1}\right) - E\left(\boldsymbol{y}_{t+J} | \boldsymbol{F}_{t-1}\right) \tag{9.3}$$

$$\boldsymbol{\Psi}_{j,t}(K) = H_{jj,t}^{-\frac{1}{2}} \boldsymbol{\Lambda}_{K,t} \boldsymbol{H}_t \boldsymbol{\epsilon}_{j,t} \tag{9.4}$$

Subsequently, the GFEVD $\left(\psi_{ij,t}(K)\right)$ illustrates the unique contribution of each variables to the forecast error variance of variable i, interpreted as how much, in percentage terms, one variable influences the forecast error variance of another variable in the system. This can be expressed as follows:

$$\psi_{ij,t}(K) = \frac{\sum_{t=1}^{K-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{K-1} \Psi_{ij,t}^2}, \qquad \sum_{j=1}^{m} \psi_{ij,t}(K) = 1, \qquad \sum_{i,j=1}^{m} \psi_{ij,t}(K) = m. \tag{9.5}$$

With these measures for GIRF and GFEVD available, we are able to accurately describe how much variable i is influenced by others and how much variable i influences all the others, and additionally question whether variable i is influencing others more than being influenced by them. For this purpose we use the following three measures:

- First, we wish to establish by how much all the other variables in the system influence variable i. This is achieved by summing the shares of the error variance for variable i due to all other variables j. This is called the ***total directional connectedness FROM all others*** and is computed as:

$$\Gamma_{i \leftarrow j,t}(K) = \frac{\sum_{j=1, i \neq j}^{m} \psi_{ij,t}(K)}{\sum_{i=1}^{m} \psi_{ij,t}(K)} * 100 \tag{9.6}$$

  The influence of all the others on variable i has to be strictly below 100% since the influence of i to itself has been excluded.
- Second, we reverse our interest and calculate the influence variable i to all the other variables j in the system. This measure is called the ***total directional connectedness to all others***. It is calculated by accumulating the effects (error variance) that variable i has to each other variables' forecast error variance:

$$\Gamma_{i \rightarrow j,t}(K) = \frac{\sum_{j=1, i \neq j}^{m} \psi_{ji,t}(K)}{\sum_{j=1}^{m} \psi_{ji,t}(K)} * 100 \tag{9.7}$$

  This measure can take values either below equal to, or above 100%.

- Last, we use the above two measures to obtain what is known as the ***NET total directional connectedness***. This measure describes whether the influence of variable i to others is greater than the influence of others to variable i, and is obtained simply as the difference between equations (9.7) and (9.6):

$$\Gamma_{i,t}(K) = \Gamma_{i\to j,t}(K) - \Gamma_{i\leftarrow j,t}(K) \tag{9.8}$$

  A positive (negative) value illustrates that variable i is driving the others more (less) than it is being driven by them.

It is worth noting that if a variable is found to be a 'net transmitter', it does not mean that it dominates each of the other individual variables in the network, rather it means that it dominates the others *on average*. In addition to the three measures above, which are aggregated summaries, we are also interested in more granular, pairwise summaries. This allows for a richer appreciation as to which variables j variable i is a transmitter to, and for it is a receiver.

We unpack the information in the GFEVDs in order to obtain ***net pairwise directional connectedness*** (NPDC) measures which are defined as follows:

$$NPDC_{ij}(K) = \left(\frac{\psi_{jit}(K) - \psi_{ijt}(K)}{k}\right) * 100.$$

Finally, it is standard to examine metrics of total system connectedness. Such measures do not relay the same richness of information available from those described above, but instead offer a single measure capable of describing whether or not overall patterns of connectedness are weak or strong within the system.

The ***total connectedness index*** (TCI). Based on Monte Carlo simulations presented in Chatziantoniou and Gabauer (2021) and Gabauer (2021) it can be shown that the own variance shares are by construction always larger or equal to all cross variance shares. This means that the TCI is within $\left[0, \frac{m-1}{m}\right]$. Since we want to know the average amount of network co-movement in per cent, which should range between [0,1], we have to slightly adjust the TCI:

$$TCI_t^g(K) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\psi}_{ij,t}^g(K)}{k-1}, \qquad 0 \leq TCI_t^g(K) \leq 1. \tag{9.9}$$

Finally, the definition of TCI can be modified to obtain *pairwise connectedness index* (PCI) scores between variables i and j as follows:

$$\begin{aligned} &PCI_{ijt}(K) \\ &= 2\left(\frac{\tilde{\psi}_{ij,t}^g(K) + \tilde{\psi}_{ji,t}^g(K)}{\tilde{\psi}_{ii,t}^g(K) + \tilde{\psi}_{ij,t}^g(K) + \tilde{\psi}_{ji,t}^g(K) + \tilde{\psi}_{jj,t}^g(K)}\right), \\ &\quad 0 \leq PCI_{ijt}(K) \leq 1. \end{aligned} \tag{9.10}$$

The raft of measures described above helps to illustrate the econometric extent and severity of connectivity between the various bond markets which we examine; to bridge the gap between statistical and economic importance, and more concretely illustrate the financial materiality of our results. This is intended to answer the singular question of whether being cognizant of the green credentials/orientation of bonds, gives rise to a financial premium.

9.4.2 Portfolio Back Testing

To examine the financial importance of our findings we will explore historical investment performance by back testing portfolios. The assumptions underpinning this are that the investor can purchase the index directly (i.e. assuming there is an investable tracker or equivalent investment vehicle for the index), that the investor is only interested in investing in bonds, and that the investor is open to international investment. These are relatively narrow assumptions yet more than sufficient for our illustrative needs.

We consider several approaches to portfolio construction including core/traditional approaches. Note, we give only brief summaries of the approaches we adopt. The estimated time-varying variance-covariance matrix of the TVP-VAR model is used for portfolio construction in the spirit of Antonakakis et al. (2021).

9.4.2.1 Minimum Variance Portfolio

One of the most common approaches used in portfolio construction is the minimum variance portfolio (MVP) procedure which tries to generate the portfolio with the lowest volatility based on multiple assets Markovitz (1959). This portfolio weights can be calculated by the following formula:

$$\boldsymbol{w}_t = \frac{\boldsymbol{H}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{H}_t^{-1}\boldsymbol{I}} \tag{9.11}$$

where $\boldsymbol{w}_t$ is an $m \times 1$ dimensional portfolio weight vector, $\boldsymbol{I}$ is an m-dimensional vector of ones and $\boldsymbol{H}_t$ the $m \times m$ dimensional conditional variance-covariance matrix in period t.

9.4.2.2 Minimum Correlation Portfolio

Another more recently developed approach to portfolio construction, due to (Christoffersen et al., 2014), obtains portfolio weights using the conditional correlation matrix, instead of the conditional covariance matrix. Before we construct this multivariate portfolio we have to describe the conditional correlations. This can be done as follows,

$$\boldsymbol{R}_t = diag(\boldsymbol{H}_t)^{-0.5}\boldsymbol{H}_t diag(\boldsymbol{H}_t)^{-0.5} \tag{9.12}$$

where $\boldsymbol{R}_t$ is an $m \times m$ dimensional matrix. With this the minimum correlation portfolio (MCP) weights are given by:

$$\boldsymbol{w}_t = \frac{\boldsymbol{R}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{R}_t^{-1}\boldsymbol{I}} \tag{9.13}$$

9.4.2.3 Minimum Connectedness Portfolio

In the spirit of the two previously mentioned portfolio techniques, we create a minimum connectedness portfolio (MCoP) by using all pairwise connectedness indices instead of the variance or correlation matrix. Minimizing the interconnectedness across variables and hence their spillovers offers a portfolio that is not as heavily affected by, or more resilient to, network shocks. Therefore variables (investment instruments) which do not influence others, and are not influenced by others, will be given a higher weight in the portfolio. This can be expressed as follows:

$$\boldsymbol{w}_t = \frac{\boldsymbol{PCI}_t^{-1}\boldsymbol{I}}{\boldsymbol{I}\boldsymbol{PCI}_t^{-1}\boldsymbol{I}} \tag{9.14}$$

where $\boldsymbol{PCI}_t$ is the pairwise connectedness index matrix, and $\boldsymbol{I}$ the identity matrix.

9.4.2.4 Risk-Parity Portfolio

In the spirit of Maillard et al. (2010), we employ the risk-parity portfolio. This method allocates the portfolio weights according to the same share of risk contribution. Theoretically speaking it is assumed that given the same risk level, the portfolio can achieve a better performance and is more resistant against market downturns and hence economic crises. Mathematically, this problem can be formalized by the following minimization problem:

$$min \quad \sum_{i,j=1}^{N} \left(w_{it}(\boldsymbol{H}_t\boldsymbol{w}_t)_i - w_{jt}(\boldsymbol{H}_t\boldsymbol{w}_t)_j\right)^2. \tag{9.15}$$

9.4.2.5 Hedging Effectiveness

Finally, in order to represent the portfolio performance, we make use of the Sharpe ratio, and a hedge effectiveness score.

The Sharpe ratio, also known as the reward-to-volatility ratio Sharpe (1966), can be written as follows:

$$SR = \frac{\bar{r}_p}{\sqrt{Var(r_p)}} \tag{9.16}$$

where r_p denotes the returns on the portfolio.[10] Higher values of *SR* indicate a higher level of returns relative to the level of risk in the portfolio.

In the spirit of Ederington (1979) hedge effectiveness is given by:

$$HE = 1 - \frac{Var(y_p)}{Var(y_{unhedged})} \tag{9.17}$$

$Var(y_p)$ represents the variance of the portfolio returns, and $Var(y_{unhedged})$ the variance of the unhedged asset. *HE* represents the percent reduction in the variance of the unhedged position. The higher the *HE* the larger is the risk reduction and vice versa.[11]

9.5 Empirical Findings and Discussion

In this section, we set out the key results from the study. We first present and discuss the results concerning total connectedness, as a first-order indicator of any semblance of 'proper' connectedness between the markets. Following this we proceed to discuss results obtained using pairwise connectedness measures. In so doing we may identify dynamics between specific types of bonds. We pay particular emphasis to developments following the outbreak of the COVID-19 pandemic. Lastly, we present and examine our portfolio investment assessment, with a view to unveiling portfolio diversification opportunities.

9.5.1 Total Connectedness (TCI)

The first set of results we present concerns averaged connectedness measures. These results are given in Table 9.3. It is worth noting that the elements of the main diagonal of Table 9.3 correspond to own-variable shocks (i.e., idiosyncratic), while all other elements, relate to the various interactions between the different bond types.

According to the results, the US and European markets are more tightly connected than China. Looking for example to the diagonal element of Table 9.3 under the Chinese green bond heading, it can be seen that 93.7% of index evolution is driven by within index shocks/behaviour, with only 6.3% of index movement being due to network connections, 1.4% of which being China's black bond market. The Chinese black bond index is more tightly connected with other markets, with approximately 7.5% of pricing spillovers emanating from the US, interestingly

[10] For simplicity we assume that the risk-free rate is equal to zero.

[11] According to Antonakakis et al. (2020b) the volatility reduction follows an F-distribution which means that an F-test can be used to reveal whether the volatility reduction of creating a portfolio is significant or not. Utilizing their Monte Carlo simulation results we select the Fligner-Killeen Test.

Table 9.3 Averaged dynamic connectedness table

	US		EU		CN		FROM
	Green bond	Black bond	Green bond	Black bond	Green bond	Black bond	
US green bond	58.0	16.1	9.4	9.7	0.3	6.5	42.0
US black bond	14.8	52.5	17.4	14.1	0.4	0.9	47.5
EU green bond	7.5	14.1	41.9	35.8	0.2	0.5	58.1
EU black bond	7.7	11.6	36.7	43.3	0.3	0.4	56.7
CN green bond	0.6	1.1	0.8	0.9	93.7	2.8	6.3
CN black bond	13.2	3.8	1.5	1.4	1.6	78.3	21.7
Contribution **TO** others	43.8	46.8	65.9	61.9	2.8	11.1	232.2
NET total directional connectedness	1.9	−0.7	7.7	5.2	−3.5	−10.6	TCI
NPDC transmitter	3.0	2.0	0.0	1.0	5.0	4.0	46.5

Notes Results are based on a TVP-VAR(0.99,0.99) with one lag and a 20-step ahead forecast horizon

the highest amount coming from the US green bond market with a connection of 6.5%.

The average TCI value corresponding to the period is 46.5%, implying that co-movements within this particular network of variables are rather moderate, since on average only 46.5% of the forecast error variance in one bond type can be associated with price innovations (shocks) from other bond types included in the network. However, the results in Table 9.3 average over the full sample results, and may inadvertently mask dynamics and the influences of specific events shaping the linkages between the different bond types. Worded alternatively, a narrow analysis of the averages may result in the loss of important information in connection with specific economic or political events that took place during the sample period, and which could potentially trigger substantial deviations from the average TCI value of 46.5%. Thus, we continue our analysis by exploiting the richer time-varying output from our fully dynamic econometric framework. We begin by examining the time-evolution of total connectedness (TCI), as given in Fig. 9.6.

Within the framework of our analysis, large values of the TCI are indicative of strong co-movements across the network. In turn, strong co-movements may be indicative of the fact that the perceived risk relating to the bond types of interest is increasingly equivalent, further reflecting analogous market confidence. In Fig. 9.6, total connectedness within our network varies considerably over time ranging from a low of below 40% to a high just shy of 70%, implying that connectedness across the various bond types not only reacts to events associated with the bond markets under investigation, but can do so swiftly, and by material amounts. A closer inspection, further indicates that the TCI exhibits two distinguishable peaks across

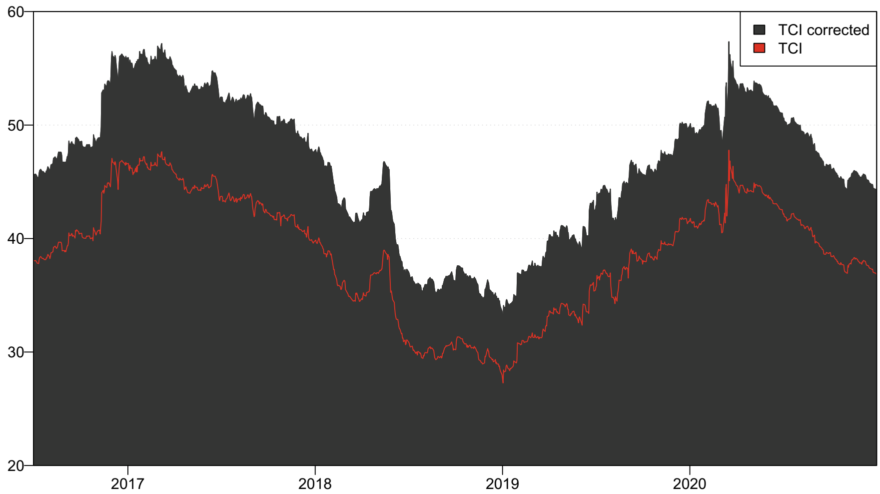

Fig. 9.6 Dynamic total connectedness (*Notes* Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 1 (BIC) and a 20-step-ahead forecast)

the sample period. In particular, TCI reaches its first peak towards the end of 2016 and the beginning of 2017. In turn, the TCI embarks on a generally descending course with some relative peaks along the way; notably, during the second and the third quarter of 2017, as well as, in the beginning of the second quarter of 2018. Regarding the more recent observations in our sample, the value of TCI passes through a trough in the back end of 2018 and then begins to rise rapidly again, reaching a new peak around the first quarter of 2020. From then on, it starts to decline again. In line with our framework, dates associated with large connectedness values, such as the two distinguishable peaks, reflect very turbulent periods whereby, the financial assets of our network are all deemed to be relatively equally risky.

We note that the period around the first peak was rich in unique or important events for international financial markets. To name but a few, this period involved the unprecedented devaluation of the Renminbi during 2015 and its subsequent inclusion in IMF's Special Drawing Rights (SDR) basket of reserve currencies in 2016, the ongoing European debt crisis (e.g., the third economic adjustment programme for Greece in 2015) combined with the peak of the refugee crisis in Europe, the 2016 EU-Referendum in the UK, as well as, elections in the US.

While there was an interval of relative tranquility starting around the second quarter of 2017—presumably reflecting an effective absorption on behalf of financial markets of developments similar to the ones outlined above, a new hike in connectedness became apparent at the dawn of 2019—reaching a second peak around the first quarter of 2020. Around this second peak there were two major destabilizing and risk-inducing developments; namely, the escalating trade dispute between China and the US and the outbreak of the COVID-19 pandemic. In point of fact, we note that the first months into the COVID-19 pandemic resulted in connectedness assuming its largest value across the sample period.

9.5.2 Net Total Directional Connectedness

We now direct attention towards the evolution of total directional connectedness. One of the most important features of the chosen econometric framework lies within its ability to distinguish and classify the different bond types that make up our network as being either net transmitting or net receiving. This information is presented in Fig. 9.7. By way of orientation, when the shaded area in Fig. 9.7 falls within a range of positive values, the corresponding bond 'type' is a net transmitter of shocks to the systems, conversely when the plot area falls in the negative range, a bond index is classified as being a net recipient of shocks.

Prominent among the results presented in Fig. 9.7 is the fact that in almost all cases the different bond types included in our study assume only one of the two roles. This is not a statistical restriction or unintended artefact, which can be verified by the results for the US black bond index which makes several movements

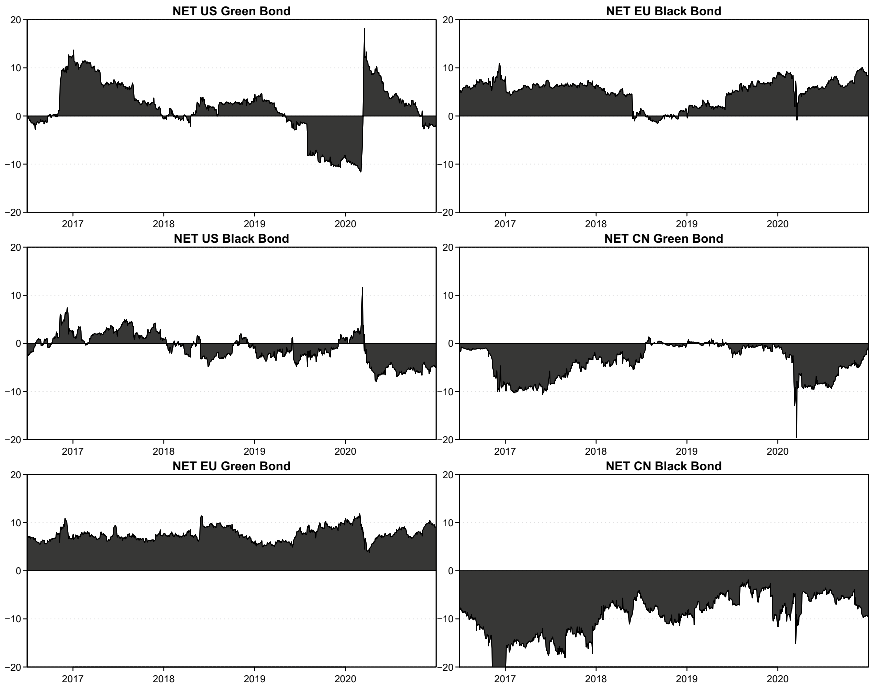

Fig. 9.7 NET total directional connectedness (*Notes* Results are based on a TVP-VAR(0.99,0.99) with one lag)

between positive and negative values. As such we fall on the conclusion that there seems to be a persistent pattern/role within the network for certain bond types to act either as net transmitters or net receivers of shocks. Notwithstanding this, the observation variation in each figure over time is indicative of a constantly evolving intensity attached to each bond types' role.

Under closer inspection of Fig. 9.7, it can be seen that both green and black Chinese bonds retain their net receiving character throughout the period of analysis, with black Chinese bonds in particular, assuming a more pronounced role as recipients for almost the entire period of study with the exception of the first quarter of 2020. During this period, which was marked by the outbreak of the COVID-19 pandemic we note that, green Chinese bonds receive at least as much as black Chinese bonds. This could be indicative of the unique and pervasive character of the COVID-19 crisis, which resulted in identical perceptions of risk in the Chinese bond market.[12] Turning to the EU market, we note that green EU bonds appear to act as a net transmitter of shocks to other markets throughout the period of study. As far as black EU bonds are concerned, their net transmitting role appears to diminish completely in the mid-2018 period and for a few months black EU bonds even assume a net receiving role (although the magnitude is rather negligible), before reverting back to their net transmitting role, from 2019 onwards. The COVID-19 outbreak does not appear to have a role-shifting impact on either green or black EU bonds; however, towards the end of the first quarter of 2020, there appears to be a short-lived drop in the relatively large transmission levels of the period and this holds for both EU bond types. Transmission resumes again to higher levels immediately after that. Finally, with regard to the US market, it is evident that from late 2016 onwards green mainly transmit shocks to other markets, with the exception of a period which lasts from around the second quarter of 2019 and ends in the first quarter of 2020. In fact, during the first quarter of 2020 green US bonds reach their highest negative values with regard to net connectedness. By contrast, black US bonds appear to be the most ambiguous among the various bond types of the study as they begin as net recipients, then, almost from mid-2017 and until early 2018 they seem to assume a rather net transmitting role, before they start receiving again on net terms almost throughout the remainder of the sample period (i.e., with a few relatively negligible exceptions). The period of the COVID-19 outbreak in early 2020 saw black US bonds assuming a brief net transmitting role which culminated with a positive value greater than 10%.

Overall, net directional connectedness levels, were affected at least to some extent during the first quarter of 2020 for both bond types of all countries. During this period apparently (i) the role of green Chinese bonds as net recipients of pricing shocks intensified, (ii) both EU bond types experienced lower levels of transmission compared to respective values recorded from 2019 onwards—which

[12] Notwithstanding a very temporary transition for China's green bonds to being a net transmitter in early 2019.

marked the second major hike of TCI during our sample period (see, Fig. 9.6), as well as (iii) the role of green US bonds as net recipients and the role of black US bonds as net transmitters both intensified.

9.5.3 Net Pairwise Total Connectedness

Despite the fact that, net total connectedness results are quite useful when it comes to identifying net transmitters and net receivers within our network of variables, these results fail to capture pairwise dynamics which might reveal additional insights and a clearer view on what is the exact role (characteristic) that each variable adopts within our network with respect to the others, and over time. In this regard, we present results relating to such pairwise (or bilateral) outcomes in an effort to deepen the examination in connection with the linkages across the bond markets of interest. Results are given in Fig. 9.8.

Starting with China, we note that Chinese green bonds predominantly receive spillovers from their Chinese black bond counterparts on net terms. While there are some periods towards the middle of the sample period where net transmitting activity occurs, the magnitude of effect during these periods is very small. Chinese green bonds also are net recipients of shocks in all other bond types both in EU and the US—noting that in these subplots 'CN Green Bond' is the second variable and the sequence of the variables matters for interpreting the direction. In all these cases we note that transmission from all other bonds to green Chinese bonds intensifies during the first two quarters of 2020. In some cases (such as transmission from black US bonds) the transmission reaches an unprecedented peak. With regard to Chinese black bonds, they tend to be receiving spillovers from all other bond types in both the EU and the US. Similar to green Chinese bonds, transmission towards black Chinese bonds appears to be intensifying during the first months of 2020.

Turning to the EU, there does not seem to be any noteworthy spillover effects between green and black bonds, at least not until mid-2018 when EU green bonds begin to transmit spillovers on net terms, at considerable levels to their black counterparts. During the first quarter of 2020 the transmission of both EU bond types to both Chinese bond types becomes considerably stronger. Interestingly enough, both green and black EU bonds seem to be net transmitters of shocks to both green and black US bonds.

As far as the US market is concerned, for the most part, black US bonds transmit pricing shocks to green US bonds and this transmission becomes stronger during the first quarter of 2020. However, we also note that from the second quarter of 2020 and almost until the end of the year green US bonds assume a rather net transmitting role. Overall, the results reveal that across countries, the position of green bonds against black bonds, either as net receivers or net transmitters of shocks in our network, is varied and more so than total connectedness measures would imply. Net pairwise connectedness results during the first quarter of 2020 which was marked by the COVID-19 outbreak, appear to confirm previously

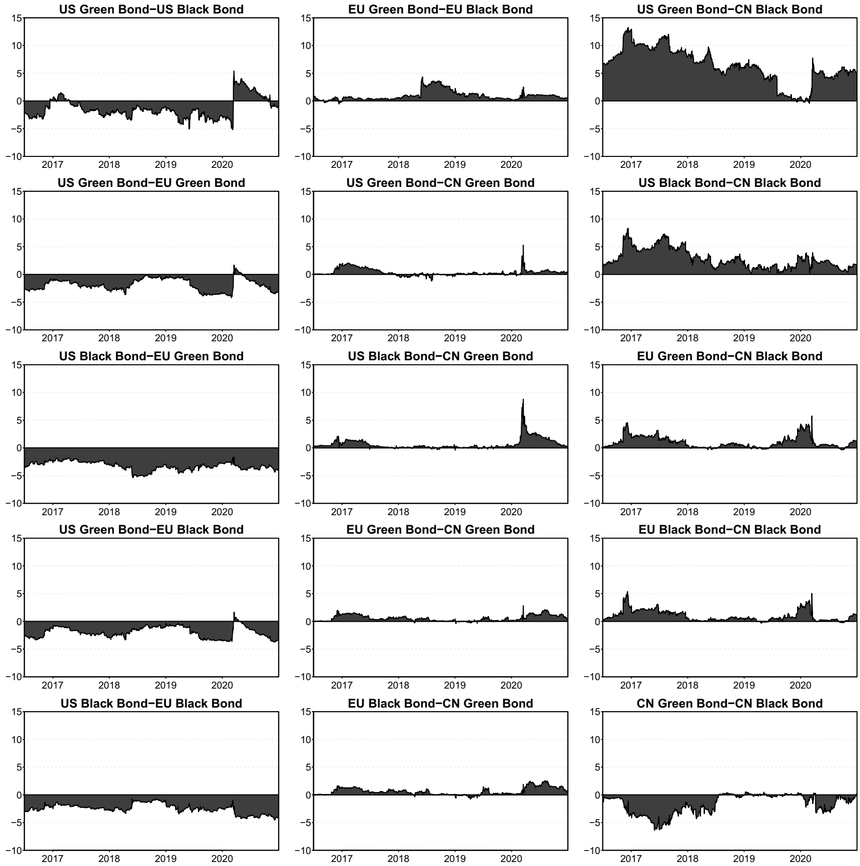

Fig. 9.8 Net pairwise directional connectedness (*Notes* Results are based on a TVP-VAR(0.99,0.99) with one lag)

reported results, further suggesting that in the onset of the COVID-19 pandemic both green and black bond markets were considerably affected. EU green and black bonds are clearly the markets that primarily transmit to all other markets on net terms; a fact that particularly underscores the importance of the EU bond market.

9.5.4 Dynamic Portfolios

In this section, we solely focus on the two well-developed markets, namely the US and EU. The main reason for this decision is caused by the fact that the SR of the Chinese Green Bond is twice as high compared to all other assets. In addition, the Chinese Green Bond is nearly constantly increasing over the whole sample period

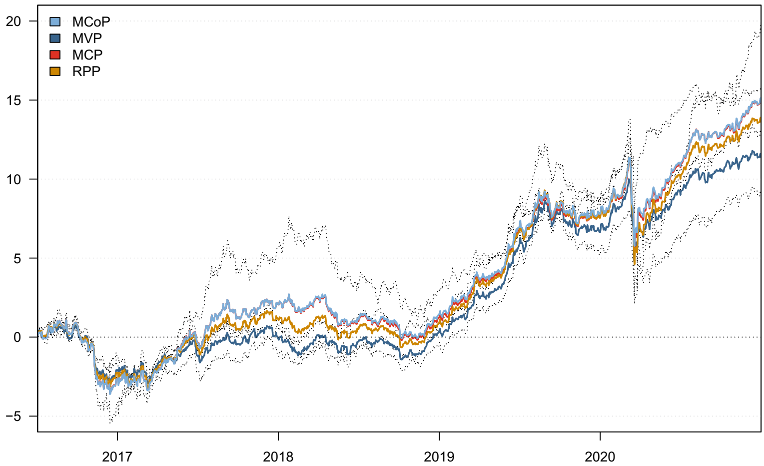

Fig. 9.9 Cumulative portfolio returns (*Notes* Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR(0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio and MCoP to the minimum connectedness portfolio. The dotted gray lines depict returns on individual bond indices)

and is significantly reducing the risk when combined with any other asset, however, this is not the case vice versa. Thus, stock selection would be more effective than portfolio creation even though the majority of the literature recommends that portfolios should be preferred as they lead to the diversification of risk.

To evaluate which portfolio technique is most appropriate we construct the four methods described in Sect. 9.4, namely: (i) minimum variance portfolios (MVP); (ii) minimum correlation portfolios (MCP); (iii) risk-parity portfolios (RPP) and minimum connectedness portfolio (MCoP). Sharpe ratios and hedge effectiveness scores are used to evaluate the relative performance of each portfolio.

Figure 9.9 plots the four alternative portfolios. The plot illustrates that four portfolio methods perform with a visible level of equivalence, sharing the same underlying dynamics include a modest dip in index values in the end of 2016, followed by a pattern of sustained growth up until the first quarter of 2020 whereby, there is again a short-lived—yet considerable, drop caused by the COVID-19 pandemic. The dotted gray lines depict the individual bond index value, and by cross-referencing against investing in a single asset it can be confirmed that portfolios outperform the European green (0.048) and black (0.041) bonds, as well as, the US green (0.057) and black (0.071) bonds in terms of their Sharpe ratios. Admittedly, this hierarchy of bond markets is not always the same over the sample period, nor is it expected to be preserved moving forward.

To give a more concrete understanding of the composition of the individual portfolios we illustrate the dynamic portfolio weights in Fig. 9.10. Under casual inspection, it is fairly immediate that the MVP composition differs markedly from

MCP, RPP and MCoP, while MCP and MCoP share closely matching compositions with each other and RPP. Addressing first the similarity between the compositions for MCP and MCoP, from a mechanical perspective this is perhaps not a tremendous surprise, since each are derived from the same time-varying variance-covariance matrix. Having said that, the transformations involved to arrive at the final information to be fed into the portfolio calculations diverge in a substantial fashion. Whereas for MCP, the variance-covariance is 'simply' converted into a correlation matrix, for MCoP a much more involved sequence of calculations are required. Hence although the initial building blocks are similar for all four methods, the divergence in transformations does not make it immediately obvious that they should result in closely correlated portfolio weights.

We would elaborate on this point further still. While under a casual inspection there appear to be many similarities in the dynamic portfolio weights for MCP and MCoP, under closer inspection there are some nuanced differences. For example, we notice that only the value of the weight for MCP exhibits two sharp increases that coincide with the two aforementioned peaks in the TCI index (i.e., around the end of 2018 and during the first quarter of 2020). Hence there are at least qualitative differences that exist while, similar nuances can be found for the other weights.

Having recognized some empirical similarity between MCP and MCoP, we dig deeper into the implications for portfolio and risk management. For this purpose, we compare and contrast the MCoP approach together with standard portfolio analysis techniques, MVP, MCP and RPP, by examining the hedging effectiveness scores and Sharpe ratios for each. These results are given by Tables 9.4 and 9.5 respectively. In reporting these we can more objectively contrast each of the portfolios' returns against each other. It is perhaps worth reminding ourselves that with regard to the competing portfolio construction techniques, the MVP approach by definition minimizes portfolio volatility, the MCP approach focuses on minimizing correlations across assets, the RPP technique tries to minimize risk contribution of each asset while the MCoP minimizes the pairwise connectedness.

Starting with Table 9.4, prior to considering the hedge effectiveness ratios, we will briefly reflect on the average portfolio allocations. The average portfolio weights indicate that green bonds contribute a non-trivial role to a fixed-income investment portfolio. By way of example, the portfolio weights for green US bonds range from approximately 4% under the MVP to around 35% under both the MCP and MCoP. Interestingly, the green US bond weights are almost constant in the event of MCP and MCoP until the COVID-19 pandemic when it dropped from around 40% to 10%. The black US bonds seem to be similarly important for all portfolio techniques as the average weights are all around 30%. The MVP, MCP, MCoP and RPP consist of 35, 26, 26 and 29% US black bonds on average, respectively. Concerning European asset weights, we see that those causes the largest differences between the MCP and MCoP as the European green bonds account for 11% of the MCP and 8% of the MCoP while 28 and 32% of the MCP and MCoP are based on the European black bonds, respectively. Those weights differ quite substantially from the MVP and RPP weights. In the case of MVP, only 2% of

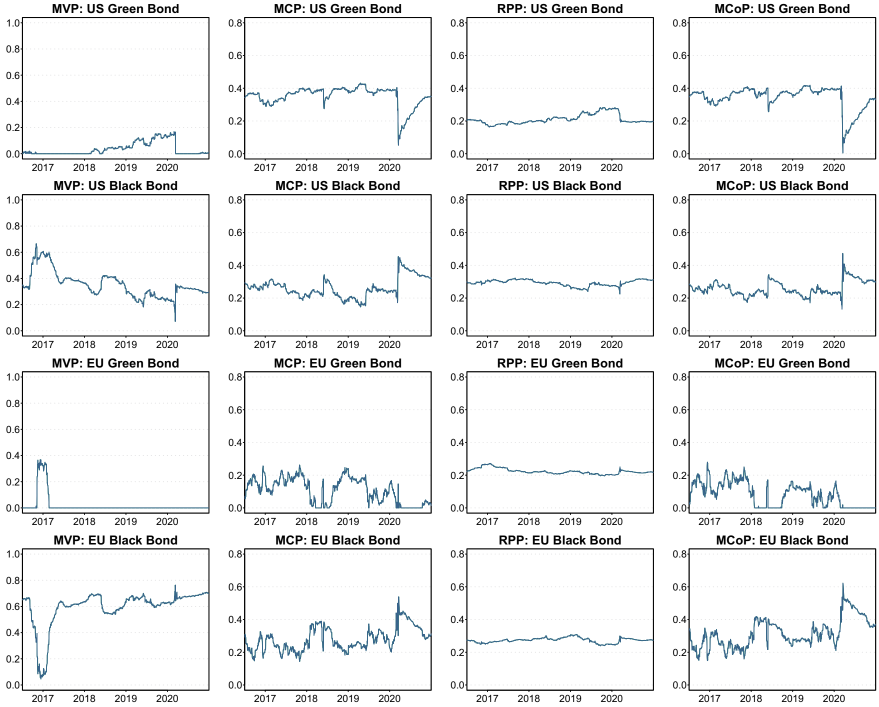

Fig. 9.10 Dynamic multivariate portfolio weights (*Notes* Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR(0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio, and MCoP to minimum connectedness portfolio)

the portfolio is based on the EU green bonds whereas 59% accounts for EU black bonds. Even though, the European black bonds are preferred over the European green bonds in the RPP the difference is much smaller. Generally, we could say that the MVP is more selective while the RPP tries to take all bonds equally into account. Both, the MCP and MCoP appear to be balanced between MVP and RPP. Interestingly though, we find that the MVP prefers EU black bonds, RPP US black bonds while MCP and MCoP focus most on US green bonds on average.

Regarding the hedge effectiveness ratios in Table 9.4, the results for MVP approach suggests that if on average we invested 4% in US green bonds, 35% in US black bonds, 2% in EU green bonds, 59% in EU black bonds, then the volatility of each asset in this portfolio would be statistically significantly lowered by 69, 25, 49, and 25%, respectively. These volatility reductions are financially meaningful, moreover, they are statistically significant at a 0.1% significance level. Turning towards the other portfolios, for the MCP approach if on average we invested 35% in US green bonds, 126% in US black bonds, 11% in EU green bonds, and 28% in EU black bonds, again we observe that the volatility of the assets in this portfolio are for the most part statistically significantly lower compared to its initial value.

Specifically, the MCP chosen allocation of capital would result in a reduction of the volatility for both green and black US bonds by 62 and 9% and green and black Eu bonds by 39 and 10%, respectively. These results are similar to the findings concerning the MCoP technique. If we invest on average 34% in US green bonds, 26% in US black bonds, 8% in EU green bonds, 32% in EU black bonds, the percentage reduction in volatility given investing in a single asset is 63, 11, 40, and 12%, respectively. Notably, all values have improved compared to the MCP and all risk reductions are statistically significant on at least the 5% significance level. Finally, the RPP approach suggests that if we invest on average 21% in US green bonds, 29% in US black bonds, 22% in EU green bonds, and 27% in EU black bonds, we would then manage to reduce the volatility of each asset by 62, 9, 39, and 10%, respectively. All of the volatility reductions are statistically significant at least on the 10% significance level.

Overall, findings relating to portfolio analysis seem to confirm the presence of a dynamic network which allows for diversification opportunities. We do not have enough evidence from this singular application of the technique to draw any firm conclusions or claim if this is likely to be the case in other applications. This is something that future research may wish to remain cognizant of, i.e. the possibility that risk-parity portfolios give rise to lower volatility with equal returns performance, relative to minimum correlation portfolios.

Next, we examine Table 9.5 which addresses and reports the reward-to-volatility (Sharpe) ratios, showing how much profit can be expected from a given portfolio with risk equal to one standard deviation. We find that the daily mean return is highest for MCP and MCoP, followed by RPP and MVP. Even though, MVP has the lowest mean return it is also exposed to the lowest risk followed by MCoP, MCP, and RPP. The MCoP portfolio displays the largest reward-to-volatility value at 0.0720 followed by MCP (0.0711), RPP (0.0655), and MVP (0.0602).

9.6 Conclusion

In this study we investigated patterns of risk transmission between green and black bonds considering three markets; China, Europe and the US. The importance of this work is set against the absence of existing literature and the increasingly widespread adoption of socially responsible investment (SRI) practices among mainstream investors. Green bonds have become a popular vehicle, both for investors and issuers, to serve the growing demand for socially responsible and impact investment. In this nascent space China has become a major international player, yet among the existing research to date, only very limited attention has been given towards their growing role and influence to the international bond market.

Here we questioned whether the outbreak of the COVID-19 pandemic had had a pronounced impact on dynamic connectedness among green and black bonds and whether there were any considerable changes in the role of the variables of our network as either net transmitters or net receivers. In addition, we further examine whether green bonds have any value enhancing contribution to portfolios

Table 9.4 Dynamic multivariate portfolio weights

	Mean	Std. Dev.	5%	95%	HE	*p*-value
Minimum variance portfolio						
US green bond	0.04	0.05	0.00	0.14	0.69	0.00
US black bond	0.35	0.10	0.23	0.57	0.25	0.00
EU green bond	0.02	0.07	0.00	0.26	0.49	0.00
EU black bond	0.59	0.14	0.16	0.69	0.25	0.00
Minimum correlation portfolio						
US green bond	0.35	0.06	0.21	0.40	0.62	0.00
US black bond	0.26	0.06	0.17	0.38	0.09	0.09
EU green bond	0.11	0.08	0.00	0.22	0.39	0.00
EU black bond	0.28	0.07	0.18	0.42	0.10	0.07
Minimum connectedness portfolio						
US green bond	0.34	0.07	0.18	0.40	0.63	0.00
US black bond	0.26	0.04	0.19	0.34	0.11	0.04
EU green bond	0.08	0.07	0.00	0.20	0.40	0.00
EU black bond	0.32	0.09	0.19	0.49	0.12	0.03
Risk-parity portfolio						
US green bond	0.21	0.03	0.18	0.28	0.62	0.00
US black bond	0.29	0.02	0.26	0.32	0.09	0.10
EU green bond	0.22	0.02	0.20	0.26	0.39	0.00
EU black bond	0.27	0.01	0.25	0.30	0.10	0.08

Notes Results are based on the time-varying variance-covariance retrieved from the TVP-VAR(0.99,0.99) with one lag

Table 9.5 Sharpe ratio

	MVP	MCP	RPP	MCoP
Mean	0.0098	0.0128	0.0118	0.0128
Std. Dev.	0.1640	0.1801	0.1802	0.1783
SR	0.0602	0.0711	0.0655	0.0720

of investments. We do so by considering green bond and conventional, or black, bond index benchmarks for each of the three regions US, Europe and China, as representing the network of fixed-income investment opportunities, and deploy recent advances in econometric estimation procedures to analyse the network connectedness between the indices, which conveniently provides at the same time the core information to conduct portfolio analysis. More specifically we adopt a fully time-varying parameter vector auto-regression (TVP-VAR) econometric framework, applied to daily data spanning July 2016 to December 2020, as well as, four distinct portfolio constructing techniques; namely, the minimum variance portfolio, the minimum correlation portfolio, the risk-parity portfolio, and the minimum connectedness portfolio.

Findings suggest that there was a substantial impact on connectedness in our network during the first quarter of 2020; however, this effect was rather short-lived. In particular, during the first quarter of 2020 which was marked by the outbreak of the COVID-19 pandemic, fixed investments that assumed a net receiving role in the network (such as green and black Chinese bonds, as well as, green US bonds) intensified their role as such. Furthermore, during the same quarter there was a noticeable shift whereby, black US bonds assumed a net transmitting role for the first time in a while. At the same time, both green and black EU bonds, lost part of their strength as net transmitters in the network.

In turn, we use the econometric results, and specifically the estimated time-varying variance-covariance matrix, to feed into a simple yet insightful dynamic portfolio construction exercise. In this we compare the risk-parity portfolio (RPP), minimum variance (MVP) against and minimum correlation (MCP) and minimum connectedness portfolios. Our core findings are to some extent invariant (or robust) to the portfolio construction method inasmuch as each approach supports the view that green bonds do have a role to play in a fixed-income investment portfolio, though admittedly regional investment allocations prove to be contingent on the portfolio construction method chosen. Interestingly, we have proven that our proposed minimum connectedness portfolio has outperformed all alternative portfolio techniques. By using the information concerning the propagation mechanism the minimum connectedness portfolio has reached the highest Sharpe ratio. Furthermore, its construction significantly reduced the investment risk in all assets.

Our analysis contributes unique evidence to the literature on the role of SRI practices as a complement to mainstream investment and is in principle relevant to at least three audiences. Firstly, we provide incremental evidence to the investment community to support the view that engagement with SRI through the market for green bonds has the potential to enhance portfolio performance. Second is to provide regulators, policy makers and compliance specialists, with a novel snapshot describing how green and black bond markets are co-evolving and interacting with each other. While we do not postulate any specific policy/regulatory concerns or options, what is clear is that green bond definitions remain somewhat 'hazy' yet they still offer investors a route to enhanced financial performance. Whether or not there is a need to speed up progress in formalizing international green bond standards would therefore seem to be an open but important question for future work to consider. Lastly, existing and potential bond issuers are provided an additional empirical benchmark to illustrate that raising green capital through green bonds does not require an investor to sacrifice on financial returns, so long as they (the investor) are able to develop a balanced fixed-income investment portfolio. This may potentially benefit issuers in the process of prospectus design, and perhaps more important in book building in the lead up to issuance.

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Are Policy Stances Consistent with the Global GHG Emission Persistence?

10

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10.1 Introduction

Greenhouse Gas Emissions (GHG) are the primary components of global warming and climate change, which are currently the most significant issues of the planet. GHG emissions have highly increased since the pre-industrial era, due to high economic and populational growth. A warm climate has a spectrum of potential ecological, physical and health impacts. Hence, there is a strong relationship between GHG emissions, prosperity and living standards (Sahu & Patnaik, 2020). Some countries reduced emissions while increasing Gross domestic product. In order to reduce GHG emissions, there are two essential areas on which we shall focus: agriculture (residential, forestry and food production) and energy (defence, transportation, industry, heat, electricity) (Ritchie & Roser, 2020).

The long-range dependence work began back in 1951 and gathered most of its critical mass by the end of the 2000s. The concept of a rescaled range analysis has evolved over time into a favoured stylized fact (Cont, 2005; Ghosh et al., 2021; Hurst, 1951; Mandelbrot, 2004; Mandelbrot & Wallis, 1969). Fundamentally, it displays the strong statistical dependence of time series data distanced by a long

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margin. The autocorrelation function declines very slowly with many lags. According to Efficient Market Theory, the farther apart the observations are, the weaker the autocorrelation function will be; however, in reality that kind of asymptotic decline remains absent in most times series (ranging from various fields). Sometimes, non-stationary time series having unit root exhibit even stronger statistical dependence after significant lags. This does not indicate a true long-range dependence or long memory. Thus, mean-reversion remains an important aspect of long memory.

Long memory properties are described by the differencing parameter (d). Usually the fractional integrating parameter (d) has a condition of $0 < d < 0.5$; indicating the stationarity of the time series as well. It does not cover any condition such as $d = 0$ or $d < 0$. Since the other coefficients (p and q) needed to be assumed and specified correctly, hence any mis-specification of those would result in a misleading long memory process (ideally a short memory). Hence, the proposed theory faced a rebuttal from Lo (1991), as he observed that it overlaps in such an estimation (Graves et al., 2017). However, the proposed null limit theory by Lo (1991) (based on modified rescaled range analysis) was coined as non-standard (Robinson, 2003). Again, it was found that for, $d \geq 0.25$, the estimate becomes non-Gaussian (Robinson, 1995, 2003). Moreover, Hosking (1981) proved that its (d) not a discrete approach to a continuous process, as he suggested discretising first following a fractionally differencing later (Hosking, 1981). Thus, it became a natural extension of an ARIMA model for a discrete version of a Wiener process. Moreover, some proved that long memory was a strictly second order property of a time series; in which case, estimation of 'd' indicating long memory would be further restricted to $0.25 \leq d < 0.5$ (Rosenblatt, 1961).

Green House Gases (GHG) mostly consist of CO_2, SO_2 and N_2O. Studies were mostly around CO_2 emissions. The aforementioned GHG globally require a similar kind of investigation. If the time series is not purely stationary, i.e. $d \neq 0$ (non-stationary at level, further stationary at 1st difference), transitory policy shocks would fade out eventually indicating the necessity for a steady and permanent policy stance. Transitory policy shocks last really long provided there is evidence of long memory with stationarity condition $d = 0$ (Belbute & Pereira, 2015). Short term one-off positive shocks such as funding energy efficiency programmes or allowing significant subsidies for alternative energy sources would work really well in a case of true existence of long memory (with stationarity condition $d = 0$).

Emission-related studies mostly concentrated on its convergence (derived from mean-reversion property). Maturity of the market depends on the convergence. Policy implication would follow suit. Results however weren't consistent enough (Barassi et al., 2011; Lee & Chang, 2009). On studying the CO_2 emission pattern across 18 OECD nations, researchers found 13 of them to be fractionally integrated. Hence, they are nothing but extended long memory processes. Moreover, these emissions despite being highly persistent, exhibit mean-reversion in the long run (Barassi et al., 2011). Emission depends on the energy usage. Ideally the persistence property of energy use should also be a long memory process. It has been found that 39 out of 107 countries (based on per capita energy consumption) are mean-reverting and persistent process exhibiting long memory. These are energy rich developed nations (Fallahi, 2014).

Relative studies about GHG emissions appeared in several countries such as Italy (Mariantonietta et al., 2018), Spain (Sobrino & Monzon, 2014), Australia (Leal et al., 2019), China (Qi et al., 2018), Colombia (Contreras et al., 2020), Asia (Le et al., 2020).

In this chapter we investigate the global GHG emissions persistency in 186 countries globally over 25 years (1990–2014), using three partially overlapping windows. It confirms the possible nature of the policy stance on GHG emissions across those nations. We use Long Memory identification through Order of fractional differencing (d) and Hurst Exponent (H) using the ARFIMA process. To the best of our knowledge, a similar study concerning the global GHG emissions including 186 countries globally for a period of 25 years has not been conducted to this day, so this is the gap our study aspires to fill. So this study contributes to the existing literature by investigating for the first time, to the best of our knowledge, global GHG emissions persistency in 186 countries globally for 25 consecutive years. Furthermore, by adopting our analysis, policymakers globally will be in a position to increase economic development, to achieve the environmental targets set and the world economy will be more efficient in all sectors (agricultural, transport, residential, construction, defence, etc.) according to the specific characteristics of each one. In conclusion, energy efficiency measures should be implemented according to the needs of each sector.

This chapter in particular is significant for three reasons: First of all, reducing GHG focuses on adopting a holistic, global, bio-economy for sustainable production in many sectors of the world economy. Secondly, in contrast to prior relevant studies, it examines 186 countries over a period of 25 years for the first time. Thirdly, policymakers would benefit from this research, as they will redefine strategies and apply targeted climate policy measures following bio-economy routes to sustainable, post GHG societies. They will improve the efficiency of industrial production and enhance renewable energy technology.

10.2 Data and Methodology

Data has been obtained from the CAIT Climate Data Explorer. 2017. Washington, DC: World Resources Institute.[1] We considered the data[2] of 186 countries yearly for 24 years, across three specified windows. Window one (1990–1998) has1488

[1] CAIT Climate Data Explorer. 2017. Washington, DC: World Resources Institute. Available online at: http://cait.wri.org.

[2] Carbon Dioxide Information Analysis Center; Boden, T.A., G. Marland, and R.J. Andres. 2017. Global, Regional, and National Fossil-Fuel CO2 Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. https://doi.org/10.3334/CDIAC/00001_V2017. Available online at: http://cdiac.ornl.gov/trends/emis/overview_2014.html. Food and Agriculture Organization of the United Nations;

observations; window two (1990–2006) has 2976 observations and window three (1990–2014) has 4464 observations.

Fundamentally, long memory is the statistical dependence between two random points of any time series that are distant. Ideally, their autocorrelation should decline with a power law signature in most cases. If the autocorrelation coefficient remains significant despite traversing quite a distance, it is nothing but a long memory. The autocorrelations coefficients decline rather slowly providing there is long memory. However, cases of spurious long memory and hysteretic are sometimes found as well. Also occasional level shifts, create false long memory alarm on select cases. True long memory is said to exist only if the time series or at least the increments of time series (once deferencied) are strictly mean reversed. Usually a weak form of efficient market hypothesis (EMH), allows the Hurst exponent to be non 0.5. In all practical purposes a fractional time series with $0 < d < 0.5$, would exhibit true long memory. The higher the value of d subject to $d < 1$ is, the more pronounced the long memory is. Hence, stationarity, fractional nature and persistence combined give rise to true long memory.

According to Granger (1980, 1981), Granger and Joyeaux (1980) and Hosking (1981), the relationship is:

$$(1 - L)^d x_t = u_t, \text{ where, } \mathrm{t} = 0, \pm 1, \pm 2 \ldots\ldots \tag{10.1}$$

$u_t = \mathrm{I(d)}$, where I is for the fractionally integrated models and 'd' can be any real number within the range of 0 to 0.5; L is called as the lag operator.

$(1 - L)^d$ can be expressed as binomial expansions for all real 'd' values.

$$\begin{aligned} (1 - L)^d &= 1 - \mathrm{dL} + \frac{d(d-1)}{2} L^2 - \frac{d(d-1)(d-2)}{6} L^3 + \\ (1 - L)^d x_t &= x_t - \mathrm{d}x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \frac{d(d-1)(d-2)}{6} L^3 + \end{aligned} \tag{10.2}$$

'd' being the degree of dependence of the series and long memory condition would remain as is:

Food and Agriculture Organization of the United Nations (FAO). 2016. FAOSTAT Emissions Database. Rome, Italy: FAO. Available at: http://www.fao.org/faostat/en/#data. International Energy Agency; International Energy Agency (IEA). 2016. CO2 Emissions from Fuel Combustion (2016 edition). Paris, France: OECD/IEA. Available online at: http://data.iea.org/ieastore/statslisting.asp. © OECD/IEA, [2016]. The World Bank; World Bank. 2017. World Development Indicators. Washington, DC. Available at: http://data.worldbank.org/. Accessed September 2017. U.S. Energy Information Administration; U.S. Energy Information Administration (EIA). 2016. International Energy Statistics Washington, DC: U.S. Department of Energy. Available online at: http://www.eia.gov/beta/international/data/browser/#/?vs=INTL.44-1-AFRC-QBTU.A&vo=0&v=H&start=1980&end=2014. U.S. Environmental Protection Agency; U.S. Environmental Protection Agency (EPA). 2012. "Global Non-CO2 GHG Emissions: 1990–2030." Washington, DC: EPA. Available at: https://www.epa.gov/global-mitigation-non-co2-greenhouse-gases/non-co2-greenhouse-gases-international-emissions-and.

$0 < d < 0.5$. Thus, estimation of Hurst exponent remains $H = \frac{2d+1}{2}$; or simply $H = d + 0.5$.

Further, we calculate the Hurst exponent $H \approx d + 0.5$ (Torre et al., 2007) to evaluate the long memory intensity. H varies between 0 and 1 and thus the Hurst exponent can have three major conditions:

When, $0.5 < H \leq 1$, then the series is persistent and shows evidence of long memory, albeit contradicting the Efficient Market Theory.
When $0 < H < 0.5$, then the series is anti-persistent or exhibiting short memory, indicating fast changes in the trend.
When $H = 0.5$, then the series follows a random walk, in accordance with the Efficient Market Theory.

10.3 Empirical Results and Interpretation

Table 10.1 reports some descriptive statistics and stationarity data for GHG emission data of 186 countries.

It has been observed from Table 10.1 that almost all the GHG data from 186 countries attains stationarity only after the 1st, 2nd, 3rd and sometimes after the 4th difference. Hence, they are non-stationary as a base process and become stationary only with their increments. This further indicates the intensity of their stationary nature. Stationarity is weak. In fact, it borders non-stationarity. This means a random policy shock would stay for a longer period and permanent policy change regarding GHG emissions in all 186 countries is not required (Belbute & Pereira, 2017).

Fourteen out of 186 countries are found to have pure stationarity as well. Interestingly, more than half of them (57%) belong to the former USSR (Russia, Ukraine, Belarus, Estonia, Latvia, Kazakhstan, Turkmenistan & Uzbekistan). Three eastern EU nations (Armenia, Serbia and Bosnia) and two African nations (Cameroon and Tunisia) feature in the same list as well. A tiny island nation Niue is included as well. These being pure stationary transitory energy policy or random shocks would fade away in no time. Hence, a permanent environmental policy is necessary for these countries. This initial evidence suggests a non-uniform policy stance (Table 10.2).

Interestingly, persistence and long memory increased by 38% from window 1 to window 3; while persistence decreased 62% from window 1 to window 3. In other words, intensity of long memory increased for 38% of the cases and decreased for 62% of the cases. Therefore, we can assume that as the window size is becoming broader, the effect of long memory becomes weaker. Empirically as the window size triples (from 1488 to 4464), the impact of long memory decreases by more than 60%. The scope of this study is rather broad (covering 186 countries from 1990 to 2014), therefore we can conclude that our finding is probably a new

Table 10.1 Descriptive statistics and stationarity data for GHG emission data of 186 countries

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Afghanistan	13.9854	18.0006	20.6215	34.7130	2.5194	0.04573****
Albania	5.6799	8.0308	7.8573	11.6920	4.9884	0.01**
Algeria	90.1712	121.4828	129.9967	202.0871	2.1843	0.04**
Andorra	0.4294	0.5434	0.5272	0.6172	1.9175	0.01353***
Angola	52.2201	78.2501	94.4248	157.8168	1.7322	0.01***
Antigua & Barbuda	0.3970	0.6686	0.7096	1.1346	1.6127	0.03234***
Argentina	233.0957	277.5082	287.8669	348.6472	1.6336	0.01062**
Armenia	5.1794	7.0136	8.4497	24.5752	8.0468	0.01
Australia	477.0781	565.9990	552.5721	648.6069	1.9220	0.02158****
Austria	73.6969	78.9379	80.1366	89.0648	2.2624	0.01*****
Azerbaijan	52.3270	56.7838	59.9264	83.5539	4.0039	0.01**
Bahamas	1.5683	1.9077	1.9905	3.1042	8.3973	0.01076**
Bahrain	13.2061	21.0231	22.6159	35.0448	1.8497	0.01***
Bangladesh	84.9340	114.4974	118.4488	167.7068	1.9517	0.01706***
Barbados	2.6423	3.1911	3.1965	3.6348	1.9267	0.01**
Belarus	76.6572	86.3074	90.7742	136.5524	5.6611	0.01
Belgium	107.5032	130.8931	128.4460	141.0580	2.4175	0.02338**
Belize	5.4621	7.4893	7.5282	9.8017	1.7400	0.01**
Benin	4.9879	7.9807	8.1587	12.7148	1.6261	0.01**
Bhutan	0.7296	0.9836	1.0023	1.5272	3.7201	0.02425***
Bolivia	20.8505	28.7941	32.4384	48.4667	2.1226	0.04175***
Bosnia & Herzegovina	6.9475	22.0277	21.3157	30.3901	2.5964	0.01
Botswana	9.3009	13.2577	13.5725	22.2055	5.2622	0.01**
Brazil	556.3648	765.5213	771.2744	1051.0013	2.0358	0.01049**
Brunei	12.1192	15.6103	16.0214	19.2080	1.6732	0.03363**
Bulgaria	54.8586	62.6915	65.2449	99.3425	8.1741	0.01**
Burkina Faso	11.0379	15.1997	16.8853	23.5054	1.6509	0.01217*
Burundi	1.9533	2.3007	2.3548	3.3016	4.3690	0.01**
Cambodia	15.2577	19.1515	20.9787	28.8387	1.7553	0.01**
Cameroon	74.9059	81.8115	80.8904	83.7133	3.4480	0.014
Canada	555.7398	681.4384	664.5707	745.1087	2.0781	0.01**
Cape Verde	0.2162	0.4347	0.4750	0.7947	1.4560	0.01**
Central African Republic	35.9112	44.0617	43.7481	49.7608	1.8241	0.01881*

(continued)

Table 10.1 (continued)

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Chad	15.4943	23.4049	22.5495	28.9219	1.2293	0.01****
Chile	45.7512	70.0427	72.9037	103.6029	2.0136	0.01****
China	3154.4563	5051.0750	6522.5031	11,911.7118	1.8486	0.01***
Colombia	116.6519	133.9722	137.3804	162.8699	2.4338	0.01**
Comoros	0.2324	0.3031	0.3120	0.4185	2.0325	0.01**
Congo	2.6054	4.9567	5.6764	7.7321	1.8679	0.01799**
Congo, Dem. Republic	30.3659	33.5368	34.3791	41.1987	2.4974	0.01491****
Cook Islands	0.0785	0.1020	0.0994	0.1118	1.9391	0.01886**
Costa Rica	8.2916	10.2894	11.0715	13.8976	1.7634	0.01498**
Cote d'Ivoire	23.3747	26.0809	26.5985	33.7401	4.0290	0.01**
Croatia	21.1611	24.4456	25.1763	30.0012	1.8166	0.01471**
Cuba	35.1193	42.3262	42.6679	53.0702	3.0869	0.02846*
Cyprus	5.0532	7.6213	7.5176	9.3564	1.9046	0.01979**
Czech Republic	116.7703	140.8975	140.7155	181.0566	4.5387	0.01**
Denmark	48.7741	67.1045	67.5097	87.8829	2.9145	0.04063**
Djibouti	0.8891	1.1394	1.1180	1.5143	2.6104	0.04376****
Dominica	0.1721	0.2180	0.2105	0.2617	1.6477	0.04556*
Dominican Republic	15.2134	27.4524	26.3453	33.2175	2.0460	0.01**
Ecuador	29.1162	39.7640	42.3986	60.6294	2.1737	0.01445**
Egypt	123.3388	187.4435	198.4890	288.3518	1.4752	0.01**
El Salvador	6.7008	11.2541	10.7190	13.2192	2.5207	0.01**
Equatorial Guinea	0.1654	12.6546	11.7652	20.7280	1.3104	0.01****
Estonia	18.9324	21.3849	23.1528	42.9105	8.2201	0.01
Ethiopia	61.9145	83.8519	87.3255	129.2132	1.8575	0.01983**
European Union (28)	4053.6594	4883.3113	4774.9614	5244.2390	3.0277	0.01781***
Fiji	1.6029	1.9348	1.9747	2.3889	2.0328	0.01**
Finland	59.5276	73.9017	73.9871	87.0648	2.8124	0.02325*
France	413.1144	492.7267	482.2297	518.8808	3.2571	0.01**
Gabon	5.3582	6.6554	6.4353	7.3869	1.3777	0.01157***
Gambia	3.7253	5.3617	5.5383	7.6859	1.7449	0.01815*
Georgia	10.9371	12.7628	16.7131	48.0278	7.0951	0.04057
Germany	854.0073	967.9244	975.5326	1154.1051	2.1240	0.04281****

(continued)

Table 10.1 (continued)

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Ghana	12.4027	19.2060	19.9996	30.8917	2.0884	0.03087*
Greece	84.1137	106.2303	107.2820	123.1803	2.0551	0.02811**
Grenada	1.5642	1.7961	1.7861	2.0022	1.8552	0.03706*
Guatemala	11.4134	20.3985	19.5967	30.8580	2.1797	0.01****
Guinea	7.5107	12.1169	11.9697	16.4436	1.7634	0.01*
Guinea-Bissau	1.2297	1.4673	1.5368	2.0272	2.3435	0.02539*
Guyana	2.4458	3.3532	3.3262	4.4776	3.4710	0.01**
Haiti	4.3472	7.0249	6.6404	8.6718	1.6920	0.01**
Honduras	10.4836	15.1714	15.7964	21.4748	1.4789	0.01**
Hungary	56.7553	73.4540	71.2365	88.2158	3.1396	0.01***
Iceland	2.7040	2.9987	2.9809	3.2251	2.6193	0.03341**
India	1188.8433	1741.9900	1918.9244	3079.8127	2.1262	0.04112****
Indonesia	380.2543	567.7198	575.9953	789.4752	2.0242	0.0206**
Iran	250.5796	476.1853	499.9920	733.6053	1.5808	0.04656***
Iraq	124.0568	173.3779	184.8330	294.8999	3.1690	0.01**
Ireland	53.6667	62.7663	62.6547	71.1437	1.5590	0.01045****
Israel	42.2885	74.9010	70.7009	94.5830	2.1288	0.01***
Italy	403.1072	497.6824	500.7049	560.6943	2.9856	0.01**
Jamaica	8.8860	10.5996	10.7569	13.6309	1.9507	0.04972***
Japan	1171.0379	1266.2313	1261.0078	1353.6294	2.1237	0.0146****
Jordan	17.3556	21.7230	23.2759	32.4030	2.5757	0.01****
Kazakhstan	154.9383	241.4410	243.9179	336.8705	1.6163	0.02451
Kenya	34.1576	37.0977	43.4239	60.5299	1.6527	0.01033**
Kiribati	0.0356	0.0583	0.0594	0.0889	1.4928	0.02052**
Korea (North)	63.8065	97.4176	100.1273	155.8404	3.6775	0.01**
Korea (South)	290.7325	526.7219	510.8230	674.7440	2.1342	0.01**
Kuwait	78.3789	148.9615	147.5070	198.9700	1.7564	0.01**
Kyrgyzstan	8.4426	11.3445	13.4419	32.1268	6.3643	0.0492**
Laos	6.0943	8.2414	8.3329	11.5517	2.0939	0.0328*
Latvia	11.1112	12.7725	14.2848	26.2346	5.8621	0.01
Lebanon	7.4390	19.0841	18.7945	28.5954	2.8126	0.01**
Lesotho	3.1546	3.8509	3.7744	4.3582	1.8755	0.01*
Liberia	0.9289	1.2611	1.3966	2.2001	2.1728	0.01501*
Libya	88.3081	108.5717	110.9764	139.5801	1.6124	0.03661*
Lithuania	19.0352	21.3620	23.6327	46.8420	8.1265	0.01*
Luxembourg	8.3315	11.5066	11.1016	12.7578	2.0601	0.01***

(continued)

Table 10.1 (continued)

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Macedonia, FYR	11.3061	12.0650	12.2192	13.3134	2.1411	0.01***
Madagascar	20.7179	24.1836	24.3707	26.8984	2.8474	0.01****
Malawi	6.3236	7.1532	7.6831	10.1969	2.1206	0.01**
Malaysia	103.2140	202.3824	206.0706	316.9021	1.6669	0.0447**
Maldives	0.1999	0.5727	0.6483	1.4230	2.1192	0.01**
Mali	15.2984	20.3308	21.3541	31.5341	1.7291	0.02835*
Malta	2.4345	2.9684	2.8755	3.2799	1.8947	0.01*
Mauritania	6.2575	8.5319	8.5019	11.2128	1.7926	0.01***
Mauritius	2.1318	4.1212	3.9943	5.8427	1.5608	0.03885**
Mexico	426.6553	606.8181	607.8423	742.1449	1.5663	0.01**
Moldova	10.9267	12.2828	15.6372	38.2770	5.8745	0.04829***
Mongolia	23.1480	27.5260	28.6780	40.8634	3.7278	0.0494*
Morocco	38.1101	56.0631	57.4760	81.6906	1.7895	0.03097*
Mozambique	18.1877	20.1826	21.6514	28.4267	2.0625	0.01733***
Myanmar	55.3424	74.9810	77.8143	107.3824	1.8930	0.01***
Namibia	7.3180	9.4723	10.0362	14.9196	4.7437	0.01447*****
Nauru	0.0457	0.0815	0.0814	0.1282	1.5208	0.01734***
Nepal	20.1544	27.9262	27.7969	37.5212	2.3206	0.03949**
Netherlands	180.1740	204.6730	202.3289	223.4976	2.7647	0.03419***
New Zealand	63.9965	73.6541	71.8146	77.7839	1.6990	0.01****
Nicaragua	7.6961	12.3626	11.7459	14.5156	1.6318	0.01**
Niger	10.7912	17.5324	18.1911	27.9757	1.9079	0.01833*
Nigeria	200.7855	256.4924	254.8762	305.0604	1.7182	0.01496***
Niue	0.0336	0.0395	0.0463	0.1012	5.8302	0.02
Norway	42.8588	47.5330	47.7411	52.5466	4.1413	0.01*
Oman	39.8603	65.4475	67.3092	106.3043	2.3544	0.01445**
Pakistan	154.1644	230.6092	242.8771	333.3829	1.6215	0.01****
Panama	7.2486	10.9407	11.7770	17.7577	2.1312	0.01949*
Papua New Guinea	9.0116	13.5599	13.5908	16.7897	3.1107	0.01**
Paraguay	21.0986	28.1655	29.1426	39.9172	2.7861	0.01**
Peru	41.3511	58.7799	62.2905	89.6600	2.0093	0.01136***
Philippines	90.0489	136.0349	133.9688	181.6361	2.6355	0.0138***
Poland	352.0590	376.4705	384.4338	426.2837	1.7309	0.01***
Portugal	56.4012	67.8688	69.9377	82.9109	1.6581	0.021**

(continued)

Table 10.1 (continued)

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Qatar	14.1619	30.8134	40.3938	88.1129	2.0064	0.04835**
Romania	108.7927	135.4848	145.0992	237.6710	4.7037	0.04364*
Russian Federation	1970.5464	2142.9537	2225.0269	2982.7624	5.3422	0.01
Rwanda	3.7247	4.5423	4.8866	6.7283	1.7320	0.01***
Saint Kitts & Nevis	0.1770	0.2801	0.2672	0.3833	1.9536	0.02677**
Saint Lucia	0.7889	1.0495	1.0250	1.1379	3.1151	0.01**
Saint Vincent & Grenadines	0.1483	0.2578	0.2483	0.3808	2.7771	0.03901*
Samoa	0.3325	0.4107	0.4028	0.4709	1.5740	0.01466**
Sao Tome & Principe	0.0941	0.1202	0.1318	0.1903	1.9518	0.01****
Saudi Arabia	187.5226	302.3265	340.8196	583.3701	2.2286	0.01***
Senegal	13.2437	18.6515	19.0271	25.4859	1.6431	0.02515*
Serbia	51.4156	63.2701	63.5316	80.6050	3.0489	0.0338
Seychelles	0.2090	0.5082	0.5045	0.7994	1.7506	0.02272**
Sierra Leone	3.3376	3.9543	4.5080	6.7313	2.7270	0.01***
Singapore	30.9867	43.2257	43.7617	52.9509	2.9939	0.02667**
Slovakia	38.1129	46.5022	47.5279	66.7070	4.8728	0.01244***
Slovenia	16.2491	18.7885	18.4486	20.7990	2.8730	0.04826**
Solomon Islands	0.3456	0.4332	0.4442	0.5706	1.7042	0.02407**
Somalia	17.7077	22.5286	22.3268	24.5166	5.2673	0.02335**
South Africa	299.7879	401.8235	405.4920	524.8950	1.4715	0.02104**
Spain	271.7052	339.7952	342.5146	431.8756	1.8167	0.0216***
Sri Lanka	22.3599	31.6324	31.2321	40.7536	1.9181	0.03731*
Sudan	77.0875	114.1945	116.7244	151.2507	1.7858	0.02303**
Suriname	2.2345	3.2173	3.0239	3.4205	1.9431	0.01083****
Swaziland	1.6209	2.6575	2.5115	2.9655	2.2718	0.01***
Sweden	50.8732	66.8418	64.4533	77.8628	1.9756	0.01**
Switzerland	47.7050	51.8598	51.7990	54.1510	4.1227	0.01**
Syria	54.1133	73.8924	74.8840	97.0788	2.0113	0.04421***
Tajikistan	6.0732	8.0169	8.7992	17.3192	4.8752	0.01826*
Tanzania	41.7170	52.3613	55.6454	78.0830	2.0898	0.01418**
Thailand	152.0323	264.5703	270.2732	366.3679	2.0085	0.03337***
Togo	2.9764	4.6775	4.8415	6.9944	1.8799	0.02035*

(continued)

Table 10.1 (continued)

Country name	Min	Median	Mean	Max	Kurtosis	ADF
Tonga	0.2243	0.2680	0.2751	0.3399	1.8170	0.01*
Trinidad & Tobago	12.8730	17.0679	18.8713	25.8122	1.3782	0.04636**
Tunisia	19.3967	28.7660	28.5971	38.1666	1.8701	0.041
Turkey	199.8824	299.4328	306.9792	431.4751	1.9401	0.01*
Turkmenistan	50.5770	72.4903	77.9131	114.9934	1.7656	0.05
Tuvalu	0.0170	0.0187	0.0200	0.0235	1.4194	0.01*
Uganda	14.2371	18.5694	21.7060	34.1129	1.9142	0.03501**
Ukraine	347.5459	413.5979	476.1499	896.8317	4.8560	0.01663
United Arab Emirates	74.6428	125.7554	138.4935	221.5072	1.7783	0.01**
United Kingdom	506.1109	643.6190	636.7958	745.6428	2.4193	0.01848****
United States of America	5831.4783	6470.9053	6401.8085	6783.5434	2.0846	0.01**
Uruguay	26.0596	30.8125	31.2800	35.4596	2.1607	0.03237**
Uzbekistan	180.6496	210.9883	207.8205	233.6175	2.0343	0.01
Vanuatu	0.4473	0.5298	0.5634	0.7291	2.0750	0.01**
Venezuela	171.1796	217.4547	222.0412	273.6175	1.9534	0.01*
Vietnam	70.5130	149.2641	158.8051	270.2983	1.6924	0.0236*
Yemen	11.9895	22.2551	23.2201	35.6522	1.6483	0.02099*
Zambia	35.3614	41.2642	41.4751	51.2010	2.9505	0.02381**
Zimbabwe	23.2327	27.7244	28.3882	34.1675	1.6546	0.01509***

*Stationary at 1st diff., **Stationary at 2nd diff., ***Stationary at 3rd diff., ****Stationary at 4th diff., *****Stationary at 5th diff. This table exhibits the descriptive statistics; most importantly the stationarity pattern in their GHG data (weak or strong) for 186 countries under consideration. More than 92% of the countries are found to have weak stationarity (achieved at the 1st difference, 2nd difference or 3rd difference). About 12% of the countries witnessed a leptokurtic distribution, indicating large volatility in their GHG data

stylized fact. As mentioned earlier, random policy shocks can be strong enough in comparison to permanent policy stance change. Mostly, the stationarity across the GHG emission data of these nations are weak and for this reason, they border non-stationarity and become trend stationary only with their stationary increments. Random policy shocks would have a lasting impact in such cases. The borderline non-stationarity trait will keep the effects from the random shock alive for a long period. We have to remember here that about twenty-two countries (half of them represent former USSR countries) do show pure stationarity. Hence, a uniform policy stance cannot be suggested. Transitory shocks (random) would fade away in them. They would require permanent policy changes. This study suggests two diametrically opposite emission policies for 172 countries with weak stationarity

Table 10.2 'd' and 'H' values derived from annual GHG emission data of 186 countries for three Windows

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Afghanistan	0.3675536	0.1408189	0.4869506	0.867554	0.640819	0.986951
Albania	0.3580413	0.0000458	0.2668743	0.858041	0.500046	0.766874
Algeria	0.4034729	0.2070251	0.1921359	0.903473	0.707025	0.692136
Andorra	0.3357125	0.3124307	0.000079	0.835713	0.812431	0.500079
Angola	0.430698	0.2307365	0.4386225	0.930698	0.730737	0.938623
Antigua & Barbuda	0.4278536	0.4177312	0.4897185	0.927854	0.917731	0.989719
Argentina	0.4346124	0.1316929	0.0909896	0.934612	0.631693	0.59099
Armenia	0.07971213	0.0000458	0.0000458	0.579712	0.500046	0.500046
Australia	0.3838711	0.0000458	0.0000458	0.883871	0.500046	0.500046
Austria	0.168468	0.02518791	0.0000458	0.668468	0.525188	0.500046
Azerbaijan	0.310332	0.0000458	0.4055687	0.810332	0.500046	0.905569
Bahamas	0.1019233	0.1376878	0.0000458	0.601923	0.637688	0.500046
Bahrain	0.2038303	0.2237649	0.1589616	0.70383	0.723765	0.658962
Bangladesh	0.2421293	0.2222432	0.1927424	0.742129	0.722243	0.692742
Barbados	0.0000458	0.4524659	0.288575	0.500046	0.952466	0.788575
Belarus	0.3558281	0.3503253	0.0000458	0.855828	0.850325	0.500046
Belgium	0.3017871	0.3979529	0.0171448	0.801787	0.897953	0.517145
Belize	0.4328165	0.4749792	0.4995719	0.932817	0.974979	0.999572
Benin	0.2607086	0.1576311	0.1466612	0.760709	0.657631	0.646661

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Bhutan	0.4208386	0.01812979	0.230252	0.920839	0.51813	0.730252
Bolivia	0.1958429	0.1007433	0.1231245	0.695843	0.600743	0.623125
Bosnia & Herzegovina	0.396786	0.0000458	0.0911851	0.896786	0.500046	0.591185
Botswana	0.4014711	0.04762985	0.1982415	0.901471	0.54763	0.698242
Brazil	0.4339951	0.1386419	0.1106142	0.933995	0.638642	0.610614
Brunei	0.000045830	0.169891	0.0971307	0.500046	0.669891	0.597131
Bulgaria	0.3296376	0.0000458	0.0000572	0.829638	0.500046	0.500057
Burkina Faso	0.4364531	0.1467938	0.111253	0.936453	0.646794	0.611253
Burundi	0.00004583	0.1420834	0.4915142	0.500046	0.642083	0.991514
Cambodia	0.3920495	0.08126091	0.111117	0.89205	0.581261	0.611117
Cameroon	0.3808336	0.06995941	0.0154194	0.880834	0.569959	0.515419
Canada	0.0000458	0.1718186	0.0928815	0.500046	0.671819	0.592882
Cape Verde	0.3664992	0.4819357	0.2041779	0.866499	0.981936	0.704178
Central African Republic	0.1232047	0.0000458	0.0000458	0.623205	0.500046	0.500046
Chad	0.0000458	0.2356496	0.1704658	0.500046	0.73565	0.670466
Chile	0.0000458	0.0000458	0.3090891	0.500046	0.500046	0.809089
China	0.1158735	0.4994069	0.4891427	0.615874	0.999407	0.989143
Colombia	0.0000458	0.01933998	0.0507436	0.500046	0.51934	0.550744

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Comoros	0.4067259	0.07728315	0.0000458	0.906726	0.577283	0.500046
Congo	0.0000458	0.377199	0.0000458	0.500046	0.877199	0.500046
Congo, Dem. Republic	0.0000803	0.01603549	0.0000458	0.50008	0.516035	0.500046
Cook Islands	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Costa Rica	0.316722	0.08122975	0.0306991	0.816722	0.58123	0.530699
Cote d'Ivoire	0.3787294	0.3292942	0.0691301	0.878729	0.829294	0.56913
Croatia	0.06644351	0.0000458	0.0000458	0.566444	0.500046	0.500046
Cuba	0.272769	0.0000458	0.0000458	0.772769	0.500046	0.500046
Cyprus	0.4028659	0.02020946	0.0000458	0.902866	0.520209	0.500046
Czech Republic	0.399542	0.0000458	0.0000500	0.899542	0.500046	0.50005
Denmark	0.0000458	0.2785297	0.0681354	0.500046	0.77853	0.568135
Djibouti	0.0000458	0.3803554	0.2807482	0.500046	0.880355	0.780748
Dominica	0.3290578	0.0000458	0.0109553	0.829058	0.500046	0.510955
Dominican Republic	0.430687	0.07467853	0.0000458	0.930687	0.574679	0.500046
Ecuador	0.0000458	0.1333600	0.0459779	0.500046	0.63336	0.545978
Egypt	0.1968282	0.2008904	0.145033	0.696828	0.70089	0.645033
El Salvador	0.04473666	0.01755786	0.0000458	0.544737	0.517558	0.500046
Equatorial Guinea	0.3608258	0.0000458	0.1543174	0.860826	0.500046	0.654317

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Estonia	0.4170524	0.0000458	0.0000458	0.917052	0.500046	0.500046
Ethiopia	0.2771292	0.1457168	0.1851173	0.777129	0.645717	0.685117
European Union (28)	0.3588764	0.0000458	0.0412837	0.858876	0.500046	0.541284
Fiji	0.3930198	0.4461495	0.4294934	0.89302	0.94615	0.929493
Finland	0.1326292	0.06675142	0.0000458	0.632629	0.566751	0.500046
France	0.00004583	0.0000458	0.0000458	0.500046	0.500046	0.500046
Gabon	0.1561327	0.2913380	0.0000458	0.656133	0.791338	0.500046
Gambia	0.4358751	0.4945697	0.4704177	0.935875	0.99457	0.970418
Georgia	0.0000458	0.4856949	0.0000458	0.500046	0.985695	0.500046
Germany	0.3904606	0.0000458	0.0000458	0.890461	0.500046	0.500046
Ghana	0.3766178	0.05404861	0.1149051	0.876618	0.554049	0.614905
Greece	0.2947934	0.1333825	0.389658	0.794793	0.633383	0.889658
Grenada	0.209277	0.4549557	0.1377067	0.709277	0.954956	0.637707
Guatemala	0.4163744	0.1525804	0.1237731	0.916374	0.65258	0.623773
Guinea	0.2042994	0.0774600	0.0603589	0.704299	0.57746	0.560359
Guinea-Bissau	0.4210727	0.4373197	0.2082177	0.921073	0.93732	0.708218
Guyana	0.1938646	0.03715324	0.1359302	0.693865	0.537153	0.63593
Haiti	0.3205549	0.1107911	0.0752309	0.820555	0.610791	0.575231

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Honduras	0.2353125	0.0000458	0.1138813	0.735313	0.500046	0.613881
Hungary	0.3769574	0.0000458	0.0000458	0.876957	0.500046	0.500046
Iceland	0.0000458	0.2690874	0.0000458	0.500046	0.769087	0.500046
India	0.4381294	0.4753003	0.4970839	0.938129	0.9753	0.997084
Indonesia	0.0000458	0.1049036	0.4993662	0.500046	0.604904	0.999366
Iran	0.4254503	0.0000458	0.0000458	0.92545	0.500046	0.500046
Iraq	0.06870919	0.0000551	0.2972039	0.568709	0.500055	0.797204
Ireland	0.499081	0.0000458	0.0000458	0.999081	0.500046	0.500046
Israel	0.00005207	0.0000458	0.0819502	0.500052	0.500046	0.58195
Italy	0.2888538	0.2147293	0.3208549	0.788854	0.714729	0.820855
Jamaica	0.2204467	0.2720499	0.1909195	0.720447	0.77205	0.69092
Japan	0.3976523	0.0000712	0.0000628	0.897652	0.500071	0.500063
Jordan	0.3977867	0.0000458	0.1431587	0.897787	0.500046	0.643159
Kazakhstan	0.0000458	0.2828291	0.0000458	0.500046	0.782829	0.500046
Kenya	0.0000458	0.01959818	0.13974	0.500046	0.519598	0.63974
Kiribati	0.3017393	0.1464496	0.0000458	0.801739	0.64645	0.500046
Korea (North)	0.389496	0.0000458	0.0717149	0.889496	0.500046	0.571715
Korea (South)	0.0348257	0.0313952	0.0000458	0.534826	0.531395	0.500046

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Kuwait	0.4207058	0.055888	0.0297287	0.920706	0.555888	0.529729
Kyrgyzstan	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Laos	0.2054154	0.1761532	0.1141541	0.705415	0.676153	0.614154
Latvia	0.21585	0.1856948	0.0000458	0.71585	0.685695	0.500046
Lebanon	0.1060906	0.01792955	0.0718375	0.606091	0.51793	0.571838
Lesotho	0.3411641	0.4317588	0.0028881	0.841164	0.931759	0.502888
Liberia	0.0000458	0.4133726	0.1910288	0.500046	0.913373	0.691029
Libya	0.3957747	0.0000458	0.1476087	0.895775	0.500046	0.647609
Lithuania	0.4045447	0.03031656	0.0396827	0.904545	0.530317	0.539683
Luxembourg	0.219142	0.0000458	0.0000458	0.719142	0.500046	0.500046
Macedonia, FYR	0.0000458	0.0000458	0.2228689	0.500046	0.500046	0.722869
Madagascar	0.4066134	0.1173371	0.0000458	0.906613	0.617337	0.500046
Malawi	0.0000458	0.0000458	0.4873783	0.500046	0.500046	0.987378
Malaysia	0.0000458	0.4615235	0.0893418	0.500046	0.961524	0.589342
Maldives	0.400962	0.4878322	0.4992232	0.900962	0.987832	0.999223
Mali	0.3411135	0.06621137	0.091904	0.841114	0.566211	0.591904
Malta	0.0000458	0.2998501	0.3910901	0.500046	0.79985	0.89109
Mauritania	0.4069065	0.1831373	0.1064172	0.906907	0.683137	0.606417

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Mauritius	0.4262064	0.0000458	0.4413879	0.926206	0.500046	0.941388
Mexico	0.4131185	0.1000436	0.072401	0.913119	0.600044	0.572401
Moldova	0.4294764	0.05132512	0.0000458	0.929476	0.551325	0.500046
Mongolia	0.3406469	0.1179882	0.1667811	0.840647	0.617988	0.666781
Morocco	0.4301331	0.1456993	0.126235	0.930133	0.645699	0.626235
Mozambique	0.0000458	0.4058975	0.1366856	0.500046	0.905898	0.636686
Myanmar	0.0000458	0.2980773	0.3619978	0.500046	0.798077	0.861998
Namibia	0.1633312	0.01963202	0.0000461	0.663331	0.519632	0.500046
Nauru	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Nepal	0.0000458	0.1619053	0.1589383	0.500046	0.661905	0.658938
Netherlands	0.3560875	0.0000458	0.0000458	0.856088	0.500046	0.500046
New Zealand	0.407121	0.4958672	0.1033627	0.907121	0.995867	0.603363
Nicaragua	0.09884899	0.3161936	0.3222492	0.598849	0.816194	0.822249
Niger	0.4366153	0.4804709	0.137014	0.936615	0.980471	0.637014
Nigeria	0.3847669	0.0474487	0.0000458	0.884767	0.547449	0.500046
Niue	0.3234668	0.1796171	0.3118166	0.823467	0.679617	0.811817
Norway	0.359882	0.000047898	0.0000458	0.859882	0.500048	0.500046
Oman	0.4165087	0.0000458	0.0862991	0.916509	0.500046	0.586299

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Pakistan	0.2433635	0.443524	0.1326436	0.743364	0.943524	0.632644
Panama	0.4081924	0.0000458	0.0700064	0.908192	0.500046	0.570006
Papua New Guinea	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Paraguay	0.0000458	0.1468807	0.2057907	0.500046	0.646881	0.705791
Peru	0.0000458	0.2174887	0.4069006	0.500046	0.717489	0.906901
Philippines	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Poland	0.0000458	0.1778592	0.1379346	0.500046	0.677859	0.637935
Portugal	0.3996121	0.00004583	0.0467634	0.899612	0.500046	0.546763
Qatar	0.4254052	0.1893004	0.17764	0.925405	0.6893	0.67764
Romania	0.3775936	0.0000458	0.0000458	0.877594	0.500046	0.500046
Russian Federation	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Rwanda	0.2279068	0.2557062	0.1958495	0.727907	0.755706	0.69585
Saint Kitts & Nevis	0.3310466	0.1703812	0.2715116	0.831047	0.670381	0.771512
Saint Lucia	0.0000458	0.2293402	0.3446488	0.500046	0.72934	0.844649
Saint Vincent & Grenadines	0.2449579	0.1145337	0.1151772	0.744958	0.614534	0.615177
Samoa	0.09439549	0.09309803	0.1468974	0.594395	0.593098	0.646897
Sao Tome & Principe	0.1597903	0.2216995	0.3154593	0.65979	0.7217	0.815459
Saudi Arabia	0.4026469	0.05481984	0.1174344	0.902647	0.55482	0.617434

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Senegal	0.2015805	0.1268716	0.0736017	0.701581	0.626872	0.573602
Serbia	0.3028748	0.2011373	0.0000455	0.802875	0.701137	0.500046
Seychelles	0.3987064	0.1951734	0.0963279	0.898706	0.695173	0.596328
Sierra Leone	0.3360648	0.4502014	0.1790994	0.836065	0.950201	0.679099
Singapore	0.0462948	0.0000420	0.0875963	0.546295	0.500042	0.587596
Slovakia	0.3866841	0.0000458	0.334634	0.886684	0.500046	0.834634
Slovenia	0.3686073	0.0000444	0.0756015	0.868607	0.500044	0.575602
Solomon Islands	0.08667527	0.4232308	0.4726424	0.586675	0.923231	0.972642
Somalia	0.2828962	0.0000458	0.458109	0.782896	0.500046	0.958109
South Africa	0.0000458	0.4779892	0.1582243	0.500046	0.977989	0.658224
Spain	0.3724126	0.1440274	0.0000458	0.872413	0.644027	0.500046
Sri Lanka	0.1497935	0.1309478	0.0545991	0.649794	0.630948	0.554599
Sudan	0.2391722	0.1283039	0.0547948	0.739172	0.628304	0.554795
Suriname	0.05401442	0.0000458	0.0646544	0.554014	0.500046	0.564654
Swaziland	0.30655	0.01827489	0.0284679	0.80655	0.518275	0.528468
Sweden	0.1937452	0.0000458	0.0303804	0.693745	0.500046	0.53038
Switzerland	0.09049555	0.1184561	0.1780404	0.590496	0.618456	0.67804
Syria	0.4309612	0.1141497	0.0000458	0.930961	0.61415	0.500046

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Tajikistan	0.4319065	0.3750502	0.388727	0.931907	0.87505	0.888727
Tanzania	0.3491791	0.07515507	0.1314609	0.849179	0.575155	0.631461
Thailand	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Togo	0.3453053	0.4192644	0.1027913	0.845305	0.919264	0.602791
Tonga	0.0000458	0.0000458	0.0000458	0.500046	0.500046	0.500046
Trinidad & Tobago	0.2214191	0.3098018	0.2461487	0.721419	0.809802	0.746149
Tunisia	0.08165556	0.1003873	0.0394364	0.581656	0.600387	0.539436
Turkey	0.0000458	0.07012665	0.0819018	0.500046	0.570127	0.581902
Turkmenistan	0.2208112	0.1731433	0.3665919	0.720811	0.673143	0.866592
Tuvalu	0.3558342	0.0000458	0.0000458	0.855834	0.500046	0.500046
Uganda	0.4092226	0.4690216	0.0778019	0.909223	0.969022	0.577802
Ukraine	0.2405904	0.0000458	0.0000458	0.74059	0.500046	0.500046
United Arab Emirates	0.4335517	0.1224701	0.1282783	0.933552	0.62247	0.628278
United Kingdom	0.1097575	0.06259626	0.0186613	0.609758	0.562596	0.518661
United States of America	0.0000458	0.1951396	0.0207459	0.500046	0.69514	0.520746
Uruguay	0.3958923	0.01511939	0.0000458	0.895892	0.515119	0.500046
Uzbekistan	0.0000458	0.07852554	0.0329287	0.500046	0.578526	0.532929
Vanuatu	0.0000458	0.0000458	0.1578756	0.500046	0.500046	0.657876

(continued)

Table 10.2 (continued)

Country name	Order of fractional differencing (d)			Hurst Exponent (H)		
	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)	Window 1 (1990–1998)	Window 2 (1990–2006)	Window 3 (1990–2014)
Venezuela	0.0000458	0.07937376	0.0000458	0.500046	0.579374	0.500046
Vietnam	0.4356168	0.2052849	0.4618234	0.935617	0.705285	0.961823
Yemen	0.4015578	0.1104388	0.0181617	0.901558	0.610439	0.518162
Zambia	0.0000458	0.03849977	0.1397879	0.500046	0.5385	0.639788
Zimbabwe	0.3576277	0.09597638	0.0909319	0.857628	0.595976	0.590932

Notes Hurst Exponent measures the degree of persistence; d represents the order of fractional differencing in the ARFIMA process. Windows 1, 2, 3 contains 1488, 2976, 4464 observations respectively. All the observations of this table exhibit Long Memory, although to a varying degree. Windows I, II and III have 24, 29 and 30% of cases where Long Memory effect is mild; similarly, Windows I, II and III have 76, 71 and 70% of cases where the Long Memory effect is rather strong. The Long Memory impact decreases with Window size increase having long memory and 14 with strong stationarity having long memory. Since all of them across all three windows exhibited long memory; persistence is proved without any doubt.

10.4 Conclusion

The study found that all 186 countries over 25 years are exhibiting persistence or long memory in their respective GHG emission data to various degrees. A total of eight countries from the former USSR or Soviet Socialist Republic, three eastern EU nations such as Armenia, Serbia and Bosnia and two African nations (Cameroon and Tunisia) feature in the list with strong stationarity coupled with long memory. Last but not the least, the island nation Niue is included in the same list. The Russian federation borders the eastern part of the EU zone. Thus, geographically the former USSR is quite close to Armenia, Serbia and Bosnia as well. This means that the extended eastern EU part alongside the ex-USSR domain represents about 79% of the countries having strong stationarity coupled with long memory. Therefore, a permanent policy stance on GHG emissions of these countries would help them to reduce their respective carbon footprint. As far as the other 172 nations are concerned, a steadfast random policy shock from time to time would restrict their GHG emission within permissible limits, helping them to reduce the global carbon footprint significantly.

This chapter can shed some light on this topic, since there are few studies regarding the GHG emissions in a huge sample of countries. Reducing GHG emissions will have important economic, social and generational implications. Our findings may be of interest to a wide range of audiences, such as civil societies, policymakers, and academic researchers. The existing literature documented that a static trade-off exists between climate control and both economic growth and social equity (Ravallion et al., 2000) and long-run relationships between GDP and CO_2 emissions (Aung et al., 2017). Furthermore, the literature stated significant relationships between environmental pollution and income (Brännlund & Ghalwash, 2008), strong interacting effects between productivity and inequality and a significant negative relationship between productivity and GHG emissions (Sahu & Patnaik, 2020).

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