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Impact of House Price on Economic Stability: Some Lessons from OECD Countries

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Abstract
Despite having abundant literature blaming a faulty financial system and exuberant price expectations as the primary causes of housing bubbles, there is a lack of research that looks at the impact of house price instability on the economy. This study aims to fill this gap by thoroughly examining the connection between house prices and economic output, and the effect of house price volatility on economic stability. Drawing from long-spanning quarterly data from 17 OECD countries from 1970 to 2019, the study develops and tests economic growth and volatility models to uncover significant insights. The empirical results show that house price returns have a significant asymmetric impact on economic growth, with negative returns having twice the effect of positive ones. Moreover, the results indicate that house price volatility significantly contributes to economic instability. In light of these findings, the paper concludes with valuable policy recommendations to enhance the housing market and improve overall economic stability. This study provides a compelling argument for the importance of closely monitoring and regulating the real estate market in order to maintain a healthy and stable economy.

Keywords House prices · Price volatility · Economic growth · Output volatility · Asymmetric effects · OECD countries

JEL Classification E32 · G51 · R30 · O47

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Introduction

The unprecedented and steep increase in house prices during the Covid-19 pandemic caused significant concern among policymakers. On the one hand, its impact on inflation was substantial, and on the other hand, the possibility of a housing market crash resulting from the potential housing bubble was worrying. As a result, many central banks, including the US Federal Reserve System, began to raise interest rates to curb rising inflation and cool down the housing market. The Chair of the US Federal Reserve, Jerome Powell, has explicitly stated that his desire to bring house prices to a fair value is one of the reasons behind the Federal Reserve's 2022 contractionary monetary policy (Mishkin, 2022).

The relationship between house prices and economic activity has been a topic of interest among economists since the Global Financial Crisis (GFC). In this study, we aim to revisit two questions related to this topic: the impact of house prices on economic growth and the possibility of asymmetry in this relationship as well as the effect of house price volatility on economic stability and its potential consequences on economic growth. On that note, there have been many studies at the aggregate and household levels that examine the impact of housing prices on key macroeconomic variables, such as economic output, consumption, residential investment, and inflation (Aladangady et al., 2022; Case, 2000; Catte et al., 2004; Disney et al., 2010; Fair, 2017; Goodhart & Hofmann, 2007, 2008; Jordà et al., 2015; Mian & Sufi, 2014). Interestingly, Beltratti & Morana (2010) found that the impact of house price shocks on the macroeconomy is even stronger than that of the stock market (p. 544).

Case and Quigley (2008) assert that problems in the housing market have significant economic consequences, such as a decrease in consumer spending, drops in housing starts and completions, and a decline in overall residential investment. They also document the strong negative impact of declining house prices on household income and the finance industry, including its impact on construction and housing services and diminished demand for home financing, as well as a rising number of mortgage defaults. Many studies find a bidirectional association among house prices and economic activity. Using aggregate data from 1963Q1 to 2012Q2 for the US, Nyakabawo et al. (2015) found causality between real GDP per capita and real house prices. Their findings show that real house prices Granger cause real GDP at a significance level, while causality from real GDP per capita to real house prices are also observed but less frequently[1].

When it comes to the impact of house prices on consumption and investment and consequently on the overall economy, the literature suggests two different channels. The first channel is the '*wealth effect*'. According to Muellbauer and Murphy (1990), homeowners whose housing wealth increases due to the increase in house price will

[1] There are several other studies which have analyzed the connection between house prices and various macroeconomic variables in both developed and developing nations. For further research, one may wish to consider the works of Cho et al. (2012), Funke and Paetz (2013), Ibrahim and Law (2014), Liu et al. (2002), Meidani et al. (2011), and Phang (2004).

increase their consumption of non-housing goods and services. However, if this rise in house price is long expected, it will not impact consumption. In short, the wealth effect would be most effective when an increase in house prices is unexpected. The second channel through which house price affects the economy is the '*collateral effect*'. Aoki et al. (2004) argue that house prices impact consumption through collateral (balance sheet) effects instead of the traditional *wealth effect*. They believe that credit frictions play a vital role in consumption and demand for housing. They note that following deregulation of the mortgage market in the UK, access to home equity is much easier, and for a given increase in house prices, more borrowing is generated. Many other works bring empirical support for both the *wealth channel*(Campbell & Cocco, 2007; McCarthy & McQuinn, 2017) and the *collateral channel*(Aron et al., 2012; Lustig & Nieuwerburgh, 2010) of the house prices. Generally, the *wealth effect* is mainly associated with consumption, while the *collateral effect* is also considered to influence investment in addition to consumption.

The relationship between house prices and economic growth has been widely studied and documented by various researchers. Miller et al. (2011) defined the collateral and wealth effects as the impact of predictable and unpredictable price change components, respectively. Their study of 379 US localities between 1980 and 2008 showed that the impact of collateral effect on growth of Gross Metropolitan Product (GMP) was three times stronger than that of the wealth effect. Simo-Kengne et al. (2012) found that while the wealth effect was more important for the aggregate growth of South Africa, the collateral effect was more pronounced in the economic growth of some regions. Fair (2017) investigated the impact of declining financial and housing wealth on macroeconomic activity in the US and found that it contributed to a 2.1% and 3.3% increase in the rate of unemployment during 2009 and 2010. Additionally, the reduction in US real GDP due to declining household wealth (i.e., both housing and financial wealth) was 4.5% and 5.4% respectively, with over 40% of that impact accounted for by the reduction in housing wealth alone.

Aizenman et al. (2019) found a positive association between house price appreciation and economic growth in 19 OECD and non-OECD countries from 1975 to 2013, but discovered that the impact of house price depreciation on economic growth was non-linear and dependent on factors specific to each country. However, the negative economic impact of declining house prices can also be substantial. Yet, there are some works based on '*collateral effect*' theory which can provide some explanation to possible asymmetric impact of house prices on economic growth. Guerrieri and Iacoviello (2017) relate the asymmetric impact of house prices on the economy to its collateral effect and considers the effect central to the 2008 Subprime Crisis. Their model shows that collateral constraints slacken as house prices boom, weakening housing wealth's economic impact. However, the model also predicts constraints to tighten when the prices collapse. The latter effect, coupled with a positive impact of interest rates on housing, brings the economy into a deep recession. Similarly, Garriga and Hedlund (2018) show that consumption is much more sensitive to house prices during the housing bust than during the boom due to mortgage debt-induced fragility. More specifically, the house price elasticity of consumption in the bust period is more than double that in the boom.

Another explanation of the asymmetrical impact of house price changes on economic growth and negative effect of house market volatility on economic stability could be the *crowding-out effect* of housing booms. In a theoretical paper analyzing the consequences of rational bubbles for financially constrained firms, Farhi and Tirole (2012) find that bubbles *crowd-in* investment when liquidity is abundant and *crowd-out* investment when liquidity is scarce. Empirical findings of Chakraborty et al. (2016) on bank lending behavior during the housing boom also support the above theoretical suggestions. They find that banks increase mortgage lending at the expense of commercial lending during the housing boom, affecting firms that depend on bank credit the most. Such a reduction in investment will negatively impact economic growth, even though the net economic impact of housing price increase could still be positive. In some country studies, as in Lin et al. (2019) for Taiwan, an increase in house price was found to result in *crowding-out* of consumption which consequently slowed the economic growth.

However, the negative economic impact of declining house prices can also be substantial. Leamer (2013) demonstrated that while residential investment only contributes a small fraction of GDP growth, it plays a significant role in causing recessions. His study showed that housing complications precede US economic recessions in 9 out of 11 cases from 1947 to 2010 wand contribute significantly to weakening GDP growth before actual recessions. In 7 out of 11 cases, the housing market was the leading cause of the US recessions studied[2]. These findings show that most reductions in residential investment are due to declining housing prices and demand. Moreover, fluctuations in housing prices may also have a substantial impact on economic volatility. In their study, Dolde and Tirtiroglu (2002) discovered a significant correlation between shifts in housing price volatility and personal income growth at both a national and regional level, using US data from 1975 to 1993. Their results indicate that increases in housing price volatility are linked to significant reductions in income growth, while decreases in housing price volatility are associated with acceleration in income growth. Additionally, the findings suggest that housing returns initially move opposite to changes in housing price volatility.

Similarly, Davis and Heathcote (2005) suggests that the volatility of residential investment has a greater impact on the business cycle than the volatility of business investment and that it moves in tandem with consumption and non-residential investment. Thus, residential investment may cause significant fluctuations in economic output through a ripple effect. These findings suggest that higher housing price volatility leads to higher economic volatility, which can negatively impact long-term economic growth, as proposed by some economic literature (Hnatkovska & Loayza, 2005; Ramey & Ramey, 1995). This supports the theory of the risk-return trade-off, suggesting that investors demand higher (lower) returns when faced with higher (lower) risk. Hence, a reduction (increase) in housing returns following an increase in housing price volatility leads to a reduction (increase) in income growth.

[2] The findings of Davis and Van Nieuwerburgh (2015) which use macroeconomic data for the US from 1955Q1 to 2013Q4 also support that conclusion and show that business investment is preceded by residential investment for about two quarters.

However, the findings on the effect of house price changes on the economy is not conclusive in the economic literature. While some works suggest a significant and asymmetrical impact of housing prices on economic growth (Aizenman et al., 2019; Miller et al., 2011), there is a lack of support backing these claims, particularly when also taking into consideration the impact of economic volatility. Furthermore, there is a shortage of empirical work examining the relationship between housing price volatility and economic volatility. Although there are studies that look at the impact of housing price volatility on economic growth (Dolde & Tirtiroglu, 2002) or on residential investment and price misalignment on the business cycle (Cuestas et al., 2022; Davis & Heathcote, 2005), there is no work that directly assesses the relationship between housing price and economic volatility[3]. Hence, further research is necessary to investigate this relationship.

Therefore, there are three important research questions the current study intends to investigate. First, do housing prices directly impact economic growth, and is there an asymmetry between the impact of negative and positive returns? Second, what is the impact of housing price volatility on economic stability? Last, can house price volatility indirectly impact economic growth through its destabilizing effect on output volatility? Therefore, we aim to answer these questions by examining the impact of housing price returns on economic growth and the impact of housing price volatility on economic volatility, as well as scrutinizing the indirect impact of housing price volatility on economic growth through the volatility channel. To address these questions, we develop two economic growth and volatility models where house price growth and volatility are the main focus variables. Long-spanning quarterly data from 1970Q1 to 2019Q4 for 17 OECD countries is used in estimating those models. After we apply panel unit root tests for stationarity and check for cointegration among the variables, we estimate our models using different panel estimation methods. While we rely mainly on the Pool Mean Group (PMG) estimator, we also use the Dynamic Fixed Effects (DFE) and Panel Dynamic OLS (Panel DOLS) estimators for robustness.

The estimation results reveal a significant positive and asymmetric impact of house price returns on economic growth, with the negative returns having twice a stronger impact than the positive ones. We also find house price volatility has a considerable amplifying effect on economic volatility, but the impact of economic volatility on economic growth was found to be insignificant. The empirical findings carry important economic implications based on which we provide some essential policy recommendations. The rest of the paper goes as follows: The next section outlines the economic growth and volatility model and describes the research methods and the data used in their analyses. Section 3 presents the empirical results and deliberates on their interpretation. Finally, the paper concludes with Sect. 4, which summarizes the empirical findings and provides necessary policy recommendations.

[3] Additionally, we discovered a research monograph by Cho et al. (2012) that delves into the relationship between house price volatility and economic stability in six East Asian countries. The authors approach the topic from both theoretical and empirical perspectives; however, their analysis is primarily based on descriptive and theoretical frameworks, without testing any empirical models to support their hypothesis.

Methodology and Data

Empirical Models

Economic Growth Model

Following Aizenman et al. (2019), we suggest estimating the economic growth model (1) to see the impact of housing booms and busts on the economy. Departing from Aizenman et al. (2019), we do not include different measures of negative house price returns. Instead, we mainly focus on their relative impact on growth compared to positive ones. Also, some of our control variables differ from those of the above authors. The growth model is specified below:

$$y_{it} = \alpha_i + \beta_{1i} HPR_{it} + \beta_{2i} |HPR_{it}| * ND_{it} + \beta_{3i} volY_{it} + \gamma_i CV_{it} + \varepsilon_{it} \tag{1}$$

where, y stands for economic growth (measured as the log difference of real GDP or real GDP per capita), HPR stands for house price returns (measured as the log difference of real House price index (HPI)), ND stands for a dummy variable which takes the value one (1) if house price returns are negative and zero (0) otherwise, $volY$ stands for economic growth volatility [4], CV stands for a vector of control variables, and subscripts i and t stand for cross-section (country) and time-period (quarter) identifiers respectively. Note that the model interacts ND with the absolute value of HPR to allow for the asymmetric effect of house price returns on economic growth. Coefficient α_i is country-specific fixed effect and β_1, β_2, β_3 and γ are the coefficients to be estimated.

We expect β_1 to be positive since an increase in house price returns should positively reflect economic growth. Coefficient β_2 captures any asymmetry in the influence of house price returns on economic growth. Since ND is the dummy for negative house price returns (HPRs), the value of $|HPR_{it}| * ND_{it}$ is positive and nonzero only if HPR is negative (zero otherwise). Thus, the total negative impact of HPR on growth will equal β_1 - β_2 while its positive impact equals β_1. Therefore, given that β_1 is expected to be positive, a negative and significant β_2 means that the negative impact of HPR on economic growth is stronger than its positive impact. On the contrary, the positive and significant value of β_2 suggests a stronger real impact of positive house price returns. However, if coefficient β_2 is insignificant, the impact of house price returns on economic growth is symmetric.

[4] We use rolling standard deviation of the growth measures for calculation of volatility in this work. Nevertheless, most of the works on volatility use ARCH or GARCH models fitted to ARMA specifications to calculate volatilities of variables. However, such models calculate implied volatility and require theoretical assumptions regarding time series behaviour of each variable which we consider to be not appropriate in our case because it will remain speculative and not necessary for proof of our hypotheses. We want to examine impact of house price volatility on economic volatility. Finally, considering quarterly nature of our data and to ensure robustness of our results, we will be using 8 and 12 quarter rolling standard deviations (SDs) as two alternative measures of volatility for model (2). However, as a default measure of a variable's volatility we will be using 8-quarter rolling SD of its returns.

Finally, we expect β_3 to be negative because an increase in output volatility is generally associated with a decline in economic growth. Many economic studies find an inverse relationship between output volatility and long-run economic growth that is robust to the inclusion of other control variables (Hnatkovska & Loayza, 2005; Ramey & Ramey, 1995). Moreover, Hnatkovska and Loayza (2005) observe that macroeconomic volatility's negative impact on growth has increased after the 1980s. Coincidently, this period also corresponds to increased house price volatility internationally[5]. Thus, as we hypothesize, any factor that intensifies economic volatility, such as an increase in house price volatility, should contribute negatively to economic growth.

As for the vector of control variables (*CV*), following Aizenman et al. (2019), we include a 4-quarter lag of GDP per capita logs (*Initial GDP/cap*) to account for the initial level of development[6]. Also, to control for growth in factor inputs, we include investment growth (*INV growth*) and population growth (*POP growth*). To reflect the financial development's impact on economy, we include private credit (*CRD*) as a proxy. The square of the private credit (*CRD squared*) is also included since the financial development may affect growth in a non-linear way (Berthelemy & Varoudakis, 1996; Easterly et al., 2001; Khan & Senhadji, 2000). Other control variables from the literature that we include are inflation (*INF*), the level of trade openness (*TOPEN*), and government spending (*GOV*).

Model of Output Volatility

Following Ćorić and Pugh (2013), we estimate the following output volatility model to test for our second hypothesis:

$$volY_{it} = \alpha_i + \beta_{1i} volHP_{it} + \gamma_i CV_{it} + \varepsilon_{it} \tag{2}$$

where $volY_{it}$ and $volHP_{it}$ are output and house price volatilities measured as either 8 or 12 quarter standard deviations of economic growth (y) and house price returns (*HPR*), respectively. The expected sign for coefficient β_1 in positive since we assume that house price volatility intensifies output volatility. The shifts in house price volatility can lead to changes in output volatility. It can be assumed that a housing price shock will affect many sectors, including (but not limited to) real estate, residential construction, owner-occupied housing, and home financing. As these effects will propagate to the rest of the economy, aggregate output volatility will likely increase. Some work suggests that residential investment leads the business cycle, and its volatility is much larger than that of business investment (Davis & Heathcote, 2005; Dolde & Tirtiroglu, 2002).

Following Ćorić and Pugh (2013) CV_{it} set as a vector of control variables. As control variables, we include private credit (*CRD*) and its squared value (*CRD*

[5] One can refer to data illustration by The Economist magazine to get a general idea about the international trend of house prices since 1970s (The Economist, 2021).

[6] More detailed definition of variables used, description of data, its sources and summary statistics can be found in Sect. 2.3 of this paper and Appendix 1.

squared) to capture the impact of financial development as in our economic growth model. Here we assume output volatility decreases as credit grows until it reaches a certain threshold, and afterwards, credit should contribute to an increase in output volatility (thus, coefficients of *CRD* and *CRD squared* are expected to be negative and positive, respectively). Other controls from economic volatility literature that we include are government spending (*GOV*), trade openness (*TOPEN*), inflation volatility (*INF volatility*), and investment volatility (*INV volatility*). Inflation and investment volatilities are expected to exacerbate output volatility, while the impacts of government spending and trade openness on output volatility can be either positive or negative (Bekaert et al., 2006; Ćorić & Pugh, 2013). Finally, α_i and ε_{it} are the fixed effect and error terms, respectively.

Estimation Procedure

The estimation procedure in this paper closely follows Loayza and Ranciere (2006), Kim et al. (2016), and similar works. First, panel unit root tests are applied to determine the stationarity properties of the variables under study. Then, we test for cointegration or the presence of long-run co-movements among the variables. Finally, we estimate our models using different panel estimation methods. While we rely mainly on the Pool Mean Group (PMG) estimator, we also use the Dynamic Fixed Effects (DFE) and Panel Dynamic OLS (Panel DOLS) estimators for robustness.

Panel Unit Root Tests

We apply Maddala and Wu (1999) test to check for unit root and that is appropriate for our unbalanced panel data. The Maddala-Wu (MW) test statistics are calculated as follows:

$$\lambda = -2\sum_{i=1}^{N} log_e \pi_i \rightarrow \chi^2(2N) \tag{3}$$

where, π_is are p-values, which are independently and uniformly distributed between (0,1). The Maddala-Wu (MW) test has a Chi-square distributional property with 2 N degrees of freedom.

Note that the MW test may not be valid if the errors exhibit cross-sectional dependence. In such a case, we can consider the cross-section augmented IPS (CIPS) test proposed by Pesaran (2007). To estimate i^{th} cross-section of the panel, Pesaran (2007) suggests using OLS with the following cross-section augmented Dickey-Fuller (CADF) regression:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \delta_i \bar{y}_{t-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \rho_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{4}$$

where, $i = 1, \ldots, N$, $t = 1, \ldots, T$, α_i is the fixed effect and β_i is the coefficient corrected for intertemporal serial correlation, which has the null of $\beta_i = 0$ for all is. In (4), $\bar{y}_{t-1} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-j}$, $\Delta \bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} \Delta y_{it}$ and p is of the optimal lags selected using the Akaike information criterion (AIC) so that the residuals are uncorrelated over time. Pesaran (2007) proposes the following statistics (CIPS) based on averaging individual CADF statistics:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\beta}_i}{\hat{\sigma}_{\beta_i}} \tag{5}$$

The critical values of the test can be found in Pesaran (2007).

Testing for Panel Cointegration

Once each variable's integration order is identified, we proceed to determine the presence of cointegration among the concerned variables. For a heterogeneous panel like ours, we can perform a cointegration test proposed by Pedroni (2004). The model heterogeneity is considered in the test, and the cointegration vectors can vary among cross-sectional units. The following long-run cointegration is to be estimated to perform the Pedroni test:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1it} + \beta_{2i} x_{2it} + \cdots + \beta_{Mi} x_{Mit} + \varepsilon_{it} \tag{6}$$

where $i = 1, \ldots, N$; $t = 1, \ldots, T$; $m = 1, \ldots, M$; and α_i represents fixed effect, β_{mi} are the slope coefficients which can vary across individual cross-sections; ε_i is the residual. The property of the residuals estimated in (8) is as follows:

$$\hat{\varepsilon}_{it} = \hat{\rho}_i \hat{\varepsilon}_{it-1} + \hat{u}_{it} \tag{7}$$

Pedroni (2004) proposes seven different test statistics for panel cointegration. Four of those are called "within" dimensions and are based on pooling. The remaining three are based on "between" dimension. The null hypothesis for both types of tests is the absence of long-run cointegration in the series. For "within" dimension, the alternative hypothesis states that $\rho_i = \rho < 1$ for all i, while for "between" dimension $\rho_i < 1$ for all i. The critical values of the test statistic are tabulated in Pedroni (2004), and the test statistics are less than the critical values required to reject the null.

We can also consider using Westerlund's (2007) panel cointegration test as an alternative. Unlike Pedroni's panel cointegration test, Westerlund error-correction-based cointegration test can be applied even if cross-sectional dependence is observed. It employs four-panel cointegration tests. The null hypothesis is the absence of cointegration, and the error correction term in a conditional error correction model is equated to zero to test the null. Rejecting the null of no error correction means that the null of no cointegration is also rejected.

Each of the Westerlund cointegration tests accommodates individual-specific short-run dynamics. Each test statistic accommodates non-strictly exogenous regressors, serially correlated error terms, individual-specific intercepts, trend terms, and slope coefficients. A bootstrap procedure handles data with cross-sectional dependence (Westerlund, 2007).

The PMG Estimator

Once we identify the presence of a long-run cointegration among the variables, we can continue with panel cointegration methods. The problem of spurious regression with standard pooled OLS is recognized in the presence of non-stationary variables. Therefore, we intend to employ three different panel cointegration methods, considered superior to the traditional OLS, in treating issues such as heterogeneity, non-stationarity, and endogeneity in the explanatory variables. These are the Pooled Mean Group (PMG), Dynamic Fixed Effect (DFE), and Panel Dynamic OLS (DOLS) techniques (Blackburne & Frank, 2007; Kao & Chiang, 2000; Pesaran et al., 1999).

The Pooled Mean Group (PMG) estimator proposed by Pesaran et al. (1999) will be our main technique for estimating the long-run equation that links economic growth and output volatility to their respective determinants. This estimator is considered an intermediate technique positioned in between averaging and pooling models of dynamic panel data. By allowing for heterogeneity in the short-run dynamics among cross-sections but constraining the long-run slopes to be the same, the PMG has the advantage of being more flexible over other methods (Pesaran et al., 1999). To obtain the PMG estimator, we need to estimate the auto-regressive distributed lag (ARDL) model given below:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-1} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{8}$$

where x_{it} is vector of (k x 1) explanatory variables for group i, μ_i is the fixed effect, λ_{ij} are the lagged dependent variables' coefficients, and δ_{ij} are k x 1 coefficient vectors. Then, Eq. (10) is re-written in the following form:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \beta'_i x_{it} + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta^{*\prime}_{ij} \Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{9}$$

where $i = 1, 2, \ldots, N$, and $t = 1, 2, \ldots, T$, $\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$, $\beta_i = \sum_{j=0}^{p} \delta_{ij}$, $\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im}$ for $j = 1, 2, \ldots, p\text{-}1$, and $\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im}$ for $j = 1, 2, \ldots, q\text{-}1$.

It is assumed that ε_{it} is disturbance distributed independently across i and t, and the roots of $\sum_{j=1}^{p} \lambda_{ij} z^j$, $i = 1, 2, \ldots, N$, sit outside the unit circle. The model further assumes long-run homogeneity, where the long-run coefficients (defined as $\theta_i = -\beta_i / \phi_i$) are assumed to be identical across the groups.

The Maximum Likelihood (ML) technique is used for the estimation of the long-run coefficients (θ_i) in the PMG method. The ML estimation of θ_i are pooled by applying the homogeneity restriction for the long-run coefficients and averaging short-run parameters of the estimated models. The ML parametric form of Eq. (9) is maximized with respect to ω, where $\omega = \left(\theta', \phi', \sigma'\right), \phi = \left(\phi_1, \phi_2, \dots, \phi_N\right)', \sigma = \left(\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2\right)'$.

The DFE and DOLS Estimators

We will use two additional panel estimation techniques to ensure our results' robustness. They are Dynamic Fixed Effects (DFE) and Dynamic OLS (DOLS) estimators. These estimators can deal with non-stationary and endogeneity issues normally encountered in macro panels like ours.

Like the PMG estimator, *The Dynamic fixed effect (DFE) estimator* allows the intercept to be country-specific but restricts the coefficients of the cointegrating vector (the long-run slopes) to be equal across all countries. However, unlike the PMG, it further restricts the short-run slope and the speed of adjustment coefficients to be equal across all panels. In general, the specification of the DFE estimator can be estimated using Eq. (9) above while allowing for panel-specific intercepts (Blackburne & Frank, 2007).

All of the DFE model coefficients are signed properly and are similar to the estimates PMG model. However, possible the endogeneity between the lagged dependent variable and the error term in the fixed effects models makes them prone to a simultaneous equation bias (Baltagi et al., 2000). Nevertheless, the Hausman test can be used to measure the endogeneity level. If the test does not reject the null hypothesis of efficiency, this would mean that the simultaneous equation bias under the DFE specification is minimal for the given set of panel data (Blackburne & Frank, 2007).

Alternatively, *the Dynamic OLS (DOLS) estimator* can be used to avoid endogeneity and serial correlation problems in the standard pooled OLS. This method is more efficient than the alternative Fully Modified OLS (FMOLS) for small samples (Kao & Chiang, 2000). To estimate the long-run cointegrating equation using the DOLS, we must start by considering the following panel regression:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it} \tag{10a}$$

where $i=1,\dots N$, $t=1,\dots T$, and y_{it} is a matrix (1,1), β is a vector of slopes, α_i is the individual fixed effect, and ε_{it} is the stationary disturbance. The vector x_{it} is first-order integrated process for all i, and can be written as:

$$x_{it} = x_{it-1} + u_{it} \tag{10b}$$

Given the above conditions, Eq. (10a) represents a system of regressions where y_{it} is cointegrated with x_{it} (Kao & Chiang, 2000).

The error terms in the DOLS allow parametric adjustment by including the lag and lead values of the regressors' differential values. This will let us obtain unbiased long-run parameters. It is achieved by assuming the relation between the residuals of the static regression (ε_{it} in Eq. (10a)) and the leads and lags of first-difference regressors as follows:

$$\varepsilon_{it} = \sum_{j=-q_1}^{q_2} c_{ij} \Delta x_{i,t+j} + v_{it} \tag{11}$$

The DOLS estimator is obtained by combining (10a) and (11) as follows:

$$y_{it} = \alpha_i + \beta x_{it} + \sum_{j=-q_1}^{q_2} c_{ij} \Delta x_{i,t+j} + v_{it} \tag{12}$$

where c_{ij} is the coefficient of a lead or lag of explanatory variables' first difference.

For this equation, consistent estimates of the long-run parameters are obtained by a simple OLS regression. The t-statistic is based on the residuals' long-run variance instead of the contemporaneous variance that is used in the regular OLS regressions.

Data and Sources

For the analysis, we gather relevant quarterly data for 17 OECD countries[7] from the OECD's house price and main economic indicators databases, the World Bank's World Development Indicators, and Bank for International Settlements' statistical databases. These data include house price returns (*HPR*), the growth rate of national and per capita real GDPs (*GDP growth* and *GDP/cap growth*), private credit and its squared value (*CRD* and *CRD squared*), population growth (*POP growth*), inflation (*INF*), investment growth (*INV growth*), trade openness (*TOPEN*) and volatility measures of some of these variables. In addition, the data of the variables exhibiting seasonal patterns are seasonally adjusted. The descriptive statistics of the variables are provided in Table 1 below.

Overall, the time span of the panel data is from the first quarter of 1970 to the fourth quarter of 2019. The panel is generally considered strongly balanced for our basic model specifications ranging between 194–198 and 187–192 quarterly observations for growth and volatility models, respectively. However, it can be considered moderately balanced for extended specifications of growth and volatility models ranging between 174–192 and 166–191 observations, respectively[8].

The tables below present the correlations between the variables. Table 2 shows a correlation between GDP volatility and most of the variables included in the volatility model at a 5% level of significance. Table 2 can also observe a significant positive correlation between GDP volatility and HP volatility, as hypothesized. Table 3 also shows a correlation between GDP growth and most of the variables included in the growth model at a 5% significance level. Especially, the correlations between GDP growth and HPR and between GDP growth and the interactive term to capture asymmetry (|HPR| x ND)

[7] Countries included are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Switzerland, United Kingdom and United States. The choice of the countries is based on availability of data to cover as many observations as possible, which is desirable for the methods of estimation being used.

[8] See the last rows intables 7 and 8 for of number of observations included in each model.

Table 1 Descriptive statistics

Variable [1]			Obs.[2]	Mean [3]	SD	Min	Max
GDP growth			199	0.006	0.011	-0.079	0.209
GDP/cap growth			199	0.005	0.011	-0.081	0.207
HPR			199	0.005	0.022	-0.089	0.141
ND			200	0.397	0.489	0	1
ǀ *HPR* ǀ x *ND*			200	0.006	0.012	0	0.089
PD			199	0.601	0.490	0	1
HPR x *PD*			199	0.011	0.015	0	0.141
Initial GDP/cap			196	10.43	0.32	9.51	11.32
CRD			199	4.85	0.41	3.35	6.00
CRD squared			199	23.69	3.88	11.25	35.95
GOV			200	3.01	0.23	2.27	3.45
TOPEN			200	3.83	0.62	2.11	5.60
INV growth			199	0.000	0.060	-1.256	1.127
INF			198	0.010	0.012	-0.031	0.090
POP growth			199	0.002	0.001	-0.009	0.013
GDP volatility	*8-quarter*	*SD*	193	0.008	0.007	0.000	0.082
	12-quarter	*SD*	189	0.009	0.007	0.001	0.070
GDP/cap volatility	*8-quarter*	*SD*	193	0.008	0.007	0.001	0.082
	12-quarter	*SD*	189	0.009	0.007	0.001	0.070
HPR volatility	*8-quarter*	*SD*	193	0.014	0.011	0.001	0.081
	12-quarter	*SD*	189	0.016	0.011	0.002	0.070
INV volatility	*8-quarter*	*SD*	193	0.027	0.048	0.001	0.777
	12-quarter	*SD*	189	0.028	0.044	0.002	0.826
INF volatility	*8-quarter*	*SD*	190	0.008	0.005	0.001	0.032
	12-quarter	*SD*	186	0.008	0.005	0.002	0.027

[1] Brief description of variables is provided in Appendix 1

[2] The average number of observations per cross-section (i.e., country)

[3] The growth variables are taken as log differences rather than scaling them by 100. Therefore, the computation of their standard deviations and volatilities are also based on the above estimations. Thus, for instance, the mean value of GDP growth in the first row should be interpreted as 0.6% (i.e., 0.006) per quarter or 2.4% in annum, and its standard deviation is equal to 1.1% (i.e., 0.011) in quarterly terms 2.2% in annum

are positive and negative, respectively, as we have hypothesized. Next, we will conduct all standard panel data testing procedures and estimate the proposed economic growth and volatility models.

The Empirical Results and their Discussion

We will start our empirical analysis with unit root tests and then test for cointegration between our dependent and focus variables. Afterwards, we will estimate our proposed models using the PMG, DFE, and Dynamic OLS estimators.

Table 2 Correlation matrix of economic volatility model variables

	GDP volatility	HPR volatility	CRD	CRD squared	GOV	TOPEN	INV volatility	INF volatility
GDP volatility	1							
HPR volatility	0.208*	1						
CRD	-0.014	-0.291*	1					
CRD squared	-0.007	-0.284*	0.998*	1				
GOV	0.000	0.132*	-0.149*	-0.152*	1			
TOPEN	0.047*	-0.056*	0.512*	0.531*	0.097*	1		
INV vol.	0.395*	0.056*	0.210*	0.221*	-0.029	0.283*	1	
INF vol.	0.222*	0.252*	-0.110*	-0.103*	-0.097*	-0.145*	0.060*	1

* Null of 'no correlation' is rejected at the 5% level of significance, respectively

Table 3 Correlation matrix of Economic growth model variables

	GDP growth	HPR	|HPR| x ND	GDP volatility	Initial GDP/cap	CRD	CRD squared	GOV	TOPEN	INV growth	INF	POP growth
GDP growth	1											
HPR	0.270*	1										
| HPR | x ND	-0.223*	-0.766*	1									
GDP volatility	0.054*	-0.036*	0.107*	1								
Initial GDP/cap	-0.116*	0.001	-0.122*	-0.048*	1							
CRD	-0.077*	-0.030	-0.076*	-0.014	0.770*	1						
CRD squared	-0.077*	-0.033	-0.070*	-0.007	0.772*	0.998*	1					
GOV	-0.045*	-0.046*	0.065*	0.000	-0.281*	-0.149*	-0.152*	1				
TOPEN	-0.031	0.035*	-0.040*	0.047*	0.567*	0.520*	0.531*	0.097*	1			
INV growth	0.094*	0.068*	-0.076*	0.005	0.025	0.008	0.009	-0.026	0.029	1		
INF	-0.025	-0.099*	0.249*	0.119*	-0.578*	-0.541*	-0.535*	0.082*	-0.370*	-0.0126	1	
POP growth	0.102*	0.136*	-0.065*	0.030	0.028	0.084*	0.088*	-0.134*	-0.079*	0.016	0.047*	1

* Null of 'no correlation' is rejected at the 5% level of significance, respectively

Table 4 Panel unit root tests

Unit root test	Modified inverse chi-squared (MW)[1]				Z-t-bar (CIPS)[2]			
Trend Included	No		Yes		No		Yes	
Variable	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff
GDP growth	25.15[a]	-	22.44[a]	-	-8.76[a]	-	-8.08[a]	-
GDP volatility	5.48[a]	-	6.34[a]	-	-3.77[a]	-	-3.01[a]	-
GDP/cap growth	24.93[a]	-	21.80[a]	-	-9.00[a]	-	-7.90[a]	-
GDP/cap volatility	5.65[a]	-	6.49[a]	-	-3.80[a]	-	-3.05[a]	-
Initial GDP/cap	0.81	24.38[a]	-2.27	20.78[a]	-1.10	-8.83[a]	0.72	-7.66[a]
HPR	16.61[a]	-	10.71[a]	-	-7.89[a]	-	-6.13[a]	-
HPR volatility	7.46[a]	-	8.75[a]	-	-6.56[a]	-	-4.35[a]	-
CRD	-0.89	16.48[a]	0.26	12.44[a]	-0.43	-7.95[a]	3.04	-7.05[a]
CRD squared	-1.41	16.01[a]	0.15	11.57[a]	-0.18	-7.66[a]	3.11	-6.56[a]
GOV	-0.38	33.96[a]	-0.50	26.70[a]	2.76	-10.13[a]	0.97	-8.51[a]
TOPEN	-3.31	49.10[a]	-2.80	40.08[a]	-0.68	-14.84[a]	2.68	-13.79[a]
INV growth	30.67[a]	-	23.64[a]	-	-12.81[a]	-	-11.27[a]	-
INV volatility	5.47[a]	-	4.69[a]	-	-0.36	-18.03[a]	0.78	-17.34[a]
INF	0.42	51.27[a]	6.98[a]	-	-9.07[a]	-	-7.12[a]	-
INF volatility	2.60[a]	-	2.46[a]	-	-2.22[b]	-	-3.02[a]	-
POP growth	3.73[a]	-	2.32[b]	-	-1.24	-12.02[a]	-1.10	-10.36[a]

Note: Superscripts a, b, and c refer to rejecting the null hypothesis at 1%, 5%, and 10% levels of significance, respectively

[1, 2] The null hypothesis of both unit root tests (i.e., MW and CIPS) is the existence of unit-roots in all panels, while the alternative hypothesis considers existence of stationarity in some panels are

The Unit Root Tests

Our main objective from performing the panel unit root test is to ensure that the variables under consideration are stationary at either level or first difference form. In other words, all variables should either be I(0) or I(1), and none of them should be I(2) or higher. The MW and CIPS panel unit root tests, as presented in Table 4, indicate that all variables do satisfy the above requirement (i.e., they are either I(0) or I(1)). Having a mixture of I(0) or I(1) variables should not be problematic since we will use the PMG estimator as our main model estimation method. Therefore, our estimation results based on the PMG method should be valid as long as none of the variables is I(2) (i.e., non-stationary in 1st difference form), which is the case here. This means we can safely proceed to the next step of our empirical analysis, which is testing for panel cointegration.

The Panel Cointegration Tests

The results from the Pedroni Panel cointegration test are provided in Table 5. We employ three different specifications of the Pedroni test. First, one allows for cross-sectional heterogeneity with a time trend imposed. Second, one only allows for

Table 5 Pedroni panel cointegration test

Specification	GDP models			GDP/cap models		
Cross-sec. heterogeneity	Yes	Yes	No	Yes	Yes	No
Time trend imposed	Yes	No	No	Yes	No	No
Test type	*GDP growth*[1]			*GDP/cap growth*[1]		
Panel v-stat	15.80	20.61	18.12	15.84	20.51	18.25
Panel rho-stat	-72.95[a]	-74.93[a]	-87.91[a]	-73.29[a]	-75.04[a]	-88.19[a]
Panel pp-stat	-53.08[a]	-46.47[a]	-54.08[a]	-52.89[a]	-46.05[a]	-54.24[a]
Panel adf-stat	-34.16[a]	-28.34[a]	-31.22[a]	-36.21[a]	-28.39[a]	-33.23[a]
Group rho-stat	-73.51[a]	-82.63[a]	-96.93[a]	-73.91[a]	-82.91[a]	-97.39[a]
Group pp-stat	-59.35[a]	-58.10[a]	-69.17[a]	-59.13[a]	-57.51[a]	-69.08[a]
Group adf-stat	-34.40[a]	-31.38[a]	-30.81[a]	-36.35[a]	-29.74[a]	-32.59[a]
Test type	*GDP volatility*[2]			*GDP/cap volatility*[2]		
Panel v-stat	6.67	9.68	8.14	6.71	9.73	8.20
Panel rho-stat	-5.34	-6.59	-5.21	-5.35	-6.61	-5.23
Panel pp-stat	-5.06[b]	-5.45[a]	-4.67[b]	-5.06[b]	-5.47[a]	-4.68[b]
Panel adf-stat	-4.28[c]	-4.12[c]	-3.49	-3.71	-4.15[c]	-3.48
Group rho-stat	-4.50	-6.30	-4.96	-4.54	-6.37	-5.00
Group pp-stat	-4.87[a]	-5.95[a]	-5.14[a]	-4.89[a]	-6.00[a]	-5.15[a]
Group adf-stat	-4.71[a]	-4.88[a]	-4.77[a]	-4.00[b]	-4.93[a]	-4.68[a]

Note: Null hypotheses for all tests are 'no cointegration' exists. Superscripts a, b and c refer to rejecting the null hypothesis at 1%, 5%, and 10% significance levels, respectively

[1,2] Unbalanced panel of 17 OECD countries from 1970 Q1 to 2019 Q4 are tested with three regressors. Regressors for growth models are HPR, GDP volatility or GDP/capita volatility, and Initial GDP/capita, while those for volatility models are HP volatility, CRD, and CRD squared

cross-sectional heterogeneity but does include time trends. The final one does not allow for cross-sectional heterogeneity nor includes a time trend.

As seen from the growth model results, cointegration between the variables exists in GDP growth and GDP/cap growth models under most Pedroni test specifications. However, cointegration between variables is mainly found for both volatility models when we allow cross-sectional heterogeneity without imposed time trends. Thus, the later findings of weak cointegration in the volatility models could be due to the cross-section dependence of the included variables.

Thus, we also run the Westerlund cointegration test, which produces reliable results even in cross-sectional dependence (See Table 6). Here, we also include the above four economic growth and volatility models with three different specifications of the Westerlund test. These test specifications impose both constant term and time trend, only imposing constant term without a time trend, and finally, a specification without a constant term and time trend. It can be seen in the table that the results from the Westerlund cointegration test are much stronger than those of the Pedroni test, especially for the volatility models. This means that our initial suspicion of cross-sectional dependence among the volatility variables is probably correct. Since cointegration among our main variables of interest for both growth and volatility models has been established, we can formally estimate those models.

Table 6 Westerlund ECM panel cointegration tests

Specification	*GDP models*			*GDP/cap models*		
Cross-sec. heterogeneity	Yes	Yes	No	Yes	Yes	No
Time trend imposed	Yes	No	No	Yes	No	No
Test type	*GDP growth*[1]			*GDP/cap growth*[1]		
Group t-stat	-8.23[a]	-8.16[a]	-6.76[a]	-8.57[a]	-8.30[a]	-7.51[a]
Group adf-stat	-123.97[a]	-122.39[a]	-101.20[a]	-126.19[a]	-119.52[a]	-106.89[a]
Panel t-stat	-41.78[a]	-40.79[a]	-38.57[a]	-41.41[a]	-40.00[a]	-37.80[a]
Panel adf-stat	-149.62[a]	-141.85[a]	-130.32[a]	-148.70[a]	-137.65[a]	-126.53[a]
Test type	*GDP volatility*[2]			*GDP/cap volatility*[2]		
Group t-stat	-4.14[a]	-3.97[a]	-3.72[a]	-4.14[a]	-3.98[a]	-3.74[a]
Group adf-stat	-29.91[a]	-27.81[a]	-24.61[a]	-30.04[a]	-28.01[a]	-24.94[a]
Panel t-stat	-14.61[a]	-14.05[a]	-12.96[a]	-14.58[a]	-14.07[a]	-12.99[a]
Panel adf-stat	-22.84[a]	-21.23[a]	-18.48[a]	-22.84[a]	-21.30[a]	-18.57[a]

Note: Null hypotheses for all tests are 'no cointegration exists'. Superscripts a, b, and c refer to rejecting the null hypothesis at 1%, 5%, and 10% significance levels, respectively

[1,2] Unbalanced panel of 17 OECD countries are tested with three covariates and AIC selected lags, and leads are between 1 and 4 and 0–3, respectively. Covariates for growth models are HPR, GDP volatility or GDP/capita volatility, and Initial GDP/capital, while those for volatility models are HP volatility, CRD, and CRD squared

The Results of the Economic Growth Model

We start with an estimation of the growth model. We use real GDP growth as the main measure for the dependent variable and the Pooled Mean Group (PMG) estimator as the main estimation method. In addition, to check for robustness, we employ the growth of per capita real GDP as the dependent variable and two alternative estimation methods, namely the *Dynamic Fixed Effects (DFE)* and *Dynamic OLS* estimators.

Our hypothesis regarding the asymmetric growth effect of negative house price returns is confirmed as indicated by the negative and significant coefficient of the interaction term (|*HPR*|**ND*). The rough estimate shows that the negative impact is about twice as large as the positive impact. This can be observed from the absolute value of the coefficient for |*HPR*|**ND* (i.e., β_2) being about the same value in magnitude when compared to the *HPR's* coefficient (i.e., β_1) (e.g., 0.055 vs. 0.051 for baseline model (3) in Table 7). This finding is similar to the results of Case et al. (2011) when investigating the impact of house wealth decline on household consumption. They show that the negative impact of the housing wealth decline on household consumption is as strong as the positive one of the housing wealth increase. In fact, their empirical finding shows the impact to be two times or even stronger. Let's look at our baseline model (3) in Table 7. We can see that one standard deviation decrease in *HPR* contributed to - $(0.055+0.051)$ x $0.022=-0.00233$ ($\approx -0.233\%$) decrease in GDP growth, which corresponds to rather significant 39% decrease from its mean value (See Table 1 for mean and standard deviation values of *HPR* and *GDP growth*).

Table 7 PMG estimates for GDP growth models

Dependent variable		*GDP growth*[1]			*GDP/cap growth*[2]		
LR coefficients for		(1)	(2)	(3)	(4)	(5)	(6)
HPR		0.091[a]	0.086[a]	0.051[a]	0.087[a]	0.076[a]	0.051[a]
		[6.47]	[6.28]	[5.24]	[5.90]	[5.53]	[5.24]
∣ *HPR* ∣ x *ND*		-0.112[a]	-0.159[a]	-0.055[a]	-0.114[a]	-0.169[a]	-0.055[a]
		[-3.93]	[-5.88]	[-2.88]	[-3.97]	[-6.20]	[-2.89]
GDP volatility		-	-0.065[c]	-0.009	-	-	-
			[-1.92]	[-0.38]			
GDP/cap volatility		-	-	-	-	-0.049	-0.009
						[-1.45]	[-0.38]
Initial GDP/cap		-	-0.007[a]	-0.013[a]	-	-0.007[a]	-0.012[a]
			[-11.06]	[-9.38]		[-11.44]	[-9.38]
CRD		-	-	-0.008	-	-	-0.008
				[-1.20]			[-1.20]
CRD squared		-	-	0.001	-	-	0.001
				[1.22]			[1.22]
GOV		-	-	-0.009[a]	-	-	-0.009[a]
				[-7.33]			[-7.34]
TOPEN		-	-	0.001	-	-	0.001
				[1.45]			[1.45]
INV growth		-	-	0.019[a]	-	-	0.019[a]
				[3.30]			[3.31]
INF		-	-	-0.099[a]	-	-	-0.010[a]
				[-6.25]			[-6.27]
POP growth		-	-	0.425[a]	-	-	-0.581[a]
				[2.89]			[-3.94]
ECT		-0.884[a]	-0.911[a]	-0.988[a]	-0.882[a]	-0.909[a]	-0.988[a]
		[-13.64]	[-15.04]	[-30.52]	[-13.79]	[-15.05]	[-30.48]
Observation per group	*Average*	197.8	191.9	190.9	197.8	191.9	190.9
	Minimum	194	191	174	194	191	174
	Maximum	198	192	192	198	192	192

Note: Superscripts a, b, and c refer to rejecting the null hypothesis of the coefficient being equal to zero at 1%, 5%, and 10% levels of significance, respectively. Numbers in parentheses are t-statistics

[1,2] Unbalanced panel of 17 OECD countries from 1970 Q1 to 2019 Q4

The impact of economic volatility (proxied by real GDP volatility) is negative, as expected and significant for the simplified model (2) in Table 7. However, looking at our baseline model (3) in Table 7, we can see that the coefficient for GDP volatility turns insignificant. Therefore, we cannot conclude that it considerably impacts GDP growth. Commenting on other control variables, we can say that the results confirm the Convergence hypothesis for the 17 OEDC countries as reflected by the negative and significant coefficient of the Initial GDP. Furthermore, we also observe the negative and significant impact of Government spending and inflation on growth.

Table 8 Robustness test of GDP growth models

Dependent variable	*GDP growth*[1]		
Techniques	PMG	DFE	DOLS
HPR	0.055[a]	0.0655[a]	0.094[a]
	[5.74]	[5.89]	[29.96]
ǀ *HPR* ǀ x *ND*	-0.052[a]	-0.069[a]	-0.077[a]
	[-2.69]	[-3.09]	[-12.64]
GDP volatility	-0.030	0.016	-0.068[a]
	[-1.18]	[0.69]	[-5.85]
Initial GDP/cap	-0.012[a]	-0.010[a]	-0.006[a]
	[-12.83]	[-9.69]	[-4.05]
CRD	-0.009	-0.016[b]	0.016
	[-1.22]	[-2.15]	[1.60]
CRD squared	0.001	0.002[b]	0.001
	[1.36]	[2.18]	[-1.44]
GOV	-0.009[a]	-0.012[a]	0.002
	[-7.32]	[-8.70]	[-0.98]
INV growth	0.015[b]	0.002	0.037[a]
	[2.47]	[0.48]	[33.37]
INF	-0.096[a]	-0.089[a]	-0.013[b]
	[-5.96]	[-4.62]	[-2.30]
ECT	-0.983[a]	-1.053[a]	-
	[-28.80]	[-75.82]	
Other tests and statistics	Hausman[2] $Chi^2 = 0.00$ (p-value = 1.00)		Adj $R^2 = 0.152$

Note: Superscripts a, b, and c refer to rejecting the null hypothesis of the coefficient being equal to zero at 1%, 5%, and 10% levels of significance, respectively. Numbers in parentheses are t-statistics

[1] Unbalanced panel of 17 OECD countries from 1970 Q1 to 2019 Q4

[2] The Hausman test assumes difference in coefficients be non-systematic as null

Meanwhile, the impact of the Investment growth is positive and significant, as expected. However, trade openness and credit variables carry insignificant coefficients in the model (3). On the other hand, when it comes to population growth, it has a positive and significant coefficient in the baseline GDP growth model (3) and a negative and significant one in the baseline model of GPD per capita growth. Therefore, the positive contribution of population growth can be explained as an additional resource in total GDP growth but negatively reflects its per capita value due to its impact on the denominator of GDP per capita. Therefore, using different techniques, we removed the population growth and trade openness in our models while keeping the credit variables due to their theoretical importance.

The above results are robust across different model specifications (Table 7) and estimation techniques (Table 8). However, our focus variables' coefficient sign and significance are marginally affected by additional control variables, different estimation techniques, and the employment of alternative proxies for economic growth. Finally, we only observe the coefficient of *GDP volatility* turns significant when the Panel Dynamic OLS (DOLS) estimator is used while its sign is negative as expected. Nevertheless, this finding is not robust enough across different model specifications and estimators to conclude that GDP volatility negatively impacts economic growth.

To sum up, from the above results, we can conclude that house price returns (*HPR*) have a significant yet strongly asymmetric impact on economic growth. The negative *HPR*'s impact is two times larger in magnitude when compared to the effect of the positive one. However, we do not have enough evidence to conclude that GDP volatility significantly impacts economic growth. In general, the coefficients of most control variables do conform to expectations.

The Results for the Output Volatility Model

The results for the output volatility models support our hypothesis. As expected, house price (HP) volatility positively and significantly impacts output volatility. Moreover, the relationship is robust under different model specifications and proxies used as the dependent variable (See Table 9). This means that output volatility rises as *HP volatility* increases. From our baseline model (3), we can see that one standard deviation increase in *HP volatility* (i.e., 0.011) translates into $0.158 \times 0.011 = 0.001738$ ($\approx$0.174%) increase in *GDP volatility*, which corresponds to a 21.7% increase from its mean value (See Table 1 for mean and standard deviation values of *HP* and *GDP volatilities*). Therefore, we can conclude that *HP volatility* can be considered an important determinant of economic instability.

Additionally, among the control variables, the impact of private credit seems interesting. Similar to those of (Easterly et al., 2001), we find the coefficients of the credit variable (*CRD*) and its squared value (*CRD squared*) to be significant, and they are respectively negatively and positively signed. This means financial development has a U-shaped impact on output volatility. In other words, output volatility decreases as credit expands, but once credit reaches and surpasses a certain threshold, output volatility increases.

However, all other control variables, including Investment volatility, i.e., INV volatility, volatility of inflation, i.e., INF volatility, Government spending (GOV), and Trade openness (*TOPEN*), do not significantly affect output volatility. (See Table 9) When we remove the latter two from the models used in our robustness test of output volatility (Table 10), INF volatility and INF volatility turn out to be significant in using some estimation techniques or volatility measures. However, their signs are not consistent throughout the models.

Nevertheless, the observations above the destabilizing effect of house price volatility, i.e., HPR volatility and U-shaped impact of credit variable on output volatility, mostly hold when different measures of economic volatility and/or estimation methods are used. First, when we change our proxy for output volatility from *GDP volatility* to *GDP/cap volatility*, the above results hold entirely (see models 4, 5, and 6 in Table 9).

Table 9 PMG estimates for output volatility models

Dependent variable		*GDP volatility*[1]			*GDP/cap volatility*[2]		
LR coefficients for		1	2	3	4	5	6
HPR volatility		0.340[a]	0.247[a]	0.158[a]	0.337[a]	0.247[a]	0.155[a]
		[7.61]	[6.22]	[4.63]	[7.58]	[6.22]	[4.57]
CRD		-	-0.046[b]	-0.049[a]	-	-0.045[b]	-0.047[b]
			[-2.27]	[-2.62]		[-2.22]	[-2.47]
CRD squared		-	0.004[c]	0.004[b]	-	0.004[c]	0.004[b]
			[1.94]	[2.27]		[1.90]	[2.12]
GOV		-	-	-0.004	-	-	-0.003
				[-1.28]			[-1.09]
TOPEN		-	-	-0.001	-	-	0.00
				[-0.60]			[-0.52]
INV volatility		-	-	0.016	-	-	0.017
				[1.29]			[1.37]
INF volatility		-	-	0.06	-	-	0.06
				[1.00]			[0.99]
ECT		-0.077[a]	-0.087[a]	-0.092[a]	-0.078[a]	-0.088[a]	-0.092[a]
		[-9.72]	[-8.73]	[-7.78]	[-9.42]	[-8.67]	[-7.90]
Observations per group	*Average*	191.6	191.6	189.2	192	191.6	189.2
	Minimum	187	187	166	187	187	166
	Maximum	192	192	191	192	192	191

Note: Superscripts a, b, and c refer to rejecting the null hypothesis of the coefficient being equal to zero at 1%, 5%, and 10% levels of significance, respectively. Numbers in parentheses are t-statistics

[1,2] Unbalanced panel of 17 OECD countries from 1970 Q1 to 2019 Q4

Table 10 Robustness test of output volatility models

Dependent variable	*GDP volatility* (8-quarter SD)[1]			*GDP volatility* (12-quarter SD)[2]		
Techniques	PMG	DFE	DOLS	PMG	DFE	DOLS
HPR volatility	0.180[a]	0.255[a]	0.108[a]	0.223[a]	0.443[a]	0.118[a]
	[5.21]	[3.45]	[12.49]	[6.03]	[3.26]	[12.59]
CRD	-0.037[c]	-0.076[b]	0.046[a]	-0.015	-0.180[a]	0.049[a]
	[-1.92]	[-2.32]	[3.23]	[-0.83]	[-2.78]	[3.30]
CRD squared	0.003	0.008[b]	-0.005[a]	0.001	0.019[a]	-0.005[a]
	[1.58]	[2.24]	[-3.33]	[0.54]	[2.77]	[-3.42]
INV volatility	0.018	0.018	0.051[a]	0.011	-0.104[b]	0.047[a]
	[1.41]	[1.17]	[19.37]	[0.72]	[-2.44]	[14.79]
INF volatility	0.103[c]	-0.228	0.403[a]	0.090	-0.563[c]	0.422[a]
	[1.74]	[-1.42]	[18.30]	[1.24]	[-1.79]	[14.68]
ECT	-0.093[a]	-0.055[a]	-	-0.062[a]	-0.025[a]	-
	[-8.51]	[-9.03]		[-8.83]	[-5.01]	
Other tests and statistics	Hausman[3] $Chi^2 = 0.00$ (p-value = 1.00)		Adj $R^2 = 0.156$	Hausman[3] $Chi^2 = 0.00$ (p-value = 1.00)		Adj $R^2 = 0.169$

Note: Superscripts a, b, and c refer to rejecting the null hypothesis of the coefficient being equal to zero at 1%, 5%, and 10% levels of significance, respectively. Numbers in parentheses are t-statistics

[1, 2] Unbalanced panel of 17 OECD countries from 1970 Q1 to 2019 Q4

[3] The Hausman test assumes difference in coefficients be non-systematic as null

Second, when we apply different estimation techniques and/or volatility measures, observation about the destabilizing effect of house price volatility on output volatility still holds. At the same time, the U-shaped impact of the credit variable becomes inconsistent (see Table 10). All in all, from the above models, we can conclude that house price volatility has a significant and positive impact on output volatility.

Interpretation of Results

Besides supporting our hypotheses, the results of our empirical models give us some additional implications regarding the long-run relationship between economic growth and house price returns and their volatilities. Firstly, the asymmetric impact of the negative house price returns on economic growth is much stronger than positive ones. This means most of the positive effects on economic growth from house price growth can be easily washed away by the much stronger negative impact of the house price declines. Hence, the bursting of a housing bubble will negatively affect the economy's health.

Using coefficients derived from our growth model, we can also estimate the average contribution of house price returns (*HPR*) to GDP growth from our results, e.g., the baseline model (3) in Table 7. Looking at the descriptive statistics in Table 1, we can see that, on average, 60.1% of quarterly *HPR*s are positive, and 39.7% are negative, with average returns of 0.011 (1.1%) and − 0.006 (-0.6%), respectively. Therefore, the remaining 0.2% HPRs must have a value equal to zero. From there, we can estimate their joint contribution to *GDP growth* as follows: The average annualized contribution of positive *HPRs* to *GDP growth* will be 0.051*0.601*0.011*4 = 0.00135 (i.e., 0.135%) and the negative one will be (0.051-(-0.055))*0.397*(-0.006)*4 = -0.00101 (i.e., -0.101%), which net out to total contribution of annual negligible 0.00034 (i.e., 0.034%) to *GDP growth*. To recap, our estimations show that the annual contribution of *HPR*, which grows at a positive 2% (4*0.5%) annually, to *GDP growth*, is negligible 0.034% or 5.67% of average *GDP growth* in the long run[9].

Secondly, House price (HP) volatility directly impacts output volatility but has no significant impact on economic growth. The direct impact is captured in Eq. (2) of Sect. 2.1, and its empirical confirmation is represented in Tables 9 and 10. The impact of HP volatility on economic volatility is positive, confirming the finding of Davis and Heathcote (2005) and Dolde and Tirtiroglu (2002). This indicates that the higher HP volatility will lead to an increase in economic volatility (to a reduction in economic stability). From our baseline model (3) in Table 9, we can see that a one standard deviation increase in the *HP volatility* translates into a 0.001738 (≈ 0.174%) increase in *GDP volatility*, which corresponds to a 21.7% increase from its mean value.

According to the results of our models' estimation, it appears that the key factor for economic growth and stability is not rapid growth in housing prices. Instead, preventing housing bubbles and reducing large fluctuations in housing prices is critical for maintaining a healthy economy. A study by Geng (2018) reveals that housing prices often deviate from their long-run sustainable levels, which can significantly impact macroeconomic and financial stability. Thus, policymakers need to observe housing prices and evaluate their sustainability regularly. Our models suggest that sudden swings or increased volatility in housing prices negatively impact economic growth and stability.

Conclusion and Policy Implications

Most of the recent literature points fingers at the faulty financial system, reckless financing methods, and exuberant expectations about future house prices as causes of the 2008 Subprime Crisis. Nevertheless, there are limited studies on how the instability of the real estate market has impacted the economy. This paper attempts to close this research gap by examining the depth of house price–output relations. Proposing to empirically estimate economic growth and volatility models while relating them to housing prices,

[9] According to Leamer (2013), the contribution of house prices to GDP growth is relatively small and in line with other research papers. Using statistics from the Bureau of Economic Analysis (BEA), Leamer (2013) shows that residential investment accounted for just 5% of total US real GDP growth between 1970 and 1984, and a mere 0.2% between 1985 and 2010. The drastic decrease in the latter period is believed to be a result of significant fluctuations in residential investment at the end of the 2000s.

we answer three research questions posed at the beginning of the paper regarding the impacts of house price returns and their volatility on economic growth and stability.

The empirical results we obtained bear crucial policy implications. First, house price returns appear to have a significant asymmetric impact on economic growth, with a negative return having twice as strong an effect as a positive one. It can be explained by the negligent positive impact of house prices, most probably due to its crowding-out effect during the period of housing booms, which turns into a contagion effect negatively impacting other sections of the economy when the real estate cycle reverses. Even if the growth phase is generally longer than the decline phase in the real estate cycle, the net contribution of house price return (HPR) towards GDP growth is negligible. Our estimations show that the annual contribution of HPR, which grows on average at a positive 2% annually, to GDP growth, is only 0.034% or 5.67% of average GDP growth in the long run for all 17 OECD countries studied.

Second, house price volatility also significantly and positively impacts economic volatility. This means that higher house price volatility will contribute to increased economic volatility (reduced economic stability). For example, our baseline model indicates that a one standard deviation increase in the house price volatility translates into a 0.174% increase in GDP volatility, corresponding to a 21.7% increase from its mean value. This finding is in line with Davis and Heathcote (2005) and Dolde and Tirtiroglu (2002) and confirms our earlier hypothesis regarding the destabilizing impact of house price fluctuations on economic stability.

Last, our results indicate that the increase in economic volatility does not significantly impact economic growth, even if its coefficient in most economic growth models is negative, as expected. However, we suspect this could be due to part of the economic volatility impact getting captured by the asymmetry dummy variable included in all growth models, which is found to be negative and highly significant in all of them. Therefore, even if our separated direct effects of house price and volatility on economic growth and volatility are found to be significant with expected coefficient signs, the indirect impact of house price volatility on economic growth ends up being insignificant.

Furthermore, the above findings of the paper demonstrate that real estate bubbles have major consequences on economic growth as the negative impact of house price decline is twice in magnitude compared to the positive impact of the house price increase. In addition, we have also verified that an increase in house price volatility leads to increased economic volatility. Some important policy implications emerging from our analysis are as follows. The positive contribution of housing booms on the national economy is widely celebrated in economic policy circles. Still, the even stronger negative drag on the economy resulting from the bursting of housing bubbles is rarely considered. Sadly, even greater long-term disasters can result from increased house price volatility, which may contribute to a permanent decline in levels of economic growth.

Our argument is also supported by a study of 20 OECD countries by Agnello et al. (2020). Analyzing long-spanning data from 1970 to 2015, the study has shown that government involvement in house financing does not always bring desired consequences. In particular, it found that government involvement in home financing through the liberalization of mortgage financing and reduction of interest may prolong housing booms. But, unfortunately, its support measures for housing decline are generally inadequate to cushion the negative end result of housing busts. Nevertheless, Foote et al. (2021) argue and empirically demonstrate that irrational expectations about future house prices formed by banks and borrowers rather than low-interest rates or relaxed lending constraints were the main trigger behind the US housing boom in the early 2000s and its consequent bust in 2007.

Irrespective of the actual causes of housing bubble, we recommend that close supervising of house prices should be one of the policy goals of the authorities in charge of monetary and fiscal policymaking. Therefore, they should consider the possible impact of their current and future policy decisions on the real estate cycle and its consequent effect on the overall economy. In this regard, Geng (2018) emphasizes the important role of structural reforms such as cutting down on rent control, improving the elasticity of housing supply, and reducing tax incentives alongside macroprudential instruments such as limiting loan-to-value ratios as a remedy. Some of the above-proposed changes as reduction in rent controls, tax incentives, or even cutting down on subsidized mortgage loans may harm the welfare of low-income households as a consequence. Nevertheless, governments can make up for that social cost by actively pursuing supply-side policies such as providing subsidized housing or adjusting regulations that encourage housing supply and improve its elasticity. Hence, they can also enhance supply and demand fundamentals in the housing market and improve the shaping of longer-term house price expectations. Over time these reforms can improve housing affordability, thus improving financial stability in the housing market and reducing households' debt accumulation.

Appendix 1

Table 11 Brief description of variables used in the models and their respective sources

Variable	Definition	Adjustments	Source
GDP growth	Economic growth, measured as log difference of quarterly real GDP of a country in 2010 US dollars.	Seasonally adjusted	OECD database
GDP/cap growth	Household income growth, measured as log difference of quarterly real GDP per capita of a country in 2010 US dollars.	Seasonally adjusted	OECD database
HPR	House price returns, measured as log difference of quarterly real house price index (HPI). Value of HPI is set to be equal to 100 for 2010.	Seasonally adjusted	OECD database
ND	Negative return dummy that takes value of 1 if *HPR* is negative and zero otherwise.	Seasonally adjusted	OECD database
Initial GDP/cap	Initial income, measured as 4-quarter lag of natural logarithm (log) of a country's real GDP per capita in 2010 US dollars.	Seasonally adjusted	OECD database
CRD	Private credit, measured as log of the ratio of the credit to non-bank sector to GDP.	Adjusted for breaks	BIS database
CRD squared	Private credit squared, measured as square of log of the ratio of private credit to GDP.	Adjusted for breaks	BIS database
GOV	Government spending, measured as log of the ratio of government spending to GDP.	Seasonally adjusted	OECD database
INV growth	Investment growth, measured as log difference of the ratio of gross fixed capital formation to GDP.	Seasonally adjusted	OECD database
TOPEN	Trade openness, measured as log of the ratio of total exports and imports combined to GDP	Seasonally adjusted	OECD database
INF	Inflation, measured as log difference of the quarterly consumer price index (CPI).	Not seasonally adjusted	OECD database
POP growth	Population growth, measured as log difference of quarterly total population.	Not seasonally adjusted	World Development Indicators / OECD

Table 11 (continued)

Variable	Definition	Adjustments	Source
GDP volatility	Economic growth volatility, measured as rolling standard deviation (SD) of GDP growth (8-quarter SDs are used for main analysis and 12-quarter SDs for robustness).	Seasonally adjusted	OECD database
GDP/cap volatility	Household income volatility, measured as rolling standard deviation (SD) of GDP/cap growth (8-quarter SDs are used for main analysis and 12-quarter SDs for robustness).	Seasonally adjusted	OECD database
HP volatility	House price volatility, measured as the rolling standard deviation (SD) of HPR. While 8-quarter SDs are mainly used, 12-quarter SDs are used for test of robustness.	Seasonally adjusted	OECD database
INF volatility	Inflation volatility, measured as rolling SD of inflation rate differences (8-quarter SDs are used for main analysis and 12-quarter SDs for robustness).	Not seasonally adjusted	OECD database
INV volatility	Investment volatility, measured as rolling SD of investment growth (8-quarter SDs are used for main analysis and 12-quarter SDs for robustness).	Seasonally adjusted	OECD database

Data Availability The datasets generated during and/oranalysed during the current study are available from thecorresponding author on reasonable request.

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