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Stock Markets Cycles and Macroeconomic Dynamics

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Abstract There is a consensus that stock markets are procyclical. However, answers to some important questions remain unclear. Do stock markets lead or lag business cycles? More interestingly, what is the duration with which they lead or lag them? This study uses different time-series filters and time-difference analysis to answer these questions by examining the dynamic interactions between three major stock indices and key macroeconomic indicators in the United States. The findings show that stock markets have been strongly procyclical, lagging industrial production by one to three months in recent decades. There have been noteworthy changes in the relationship between inflation and stock market cycles. The correlations changed from negative in the 1980s and 1990s to positive in the 2000s and 2010s. The results also reveal close associations between the stock indices, offering new insights into the interplay between financial markets and economic cycles.

Keywords Hamilton filter · Time-difference analysis · Stock market indices · Industrial production · Employment · Inflation · U.S. economy

JEL Codes C22 · C58 · E20 · E30 · E60 · G10

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Introduction

A rational stock market utilizes all available information to forecast real economic activity. If it does well, expectations for future economic conditions are incorporated into current stock prices, and investors may see stock market performance as a predictor of real economic activity (Fischer & Merton, 1984). Stock markets also react to changes in future economic prospects. These reactions can lead to market fluctuations and even crashes. Thus, understanding the interactions between the economy and stock markets is crucial. Economic fundamentals directly affect stock performance, and stock indices can signal upcoming economic shifts (Schwert, 1990). For example, rising output increases investment returns, which in turn stimulates capital spending. An efficient market anticipates this and rallies ahead of real economic changes. Conversely, a bleak economic outlook may lead to downward revisions of future profits. Firms might then pause investing while awaiting clarity. This can reduce capital spending and output. Here, stock market declines precede drops in real economic activity.

Financial investors consider industrial production as a key business cycle indicator. The promise of economic growth increases expected business profits, leading to higher stock prices. In contrast, economic slowdowns can lead to asset liquidation and falling stock prices. Changes in employment are also correlated with stock market returns, reflecting broader economic trends. Growing employment suggests economic expansion and higher future profits. However, economic expansion ultimately puts upward pressure on wages, which can reduce a firm's profitability. Although economic expansions can increase stock prices, reduced profitability may cause them to fall.

The interconnections between stock markets and the macroeconomy have been studied extensively. However, key questions persist around whether stock markets lead or lag business cycles. More interestingly, by how much time does one lead or lag the other? Simply stating that stock markets precede business cycles provides little practical insight. More useful conclusions would measure exactly the length of time with which stock market cycles lead or lag business cycles. Moreover, different stock indices may lead the business cycle with different durations. Providing insights into the lengths of these durations is one of the primary contributions of this paper.

The relationship between inflation and the stock market is ambiguous (Wang & Li, 2020). During periods of economic growth, increased profitability often leads to bullish stock markets, coinciding with inflation driven by robust economic activity. Contrastingly, in times of economic stress, such as during high oil prices in the 1970s, expectations of higher inflation and lower economic output can lead investors to anticipate decreased profitability and stock sell-offs, aligning inflation with bearish markets. The influence of tax codes on business profits also plays a role. Inflation diminishes the real value of tax deductions on depreciation, increasing real tax liabilities and reducing after-tax profits, potentially leading to lower stock prices (DeFina, 1991; Feldstein, 1980; Quayes & Jamal, 2008).

This points to the intricacies of the associations between the stock market and the macroeconomy. This study is devoted to analyzing these associations for the United States (U.S.) stock market and the macroeconomy. Specifically, the Hamilton filter (Hamilton, 2018) is employed to extract the cyclical components from three stock indices, the Standard & Poor's 500 (S&P 500), the Dow Jones Industrial Average (Dow), and the Nasdaq Composite (Nasdaq) and three key macroeconomic variables, the Industrial Production Index (IPI), total non-farm employment (NFE), and the Consumer Price Index (CPI). Prior studies mainly relied on the Hodrick-Prescott filter to derive cyclical components from observed series. However, Hamilton (2018) argued that the Hodrick-Prescott filter can generate spurious cycles that are disconnected from the underlying data-generating processes. Schüler (2018a) showed that the Hodrick-Prescott field yields spurious cycles. Hamilton's method is based on a few past observations and overcomes several shortcomings of the Hodrick-Prescott filter. The current study is the first to combine this approach with time-difference analysis (Fiorito & Kollintzas, 1994; Serletis & Kemp, 1998) to examine the lead-lag relationships between stock indices and macroeconomic variables and provide specific answers about the lengths of time characterizing these relationships.

The findings indicate a strong, positive correlation between U.S. stock indices and the business cycle between 1990 and 2020, with stock markets typically lagging industrial production by one to three months. The analysis also reveals that the associations between the U.S. stock market indices and inflation have changed noticeably over time. In the 1980s and 1990s, they were negatively correlated, whereas, during the 2000s and 2010s, they were strongly and positively correlated. There is evidence, albeit less compelling, of a negative association between the real economy and stock market cycles during the 1980s. Unsurprisingly, the three stock indices have exhibited strong co-movement throughout the last 40 years.

Prior Literature: A Brief Review

Early studies indicated that specific macroeconomic indicators drive financial market sentiments. For example, Ross (1976) argued that changes in certain macroeconomic variables cause changes in systematic risk factors and, thus, affect stock returns. Shiller (1980) suggested that stock prices are dependent on future expected cash flows and future discount rates. He emphasized the importance of economic factors in shaping both the expected earnings potential of companies and investor appetite for taking on risk. Schwert (1990) attributed the huge surge in stock returns in the U.S. from 1889 to 1988 to industrial production growth.

More recent studies also showed that macroeconomic variables are good candidates for predicting stock market returns. Rapach et al. (2005) reported that macroeconomic variables are effective predictors of stock market returns. Chen (2009) concluded that the real macroeconomy affects the stock market through investment opportunities and consumption, with stock returns responding to policies affecting savings, investments, and the money supply. Relatedly, Liu and Shrestha (2008) and Peiro (2016) found that macroeconomic variables, such as industrial production and long-term interest rates, explain movements in stock prices.

Chen and Chiang (2016) reported a causal relationship between the macroeconomy and the stock market. Borjigin et al. (2018), who examined causality between the macroeconomy and the stock market in China, found evidence for a strong, nonlinear, bi-directional causality. A more recent study by Wang and Li (2020), using Chinese monthly data from 1995 to 2018, indicated that stock returns were related to industrial production growth (a proxy for output growth), inflation, and interest rates.[1] Based on their overall findings, however, Wang and Li (2020) concluded that stock market indices could not be used as leading indicators of the macroeconomy and that the real macroeconomy cannot predict booms or busts in the stock market. In this regard, the conclusions of Wang and Li (2020) support those of earlier studies by Kwon and Shin (1999) and Gan et al. (2006), which suggested that although stock indices are cointegrated with major macroeconomic variables, they are not leading indicators of real macroeconomic performance.[2]

Studies by Si et al. (2019) and Kim and In (2003) used wavelet analysis to examine the associations between financial markets and the real economy. Si et al. (2019) found that stock market cycles led business cycles in the short run, whereas the reverse was true over the long run. They also found that stock market cycles behaved differently during expansionary and recessionary phases of the business cycles. Kim and In (2003) also concluded that the association between the stock market and the macroeconomy changed over time.

However, the relationship between inflation and stock prices proved more nuanced. While some studies identified a positive association between inflation and stock prices (Abdullah & Hayworth, 1993; Camilleri et al., 2019; Ratanapakorn & Sharma, 2007), others pointed to a negative association (Quayes & Jamal, 2008).[3]

Given the mixed evidence on whether stock markets lead or lag the macroeconomy, it is unsurprising that this issue continues to be debated. The present study contributes to this debate.

Methodological Framework and Data

Methodological Framework

This study utilized a recently developed method proposed by Hamilton (2018) to extract the cyclical components from non-stationary time series by estimating an autoregressive model using ordinary least squares. Hamilton's method is straightforward to implement and uses only a few observations, the number of which depends upon the frequency of the data. Critical to this method is the characterization of the trend. Usually, a trend is defined over an infinite horizon. However, Hamilton (2018)

[1] These studies are not entirely conclusive, given the absence of causality found in the work by Gallegati (2008) and Girardin and Joyeux (2013).

[2] This work only suggests that stock markets and the macroeconomy share a common long-run trend.

[3] DeFina (1991) noted that in the 1970s, when inflation accelerated, stock prices fell almost 50% in real terms. Equity values increased markedly in the 1980s, a period of disinflation in the U.S.

suggested using a two-year horizon, arguing that it is both practical and useful. For a two-year horizon, it is possible and meaningful to make informed conjectures and form reasonable expectations based on limited sample sizes. Hamilton (2018) pointed out that irregular and unforeseeable cyclical developments are the primary reasons for incorrectly predicting the value of a series two years in advance.

Cyclical components are often derived as deviations of the actual series from its trend component. For example, Beveridge and Nelson (1981) and Hodrick and Prescott (1997) defined the cyclical component c_t at time t as $y_t - g_t$, where y_t is the observed series, and g_t is the derived long-run trend of y_t.[4] According to Hamilton (2018), the cyclical component at time $(t+h)$ is well-approximated by $y_{t+h} - y_t$. In other words, the cyclical component at time t is simply $y_t - y_{t-h}$. He proposed a forecast for y_{t+h} that relies on the recent p values, where both h and p are integer multiples of the number of periods in a year. Accordingly, in the case of monthly data, h and p are represented by 24 and 12, respectively. This forecast can be formally described as

$$y_{t+24} = \alpha_0 + \alpha_1 y_t + \alpha_2 y_{t-1} + \alpha_3 y_{t-2} + \cdots + \alpha_{12} y_{t-11} + v_{t+24}. \quad (1)$$

Put differently,

$$\hat{v}_{t+24} = y_{t+24} - \left(\hat{\alpha}_0 + \hat{\alpha}_1 y_t + \hat{\alpha}_2 y_{t-1} + \hat{\alpha}_3 y_{t-2} + \cdots + \hat{\alpha}_{12} y_{t-11}\right). \quad (2)$$

The time subscripts in Eq. (1) and Eq. (2) can be adjusted to represent the original time series and the residuals, respectively, at time t. While Eq. (1) can be rewritten as

$$y_t = \alpha_0 + \alpha_1 y_{t-24} + \alpha_1 y_{t-25} + \alpha_2 y_{t-26} + \cdots + \alpha_{12} y_{t-35} + v_t, \quad (3)$$

Equation (2) can be rewritten as

$$\hat{v}_t = y_t - \left(\hat{\alpha}_0 + \hat{\alpha}_1 y_{t-24} + \hat{\alpha}_2 y_{t-25} + \hat{\alpha}_3 y_{t-26} + \cdots + \hat{\alpha}_{12} y_{t-35}\right). \quad (4)$$

Equation (4) yields the cyclical component.

Using this method, we decomposed (100 times the natural log of) each of the six time series. After that, following Fiorito and Kollintzas (1994) and Serletis and Kemp (1998), the magnitudes and signs of the cross-correlations between the resulting cyclical components of the macroeconomic time series and stock indices were examined. The magnitudes revealed the strengths of the cyclical associations, whereas the signs revealed their directions. Specifically, the cross-correlations of the cyclical component of a macroeconomic time series, m_t, with that of a stock index, s_{t+1}, were denoted by $\rho(l)$, where $l \in (0, \pm 1, 2, \ldots 6)$. If the maximum value of $|\rho(l)|$ was obtained for a negative (positive) value of l, then the stock index, s_t, was considered to lead (lag) the macroeconomic series, m_t. The two series were considered synchronous if the maximum value of $|\rho(l)|$ occurred at $l=0$.

[4] The Hodrick-Prescott filter yields a smooth trend g_t of a time series y_t according to the equation, $\min_{g_t}\left\{ \sum_{t=1}^{T} \left(y_t - g_t\right)^2 + \lambda \sum_{t=2}^{T-1} \left[\left(g_{t+1} - g_t\right) - \left(g_t - g_{t-1}\right)\right]^2 \right\}$.

Whether the stock index was procyclical, countercyclical, or not associated with the business cycle was determined by the sign of $\rho(0)$. For positive (negative) values that were significantly different from 0, s_t was deemed procyclical (countercyclical). However, if $\rho(0)$ was close to 0, then s_t was considered unrelated to the business cycle. Furthermore, the strengths of the correlations between the cycles were ascertained by the magnitudes of $|\rho(0)|$. As such, following Smith (1992) and Vatsa and Miljkovic (2022), for $|\rho(0)|$ less than a threshold θ, s_t was deemed contemporaneously uncorrelated with m_t. θ was determined by setting 1.96 (the critical value associated with the 5% significance level) equal to $\rho\sqrt{n-2}/\sqrt{1-\rho^2}$ and then solving for ρ. Next, $\theta < |\rho(0)| < 0.5$ indicated a weak contemporaneous correlation between the two. Lastly, $0.5 \leq |\rho(0)| \leq 1$ suggested strong contemporaneous correlation (Fiorito & Kollintzas, 1994).

It bears emphasizing that although the macroeconomic time series are seasonally adjusted, the stock indices are not. Ignoring the differences in seasonal properties across different time series may lead to incorrect conclusions. For example, applying the Hodrick-Prescott filter to isolate trends from cycles leaves seasonality embedded in the cyclical component (Buss, 2010). This may lead the researcher to incorrectly perceive a recurring seasonal pattern as cyclical changes. The cycles may possess implausible regularity. Thus, it is important to use methods that are robust to different seasonal properties of the data. Hamilton (2018) and Vatsa (2021) have convincingly demonstrated that the Hamilton filter is robust to differences in the seasonal patterns present in the data.

Although one may use off-the-shelf statistical methods such as X-13 autoregressive integrated moving average (ARIMA) or seasonal-trend decomposition using locally estimated scatterplot smoothing (LOESS) to derive seasonally adjusted data and then apply any filtering technique to extract the cyclical components, this approach is ill-advised on the following grounds. A one-size-fits-all approach that applies the same adjustment method to multiple series with different seasonal properties may leave seasonality embedded in some series while removing it from others. Consequently, the cyclical components of some series might be free of seasonality, and those of others might not. One may approach seasonal adjustment more discriminately by applying different techniques to different series. However, this is an ad hoc approach, susceptible to the biases and inclinations of the researcher. Seasonal decomposition can be obviated by using filtering techniques that are robust to the seasonal properties of the data. The Hamilton filter is desirable in this regard.

The Hamilton filter has also come under criticism. For example, Schüler (2018b) argued that the filter is based on ad hoc assumptions and amplifies cycles that are longer than regular business cycles while muting the shorter-term fluctuations. Specifically, Schüler (2018b) questioned the use of the two-year forecast horizon on which Hamilton based his regression-based filter. However, Schüler (2018b) also suggested that the Hamilton filter produces more robust cyclical estimates than the Hodrick-Prescott filter at the end of the samples and, thus, may be used gainfully for designing policies.

Given the limitations and advantages of the Hamilton and Hodrick-Prescott filters, using multiple methods to triangulate the results will help mitigate the impact of the shortcomings of one method or the other. With this in mind, the robustness of the results obtained from the Hamilton filter was confirmed using a simple random walk model. As the analysis used monthly data and considered a two-year forecast horizon, Eq. (5) can be used to approximate the cyclical components as:

$$\hat{v}_{t+24} = y_{t+24} - y_t. \tag{5}$$

In large samples, Eq. (1) converges to Eq. (5), with $\hat{v}_{t+24}$ capturing how much the series changes over two years (Hamilton, 2018). Equation (5) presents an intuitive and simple filtering technique that can be readily implemented to verify the results obtained from alternate methods. The cross-correlations obtained from Eq. (5) are presented as comparators for those obtained from Eq. (4). Last, the Hodrick-Prescott filter was used to derive stock market and macroeconomic cycles and to estimate correlations between them. After all, the Hamilton filter has been put forth as a better alternative to the Hodrick-Prescott filter. A comparison of the results yielded by the two filters is in order.

Data

Data on the S&P 500, the Dow, and Nasdaq were sourced from the Datastream database (Refinitiv, 2020). The macroeconomic data were obtained from the Federal Reserve Economic Data (FRED) database (Federal Reserve Bank of St. Louis., 2020). Monthly data from January 1980 to April 2020 were used for each series except for the Dow, for which data from January 1986 to April 2020 were used.[5] The IPI was used instead of the real gross domestic product (GDP) as monthly data for the latter were unavailable. The timeliness with which the IPI is reported makes it a useful barometer of real macroeconomic activity. Another advantage of using the IPI is that it is more sensitive to short-run fluctuations in economic activity than the real GDP and can capture sudden changes in demand, supply chain disruptions, and other shocks stemming from trade policy and movements in exchange rates. Furthermore, using quarterly data, the highest frequency for the real GDP, may not reveal the cyclical variations in stock market activity as clearly as monthly data, defeating one of the primary objectives of this study. NFE, which accounts for approximately 80% of the workers contributing to the total U.S. output, was used to confirm the results obtained using the IPI. Together, the two variables provide a more comprehensive view of the nexus between the real macroeconomy and various stock indices. Last, the CPI was used to study the link between inflation and the stock market.

The macroeconomic variables and the stock indices are plotted in Figs. 1 and 2, respectively. These provide useful insights into the trends and patterns in, correlations among, and stationarity properties of the data. All the variables trend upward throughout the sample period. Among the macroeconomic variables, the IPI and NFE exhibited similar patterns. However, the CPI behaved somewhat differently. It followed an approximately linear trend in the long run, showing no notable changes

[5] Although obtaining higher-frequency stock market data is possible, macroeconomic data are unavailable at frequencies higher than monthly.

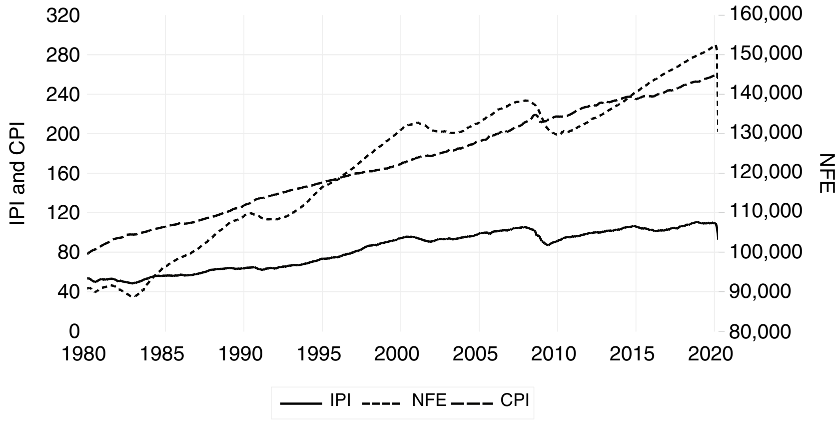

Fig. 1 Macroeconomic series (1980–2020): Industrial production index, non-farm employment, CPI. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

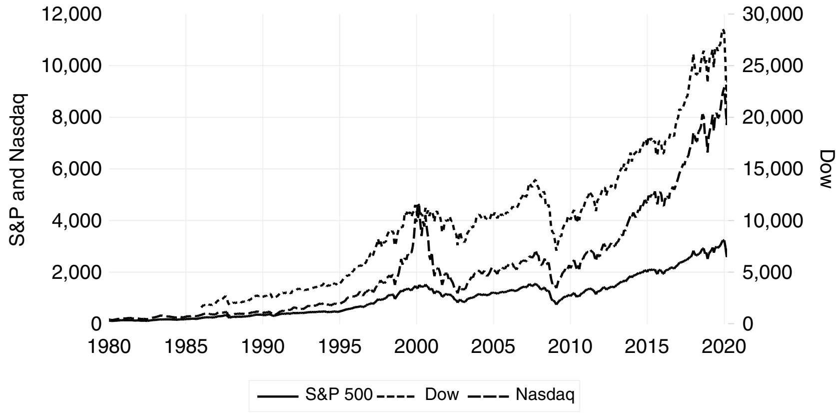

Fig. 2 Trends in the S&P 500, the Dow, and Nasdaq. For the S&P and Nasdaq, data from January 1980 to April 2020 are shown. For the Dow, data from January 1986 to April 2020 are shown, Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

even during the recessionary phases. The three stock indices show strikingly similar behaviors, rising and falling together.

Empirical Evidence

Figures 3, 4, and 5 illustrate stock market cycles relative to macroeconomic cycles derived using the Hamilton filter. Figure 3 presents cycles in the three U.S. stock indices relative to the IPI since 1980, while Fig. 4 substitutes NFE for industrial production. Figure 5 examines U.S. stock market cycles relative to the U.S. inflation rate.

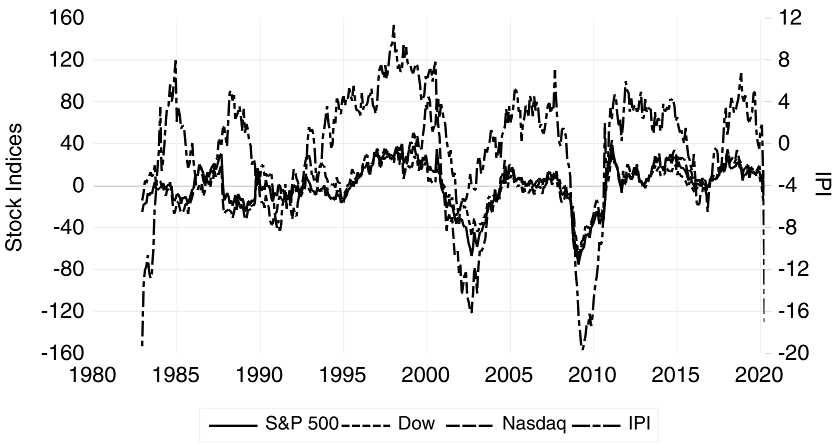

Fig. 3 Stock market cycles relative to output cycles (Dec. 1982-Apr. 2020). Cycles for the Dow are for the period December 1988–April 2020. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

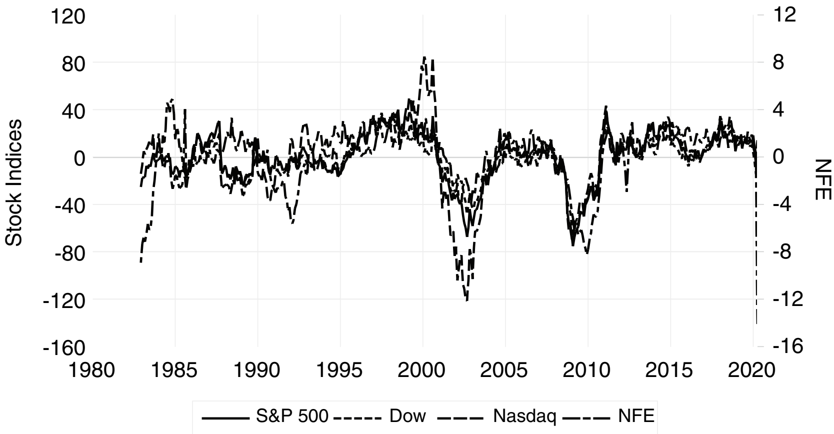

Fig. 4 Stock mrket cycles relative to employment cycles (Dec. 1982-April 2020). Cycles for the Dow are for the period December 1988–April 2020. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

The correlations and the summary statistics in Table 1 support the observations noted above. First, the monthly growth rates of the three stock indices are strongly correlated. Second, the IPI is strongly correlated with only the NFE. Third, inflation is uncorrelated with the growth rates of the other variables. Fourth, and surprisingly, the monthly growth rate of the IPI is uncorrelated with those of the various stock market indices.

Noting the general upward trends in the six time series, two deterministic regressors were included, namely the intercept and a linear trend, to examine the stationary

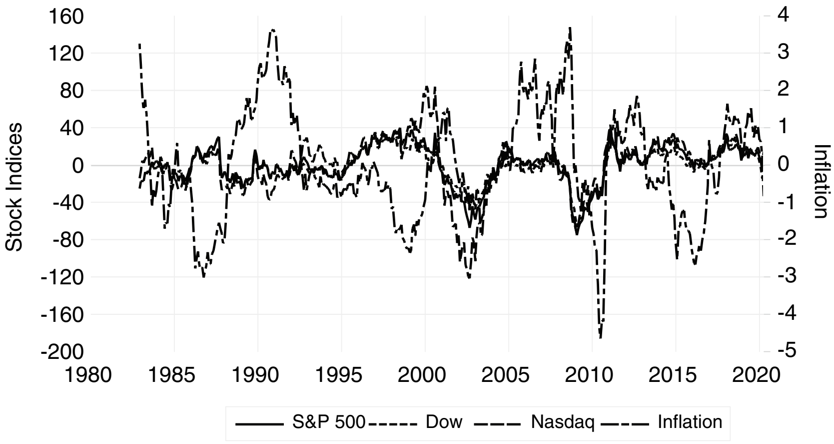

Fig. 5 Stock mrket cycles relative to inflation (Dec. 1982-April 2020). Cycles for the Dow are for the period December 1988–April 2020. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

Table 1 Summary statistics of and cross-correlations between stock market and macroeconomic time series

	IPI	NFE	CPI	S&P 500	Dow	Nasdaq
Panel A						
Mean	82.6	122,066.7	172.0	1171.1	10,235.7	2145.6
Max	110.6	152,463.0	259.0	3230.8	28,538.4	9150.9
Min	48.2	88,771.0	78.0	211.8	1570.9	131
Std. Dev.	19.6	17,958.6	51.3	728.1	6583.6	2070.7
CoV	23.8	14.7	29.8	62.2	64.3	96.5
Observations	484	484	484	484	412	484
Panel B						
IPI	1.00	0.73	0.20	−0.08	−0.07	−0.09
NFE	0.73	1.00	0.22	−0.08	−0.07	−0.08
CPI	0.20	0.22	1.00	−0.01	−0.02	−0.02
S&P 500	−0.08	−0.08	−0.01	1.00	0.96	0.86
Dow	−0.07	−0.07	−0.02	0.96	1.00	0.78
Nasdaq	−0.09	−0.08	−0.02	0.86	0.78	1.00

CoV denotes the coefficient of variation. Panel B shows correlations between growth rates. The estimates are based on the full sample from January 1980 to April 2020 for every series except for the Dow, for which data from January 1986 to April 2020 were used. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

Table 2 Results of Phillips-Perron unit root tests

	IPI	NFE	CPI	S&P 500	Dow	Nasdaq
Drift and Trend						
Test Statistics	0.123	0.081	−4.419**	−1.918	−2.250	−2.485
Drift	−2.163	−4.332	6.490**	7.896*	16.945*	12.376*
Trend	−0.001	−0.001	0.002**	0.008	0.011	0.016*
Drift Only						
Test Statistics	−1.566	−1.982	−6.893**	−0.002	−1.667	−1.263
Drift	1.368*	5.131*	2.088	2.440	4.967	2.440
Observations	483	483	483	483	411	483

**(*) denotes rejection of the null hypothesis that a unit root is present at the 0.01(0.05) significance level. The unit root tests are conducted for the full sample. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

properties of the series. The drawback of including both deterministic terms is that estimating unnecessary parameters reduces degrees of freedom and the power of unit root tests. However, incorrectly ignoring the trend may reduce the power of the test to zero. Therefore, unit root tests without the linear trend were also conducted where necessary.

The results of the Phillips and Perron (1988) unit root tests presented in Table 2 suggest that the CPI is trend-stationary.[6] The other five series are non-stationary. The cross-correlations between the macroeconomic time series and the stock indices, estimated using the Hamilton filter, the random walk model, and the Hodrick-Prescott filter, are presented in Tables 3, 4, 5, 6. As correlations can change over time, the results are presented in separate tables for each of the four decades between 1980 and 2020.

Consider the cross-correlations between the IPI and the three stock indices during the 1980s presented in Table 3. Although the three methods yield correlation coefficients of different magnitudes, overall, the evidence points to the stock indices being weakly countercyclical. The random walk model, however, suggests strong countercyclicality in the case of the Dow. The contemporaneous cross-correlations between the stock indices and NFE were negative and greater than −0.5, indicating a weakly negative association between them. The contemporaneous correlations between stock indices and inflation were also negative, albeit larger than those for IPI and NFE. The bottom panel shows that the three stock indices were strongly and positively correlated. Moreover, the correlations $\rho(0)$ are the strongest, signifying that the stock indices exhibited strong co-movement.

In the 1990s, the correlations between stock market cycles and the macroeconomic variables changed markedly. Table 4 shows that stock markets were strongly procyclical during this period. Both the Hamilton filter and the random walk model

[6] According to Schwert (1989), the lag length is determined using the formula $Int\left\{4\left(\left(\frac{T}{100}\right)^{0.25}\right)\right\}$.

Table 3 Cross-correlations: Stock indices and the macroeconomy; January 1980 to December 1990

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Corr. with IPI														
S&P 500	HF	0.13	0.02	−0.04	−0.12	−0.20	−0.29	**−0.38**	−0.41	−0.47	−0.50	−0.51	−0.51	−0.50
	HP	0.39	0.35	0.29	0.19	0.06	−0.07	**−0.20**	−0.29	−0.37	−0.45	−0.51	−0.54	−0.55
	RW	0.42	0.36	0.30	0.24	0.16	0.08	**−0.01**	−0.09	−0.17	−0.24	−0.30	−0.34	−0.37
Nasdaq	HF	−0.05	−0.16	−0.21	−0.27	−0.33	−0.41	**−0.45**	−0.47	−0.48	−0.51	−0.49	−0.49	−0.46
	HP	0.35	0.31	0.27	0.16	0.04	−0.10	**−0.23**	−0.32	−0.40	−0.47	−0.52	−0.54	−0.55
	RW	0.11	0.05	−0.02	−0.08	−0.15	−0.23	**−0.31**	−0.39	−0.45	−0.51	−0.54	−0.56	−0.56
Dow	HF	−0.43	−0.40	−0.27	−0.16	−0.03	−0.14	**−0.34**	−0.23	−0.11	−0.03	0.32	0.35	0.23
	HP	0.18	0.05	0.02	−0.02	−0.12	−0.23	**−0.34**	−0.43	−0.49	−0.54	−0.56	−0.58	−0.56
	RW	−0.29	−0.40	−0.44	−0.44	−0.46	−0.50	**−0.58**	−0.61	−0.63	−0.68	−0.67	−0.63	−0.58
Corr. with NFE														
S&P 500	HF	0.15	0.08	0.01	−0.03	−0.08	−0.12	**−0.21**	−0.26	−0.30	−0.32	−0.31	−0.34	−0.32
	HP	0.25	0.21	0.14	0.06	−0.04	−0.13	**−0.22**	−0.28	−0.34	−0.39	−0.42	−0.44	−0.44
	RW	0.36	0.32	0.28	0.24	0.21	0.16	**0.10**	0.05	0.00	−0.04	−0.07	−0.10	−0.11
Nasdaq	HF	0.00	−0.09	−0.15	−0.17	−0.22	−0.26	**−0.32**	−0.36	−0.36	−0.39	−0.38	−0.39	−0.36
	HP	0.22	0.18	0.11	0.02	−0.08	−0.17	**−0.26**	−0.34	−0.40	−0.45	−0.48	−0.50	−0.50
	RW	−0.07	−0.11	−0.15	−0.17	−0.19	−0.23	**−0.27**	−0.31	−0.35	−0.39	−0.40	−0.40	−0.39
Dow	HF	−0.55	−0.52	−0.48	−0.22	−0.02	−0.05	**−0.24**	−0.16	−0.01	0.13	0.45	0.25	0.35
	HP	0.00	−0.04	−0.06	−0.06	−0.07	−0.10	**−0.12**	−0.14	−0.14	−0.17	−0.17	−0.18	−0.18
	RW	−0.59	−0.63	−0.63	−0.54	−0.46	−0.44	**−0.44**	−0.40	−0.40	−0.42	−0.36	−0.32	−0.25
Corr. with CPI														
S&P 500	HF	−0.42	−0.46	−0.49	−0.50	−0.51	−0.51	**−0.51**	−0.51	−0.46	−0.41	−0.37	−0.33	−0.31
	HP	0.03	−0.05	−0.14	−0.23	−0.33	−0.40	**−0.44**	−0.44	−0.41	−0.38	−0.35	−0.33	−0.34
	RW	−0.63	−0.66	−0.67	−0.69	−0.70	−0.70	**−0.68**	−0.63	−0.57	−0.50	−0.44	−0.36	−0.30

Table 3 (continued)

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Nasdaq	HF	−0.51	−0.55	−0.56	−0.58	−0.59	−0.59	**−0.60**	−0.59	−0.54	−0.48	−0.44	−0.39	−0.37
	HP	−0.01	−0.07	−0.15	−0.26	−0.36	−0.44	**−0.49**	−0.48	−0.44	−0.37	−0.30	−0.26	−0.26
	RW	−0.36	−0.38	−0.39	−0.43	−0.46	−0.46	**−0.43**	−0.37	−0.29	−0.19	−0.11	−0.03	0.02
Dow	HF	0.67	0.73	0.76	0.69	0.48	0.24	**0.06**	−0.16	−0.24	−0.26	−0.39	−0.34	−0.40
	HP	0.18	0.21	0.20	0.14	0.01	−0.09	**−0.16**	−0.19	−0.18	−0.18	−0.18	−0.21	−0.30
	RW	0.53	0.65	0.72	0.68	0.56	0.44	**0.36**	0.30	0.27	0.31	0.34	0.34	0.30
Corr. with S&P 500														
Nasdaq	HF	0.43	0.50	0.54	0.59	0.66	0.79	**0.86**	0.71	0.55	0.43	0.34	0.28	0.21
	HP	0.15	0.28	0.38	0.51	0.65	0.81	**0.93**	0.80	0.62	0.44	0.29	0.19	0.07
	RW	0.49	0.56	0.60	0.65	0.72	0.81	**0.85**	0.72	0.56	0.42	0.30	0.22	0.12
Dow	HF	−0.03	−0.03	−0.04	0.01	0.24	0.61	**0.95**	0.72	0.31	−0.02	−0.30	−0.23	0.03
	HP	−0.05	0.04	0.10	0.25	0.47	0.74	**0.97**	0.80	0.57	0.39	0.25	0.18	0.11
	RW	0.08	0.15	0.17	0.29	0.46	0.71	**0.97**	0.80	0.61	0.48	0.38	0.34	0.32

The thresholds for the HF, HP, and RW for the Dow are 0.43, 0.26, and 0.35, respectively; in other cases, the thresholds are 0.20, 0.19, and 0.17. Thresholds vary due to differences in the sample sizes available for the cyclical components derived from the three methods. The Ns for the Dow are 19 (HF), 54 (HP), and 30 (RW). For the Nasdaq and the S&P 500, they are 91 (HF), 126 (HP), and 102 (RW). Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

Table 4 Cross-correlations: Stock indices and the macroeconomy; January 1990 to December 1999

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Corr. with IPI														
S&P 500	HF	0.65	0.68	0.70	0.71	0.71	0.71	**0.71**	0.71	0.71	0.72	0.73	0.74	0.75
	HP	0.23	0.22	0.21	0.13	0.03	−0.11	**−0.20**	−0.21	−0.20	−0.17	−0.14	−0.11	−0.10
	RW	0.54	0.55	0.57	0.57	0.57	0.58	**0.58**	0.58	0.59	0.61	0.62	0.64	0.65
Nasdaq	HF	0.71	0.72	0.74	0.75	0.73	0.71	**0.67**	0.64	0.62	0.60	0.60	0.60	0.61
	HP	0.18	0.17	0.18	0.13	0.04	−0.08	**−0.17**	−0.18	−0.14	−0.11	−0.10	−0.10	−0.08
	RW	0.63	0.64	0.64	0.63	0.61	0.58	**0.53**	0.50	0.49	0.47	0.47	0.48	0.48
Dow	HF	0.71	0.73	0.75	0.75	0.75	0.74	**0.74**	0.73	0.73	0.74	0.74	0.74	0.74
	HP	0.29	0.28	0.27	0.20	0.08	−0.07	**−0.17**	−0.19	−0.22	−0.23	−0.23	−0.21	−0.23
	RW	0.58	0.58	0.59	0.59	0.58	0.58	**0.58**	0.58	0.58	0.60	0.60	0.62	0.62
Corr. with NFE														
S&P 500	HF	0.47	0.49	0.49	0.49	0.48	0.47	**0.46**	0.46	0.47	0.48	0.49	0.48	0.48
	HP	0.08	0.00	−0.10	−0.20	−0.26	−0.31	**−0.35**	−0.36	−0.38	−0.38	−0.35	−0.36	−0.35
	RW	0.32	0.33	0.35	0.36	0.36	0.36	**0.36**	0.36	0.37	0.38	0.39	0.39	0.40
Nasdaq	HF	0.60	0.60	0.57	0.54	0.51	0.46	**0.41**	0.39	0.38	0.38	0.38	0.37	0.37
	HP	0.10	0.04	−0.05	−0.13	−0.20	−0.24	**−0.26**	−0.25	−0.23	−0.22	−0.21	−0.23	−0.22
	RW	0.37	0.35	0.32	0.29	0.26	0.22	**0.19**	0.17	0.16	0.15	0.15	0.14	0.14
Dow	HF	0.51	0.53	0.53	0.54	0.53	0.52	**0.51**	0.51	0.52	0.53	0.53	0.52	0.52
	HP	0.10	0.05	−0.03	−0.10	−0.15	−0.20	**−0.23**	−0.24	−0.27	−0.29	−0.29	−0.31	−0.33
	RW	0.37	0.39	0.41	0.43	0.43	0.44	**0.44**	0.45	0.46	0.46	0.46	0.46	0.46
Corr. with CPI														
S&P 500	HF	−0.52	−0.52	−0.52	−0.52	−0.54	−0.56	**−0.57**	−0.57	−0.56	−0.55	−0.54	−0.53	−0.54
	HP	−0.12	−0.18	−0.21	−0.25	−0.32	−0.34	**−0.36**	−0.29	−0.20	−0.13	−0.06	−0.00	0.01
	RW	−0.48	−0.48	−0.47	−0.47	−0.49	−0.51	**−0.53**	−0.53	−0.52	−0.52	−0.50	−0.51	−0.51

Table 4 (continued)

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Nasdaq	HF	−0.75	−0.75	−0.75	−0.76	−0.78	−0.78	**−0.77**	−0.75	−0.72	−0.70	−0.69	−0.68	−0.68
	HP	0.03	−0.04	−0.09	−0.16	−0.24	−0.28	**−0.30**	−0.27	−0.22	−0.19	−0.17	−0.16	−0.19
	RW	−0.68	−0.68	−0.68	−0.69	−0.71	−0.73	**−0.72**	−0.71	−0.69	−0.67	−0.66	−0.66	−0.66
Dow	HF	−0.51	−0.50	−0.49	−0.49	−0.50	−0.51	**−0.53**	−0.53	−0.52	−0.52	−0.51	−0.50	−0.51
	HP	0.09	0.03	−0.02	−0.06	−0.14	−0.18	**−0.21**	−0.18	−0.11	−0.04	0.03	0.08	0.10
	RW	−0.43	−0.42	−0.40	−0.39	−0.40	−0.43	**−0.45**	−0.45	−0.44	−0.44	−0.43	−0.43	−0.43
Corr. with S&P 500														
Nasdaq	HF	0.66	0.65	0.66	0.70	0.73	0.77	**0.80**	0.76	0.72	0.69	0.66	0.65	0.66
	HP	−0.08	−0.05	0.01	0.15	0.35	0.58	**0.81**	0.64	0.49	0.32	0.19	0.11	0.15
	RW	0.54	0.53	0.55	0.59	0.64	0.68	**0.72**	0.66	0.61	0.56	0.52	0.50	0.52
Dow	HF	0.88	0.87	0.87	0.89	0.91	0.92	**0.96**	0.91	0.88	0.84	0.81	0.78	0.76
	HP	−0.06	−0.10	−0.07	0.09	0.35	0.56	**0.89**	0.65	0.44	0.25	0.14	0.10	0.03
	RW	0.80	0.79	0.79	0.82	0.85	0.88	**0.93**	0.86	0.81	0.76	0.70	0.67	0.63

The threshold, θ, is 0.18. $N = 120$. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

Table 5 Cross-correlations: Stock indices and the macroeconomy; January 2000 to December 2009

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Corr. with IPI														
S&P 500	HF	0.70	0.74	0.78	0.81	0.83	0.83	**0.82**	0.82	0.79	0.75	0.71	0.68	0.64
	HP	0.65	0.72	0.77	0.81	0.80	0.75	**0.69**	0.62	0.52	0.40	0.29	0.20	0.10
	RW	0.71	0.76	0.79	0.82	0.84	0.84	**0.83**	0.82	0.80	0.76	0.73	0.69	0.65
Nasdaq	HF	0.53	0.57	0.60	0.62	0.63	0.63	**0.63**	0.62	0.60	0.57	0.53	0.49	0.45
	HP	0.56	0.61	0.64	0.66	0.64	0.58	**0.52**	0.47	0.39	0.29	0.20	0.13	0.05
	RW	0.56	0.59	0.62	0.64	0.65	0.65	**0.64**	0.62	0.60	0.56	0.52	0.48	0.43
Dow	HF	0.70	0.75	0.80	0.84	0.86	0.86	**0.86**	0.86	0.83	0.80	0.76	0.73	0.69
	HP	0.63	0.70	0.76	0.80	0.79	0.75	**0.69**	0.63	0.53	0.41	0.30	0.21	0.12
	RW	0.71	0.76	0.81	0.84	0.86	0.87	**0.87**	0.86	0.84	0.80	0.77	0.74	0.69
Corr. with NFE														
S&P 500	HF	0.80	0.83	0.84	0.86	0.87	0.86	**0.84**	0.81	0.77	0.73	0.68	0.65	0.61
	HP	0.82	0.83	0.80	0.76	0.70	0.61	**0.50**	0.40	0.30	0.19	0.09	0.02	– 0.04
	RW	0.90	0.91	0.91	0.90	0.89	0.86	**0.83**	0.79	0.75	0.69	0.64	0.59	0.53
Nasdaq	HF	0.66	0.68	0.69	0.70	0.71	0.70	**0.68**	0.65	0.61	0.57	0.52	0.48	0.44
	HP	0.68	0.66	0.63	0.58	0.51	0.43	**0.34**	0.25	0.17	0.08	−0.01	−0.07	−0.13
	RW	0.75	0.75	0.74	0.72	0.70	0.67	**0.63**	0.59	0.53	0.47	0.41	0.35	0.28
Dow	HF	0.78	0.81	0.84	0.86	0.87	0.86	**0.84**	0.82	0.79	0.75	0.72	0.69	0.64
	HP	0.78	0.79	0.78	0.74	0.68	0.60	**0.50**	0.40	0.30	0.19	0.10	0.03	−0.03
	RW	0.87	0.89	0.89	0.89	0.89	0.87	**0.84**	0.81	0.77	0.72	0.68	0.64	0.59
Corr. with CPI														
S&P 500	HF	0.65	0.65	0.64	0.62	0.60	0.56	**0.50**	0.44	0.37	0.30	0.22	0.17	0.12
	HP	0.40	0.44	0.47	0.49	0.49	0.43	**0.33**	0.22	0.10	−0.05	−0.21	−0.33	−0.41
	RW	0.75	0.74	0.72	0.69	0.67	0.62	**0.56**	0.49	0.42	0.34	0.26	0.20	0.14

Table 5 (continued)

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Nasdaq	HF	0.53	0.53	0.51	0.48	0.45	0.42	**0.37**	0.32	0.27	0.22	0.16	0.12	0.08
	HP	0.32	0.33	0.33	0.32	0.30	0.25	**0.16**	0.06	−0.04	−0.15	−0.27	−0.34	−0.38
	RW	0.59	0.57	0.54	0.50	0.46	0.41	**0.36**	0.29	0.22	0.15	0.08	0.03	−0.03
Dow	HF	0.63	0.63	0.62	0.60	0.59	0.55	**0.49**	0.44	0.38	0.30	0.22	0.17	0.12
	HP	0.39	0.43	0.45	0.47	0.47	0.41	**0.32**	0.24	0.13	−0.01	−0.17	−0.29	−0.38
	RW	0.73	0.72	0.71	0.69	0.67	0.62	**0.56**	0.50	0.43	0.35	0.27	0.22	0.16
Corr. with S&P 500														
Nasdaq	HF	0.73	0.76	0.80	0.82	0.85	0.87	**0.89**	0.85	0.81	0.77	0.72	0.66	0.60
	HP	0.42	0.50	0.59	0.65	0.71	0.78	**0.83**	0.72	0.61	0.52	0.40	0.28	0.17
	RW	0.74	0.77	0.80	0.83	0.85	0.87	**0.88**	0.84	0.79	0.74	0.68	0.62	0.55
Dow	HF	0.67	0.73	0.78	0.83	0.87	0.92	**0.97**	0.95	0.92	0.90	0.86	0.81	0.76
	HP	0.28	0.40	0.52	0.63	0.72	0.85	**0.96**	0.89	0.79	0.71	0.61	0.48	0.35
	RW	0.67	0.73	0.78	0.83	0.87	0.92	**0.96**	0.94	0.92	0.89	0.85	0.80	0.74

The threshold, θ, is 0.18. $N = 120$. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020)

Table 6 Cross-Correlations: Stock indices and the macroeconomy; January 2010 to December 2019

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Corr. with IPI														
S&P 500	HF	0.65	0.67	0.69	0.73	0.75	0.74	**0.74**	0.74	0.71	0.65	0.57	0.48	0.34
	HP	0.48	0.46	0.44	0.45	0.40	0.34	**0.30**	0.28	0.28	0.29	0.28	0.21	0.13
	RW	0.74	0.77	0.79	0.80	0.80	0.77	**0.74**	0.69	0.63	0.55	0.45	0.33	0.19
Nasdaq	HF	0.61	0.63	0.64	0.70	0.71	0.68	**0.67**	0.67	0.64	0.58	0.51	0.42	0.29
	HP	0.46	0.45	0.43	0.46	0.40	0.34	**0.29**	0.27	0.28	0.29	0.29	0.24	0.16
	RW	0.73	0.75	0.75	0.76	0.74	0.69	**0.63**	0.57	0.50	0.42	0.32	0.20	0.06
Dow	HF	0.72	0.73	0.75	0.79	0.80	0.79	**0.79**	0.78	0.74	0.67	0.59	0.48	0.34
	HP	0.58	0.55	0.54	0.54	0.49	0.44	**0.40**	0.38	0.37	0.36	0.31	0.21	0.12
	RW	0.81	0.83	0.85	0.86	0.86	0.82	**0.78**	0.73	0.65	0.55	0.44	0.30	0.14
Corr. with NFE														
S&P 500	HF	0.70	0.71	0.73	0.75	0.78	0.79	**0.76**	0.70	0.62	0.54	0.45	0.31	0.18
	HP	0.17	0.07	0.02	−0.01	−0.06	−0.08	**−0.10**	−0.13	−0.12	−0.07	−0.05	−0.15	−0.24
	RW	0.78	0.75	0.71	0.66	0.60	0.54	**0.46**	0.38	0.30	0.22	0.14	0.03	−0.08
Nasdaq	HF	0.67	0.68	0.69	0.71	0.72	0.72	**0.69**	0.62	0.54	0.46	0.38	0.26	0.16
	HP	0.08	−0.00	−0.06	−0.08	−0.13	−0.17	**−0.19**	−0.24	−0.24	−0.19	−0.15	−0.20	−0.26
	RW	0.67	0.63	0.58	0.52	0.44	0.36	**0.28**	0.19	0.12	0.06	−0.01	−0.10	−0.19
Dow	HF	0.68	0.69	0.70	0.72	0.74	0.75	**0.73**	0.68	0.63	0.56	0.48	0.36	0.23
	HP	0.29	0.19	0.13	0.09	0.04	0.03	**−0.00**	−0.04	−0.04	−0.01	−0.02	−0.15	−0.26
	RW	0.75	0.71	0.67	0.62	0.57	0.50	**0.43**	0.34	0.26	0.18	0.09	−0.02	−0.13
Corr. with CPI														
S&P 500	HF	0.38	0.41	0.44	0.48	0.52	0.56	**0.53**	0.48	0.41	0.32	0.21	0.11	0.03
	HP	0.23	0.21	0.19	0.22	0.25	0.30	**0.25**	0.16	0.09	0.04	−0.00	−0.05	−0.09
	RW	0.36	0.39	0.42	0.47	0.51	0.53	**0.49**	0.43	0.35	0.24	0.13	0.03	−0.05

Table 6 (continued)

	Filter	ρ (6)	ρ (5)	ρ (4)	ρ (3)	ρ (2)	ρ (1)	ρ (0)	ρ (−1)	ρ (−2)	ρ (−3)	ρ (−4)	ρ (−5)	ρ (−6)
Nasdaq	HF	0.36	0.38	0.40	0.44	0.48	0.52	**0.48**	0.42	0.34	0.25	0.14	0.06	0.00
	HP	0.17	0.13	0.12	0.14	0.16	0.22	**0.18**	0.09	0.04	0.00	−0.03	−0.07	−0.09
	RW	0.35	0.37	0.39	0.43	0.46	0.47	**0.41**	0.32	0.22	0.11	−0.00	−0.09	−0.15
Dow	HF	0.53	0.56	0.59	0.63	0.68	0.71	**0.69**	0.65	0.60	0.52	0.42	0.31	0.22
	HP	0.33	0.30	0.28	0.30	0.33	0.38	**0.33**	0.24	0.19	0.16	0.12	0.07	0.02
	RW	0.51	0.54	0.57	0.61	0.65	0.66	**0.63**	0.57	0.49	0.39	0.27	0.15	0.05
Corr. with S&P 500														
Nasdaq	HF	0.52	0.59	0.67	0.75	0.81	0.89	**0.96**	0.86	0.77	0.67	0.55	0.39	0.25
	HP	0.03	0.13	0.17	0.31	0.45	0.64	**0.94**	0.70	0.54	0.40	0.28	0.24	0.18
	RW	0.46	0.55	0.65	0.74	0.81	0.88	**0.95**	0.85	0.73	0.61	0.46	0.28	0.11
Dow	HF	0.59	0.63	0.69	0.75	0.81	0.87	**0.94**	0.87	0.80	0.72	0.60	0.45	0.29
	HP	0.10	0.18	0.23	0.35	0.50	0.67	**0.94**	0.66	0.47	0.34	0.22	0.17	0.10
	RW	0.51	0.58	0.66	0.73	0.80	0.88	**0.94**	0.86	0.77	0.66	0.52	0.33	0.15

The threshold, θ, is 0.18. N = 118. Data sources: FRED (Federal Reserve Bank of St. Louis, 2020) and Datastream (Refinitiv, 2020) yielded similar findings. The Hodrick-Prescott filter, on the other hand, produced starkly different results, suggesting that while the S&P 500 was weakly countercyclical, the Nasdaq and the Dow were not contemporaneously correlated with the business cycle. The correlations between the stock market cycles and inflation were negative. The results produced by the Hamilton filter and the random walk model were quite similar. These methods produced much stronger correlations than the Hodrick-Prescott filter. The Nasdaq and the Dow continued to show strong co-movement with the S&P 500 during the 1990s.

The correlations for the 2000s are presented in Table 5. Once again, the Hamilton filter and the random walk model produced similar results, showing that all three stock indices were strongly procyclical. The contemporaneous correlations with the IPI were above 0.80 for the S&P 500 and the Dow and greater than 0.60 for the Nasdaq. Although the Hodrick-Prescott filter produced smaller correlations than the other two filters, the correlations were large enough to lead one to the same conclusion. Stock markets were strongly procyclical in the 2000s. The correlations of the stock indices with NFE corroborate this evidence.

As for the lead-lag associations, the maximum values of the correlations of the stock indices with the IPI and NFE were observed for $l > 0$, indicating that stock markets lagged business cycles. In the case of the IPI, the maximum values were observed for $1 \leq l \leq 3$. The results showed evidence of a strong positive contemporaneous correlation between inflation and the S&P 500. The evidence was mixed for the Nasdaq and the Dow, with the correlations being slightly larger for the latter. In each case, the Hodrick-Prescott filter produced noticeably lower correlations. Apropos the lead-lag associations, there is compelling evidence that stock market cycles lagged inflation during the 2000s.

The results for the 2010s presented in Table 6 bear a striking resemblance to those for the 2000s, suggesting that the associations between the stock market and macroeconomic cycles remained relatively stable during the first two decades of the twenty-first century. The contemporaneous correlations between the stock indices and the IPI were positive and greater than 0.60 per the Hamilton filter and the random walk model. The Hodrick-Prescott filter produced positive correlations, albeit considerably smaller in magnitude. For NFE, the Hamilton filter and the random walk model produced positive correlations, precisely what one might expect given the procyclicality of stock indices evidenced by their positive correlations with the IPI. Furthermore, given that the maximum value of $|\rho(l)|$ occurred at $l > 0$, we conclude that stock markets lagged macroeconomic activity during the 2010s.

In contrast to the Hamilton filter and the random walk model, the Hodrick-Prescott filter yielded negative correlations between the NFE and stock index cycles. This brings the veracity of the Hodrick-Prescott filter into question. If stock indices are procyclical, they should be positively correlated with NFE. However, the Hodrick-Prescott filter generated positive correlations between the stock market indices and the IPI and negative ones between the indices and NFE. These results are inconsistent and counterintuitive.

The relationship between inflation and stock market cycles was positive, with the correlations being the strongest in the case of the Dow. The bottom panel of Table 6 shows that the co-movement between the stock indices remained strong during the 2010s, with the correlations ranging between 0.94 and 0.96.

The association between inflation and stock market cycles has changed over time. During the 1980s, inflation was tamed while the stock markets rose to new heights, notwithstanding the 1987 crash. The results show a negative association between inflation and stock market performance during the 1980s. Each of the three filters suggests that inflation and stock market cycles were inversely related during the 1980s and 1990s, confirming the findings of several previous studies (e.g., Eldomiaty et al., 2019; Quayes & Jamal, 2008). The early 1980s experienced high inflation following the oil price shocks in the late 1970s, which sent oil prices spiraling upward. The Federal Reserve Bank responded by raising the interest rates to stem inflation. It succeeded, and interest rates started declining toward the end of 1981. While inflation fell reasonably consistently until 1986, the economy grew appreciably, boosting investor sentiment and leading to a protracted bull market in the 1980s. Thus, declining inflation coincided with rising stock prices.

Although the 1990s started with a short-lived recession, the decade was marked by a long economic boom. The stock market registered impressive gains in the latter half of the decade; output and employment also increased. The marked increase in productivity allowed the economy to grow rapidly without building inflationary pressures. These dynamics help explain why the stock market was negatively associated with inflation but positively associated with the real economy in the 1990s.

In the twenty-first century, inflation and stock market cycles have shown strong positive associations. During the 2000s, low interest rates, globalization, high economic growth in emerging markets, and the housing credit boom contributed to demand-pull inflation and abundant liquidity, some of which flowed into the stock markets, boosting asset prices. During the 2007–2008 global financial crises, stock markets plummeted, and inflation subsided, reinforcing the positive association. Prices and stock markets recovered in the aftermath of the crisis and on the back of fiscal stimuli and quantitative easing. Then, in 2014–2015, a glut in the oil markets and the Organization of the Petroleum Exporting Countries' refusal to cut supplies caused commodity prices to fall precipitously. In parallel, the global economic slowdown, China's stock market turmoil, the Greek debt default, and monetary policy uncertainty contributed to declines in stock indices.

Summary and Conclusion

This study used various filtering techniques to isolate cyclical components from the U.S. stock indices and macroeconomic variables. Time-difference analysis was conducted to explore lead-lag relationships between the stock index and macroeconomic cycles. As correlations and lead-lag associations may change over time, the period 1980–2020 was split into four decade-long subsets. Three core findings emerged: First, stock markets shifted from being countercyclical in the 1980s and 1990s to being procyclical in the twenty-first century when they trailed business cycles by 1–3 months. Second, correlations between stock markets and inflation turned positive in the 2000s and 2010s after being negative in the 1980s and the 1990s. Finally, results diverged considerably between filtering techniques. The Hamilton filter and random walk models produced broadly consistent results, while those generated by the Hodrick-Prescott filter differed substantially.

Specifically, the Hodrick-Prescott filter yielded inconsistent correlations between stock markets and the real economy, positive with industrial production, indicating procyclicality, but negative with employment, suggesting countercyclicality. This produced results that are at odds with commonly held views. Even though the U.S. stock markets boomed in the 1990s, and the economy grew appreciably, the results produced by the Hodrick-Prescott filter point to a negative correlation between the stock market and IPI cycles for that period. The Hamilton filter and random walk results better resonate with established economic narratives about recent decades. The inconsistencies of the Hodrick-Prescott filter bring its viability into question. Techniques failing to reproduce well-known associations between financial markets and the real economy may prove unreliable in assessing precise lead-lag relationships.

The results do not support the continued inclusion of the S&P 500 in the Composite Index of Leading Indicators, which is used to predict the direction of the U.S. economy. They show that the S&P 500 lagged industrial production by one to three months in recent decades. Interestingly, the Dow shared a stronger correlation with U.S. industrial production than the S&P 500 and Nasdaq during the twenty-first century.

Previous studies (Apergis & Eleftheriou, 2002; Fama, 1981; Osamwonyi & Evbayiro-Osagie, 2012) posited a negative association between inflation and stock market performance. We found this to be the case in the 1980s and 1990s. However, the correlations were decidedly positive during the 2000s and 2010s, with inflation leading stock market cycles by one month during the 2010s. The interlinkages between stock markets and the macroeconomy are dynamic and complex. This study provides updated evidence on how they are interlinked and how these interlinkages have evolved over the last 40 years. It stresses the importance of employing different methods and considering various macroeconomic variables to gain a comprehensive understanding of the interactions between stock markets and the broader economy.

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