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Journal of Economic Analysis

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Are Industry Returns Informative about Other Industries and Fundamentals?

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ABSTRACT

This paper examines the information content of selected US industries focusing on the dynamic linkages among these industries, the stock market and a number of fundamental variables. The period of investigation spans from January 1960 to December 2021. The empirical strategy includes several methodologies such as regressions, vector autoregressions and volatility models. The idea is to investigate the dynamic linkages among these series at both the mean and the volatility levels. The results point to significant industry returns' explanatory power for many predictors of economic activity including the stock market. Further, time-varying analysis of the linkages among the industries and the stock market's returns reveal that certain industries such as *Oil* and *Financials* provide consistent information leadership over other industries and across decades. Further, upon assessing the industry–market return volatility spillovers, it was found that a market risk–return profile may not always be economically significant and timely for investors. Finally, crises, financial or otherwise, affect industries but to differing degrees.

KEYWORDS

Industry returns; fundamentals; information content; VAR; volatility

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ISSN 2811-0943
doi: 10.58567/jea04010001

Received 16 January 2024; Accepted 29 February 2024; Available online 4 March 2024.

1. Introduction

Investment and portfolio research has shown a long-standing interest in the linkages between macroeconomic fundamentals and stock returns. Early studies covered a wide range of issues pertaining to a strong relationship between economic indicators and stock performance. Specifically, from the deployment of macro variables to explain and forecast future returns (Fama, 1990, Schwert, 1990, Barro, 1990, Chen, 1991, and Flannery and Protopapadakis, 2002) to the importance of information and other investor biases (Merton, 1987, Schiller, 2000), specific trading characteristics (Lo and MacKinlay, 1990, Chordia and Swaminathan, 2000), and analysts' coverage (Brennan et *al*., 1993).

Overall, research on the impact of macroeconomic fundamentals upon financial asset returns in particular abounds, albeit with mixed conclusions. For example, and in contrast with the work cited above, stock market fluctuations have been attributable to non-fundamental factors such as excessive speculation and irrational exuberance (Campell and Shiller, 1988, Carlson and Sargent, 1997, Shiller, 2000), informational segmentation of markets (Cohen and Frazzini, 2008), slow diffusion of information (Hou, 2007, Menzly and Ozbas, 2010), or to the speed of incorporation of information into stock prices being dependent on firm structure (Cohen and Lou, 2012). In essence, what was implied by the above work is that a given industry may be capable of effectively and efficiently processing information about the fundamentals in order to forecast stock market returns. Thus, I set out to examine the dynamic (lead-lag) linkages among a set of representative macroeconomic fundamentals, such as industrial production, the unemployment rate and yield spreads, and seventeen industries covering all aspects of the United States economy, from January 1960 to December 2021.

The preponderance of papers examining the linkages between stock returns and macro fundamentals were done at the firm level. Given the general absence of papers investigating the issue at the industry level, this paper aims to fill the gap in the empirical financial and industrial literature. Specifically, the paper has the following six goals. First, to explore the relationships between each industry's portfolio returns and macroeconomic fundamentals, with and without the influence of the stock market. The results that several industries served as information leaders for specific fundamental variables suggest that industry returns contained important information about future economic activity, which could be exploited by other industries. Second, the investigation of whether industries are able to forecast economic fundamentals. Consistent with prior literature, it was found that the *Oil* and *Financials* industries constituted a major source of information for other industries. The oil industry is a major input to production and thus all industries are affected by changes in prices as well as volatility. By the same token, the financial industry provides information about the general state of the stock market where all industries' stocks are traded. Consequently, it is no surprise that these industries can serve as indicators to an industry's economic and/or financial success or lack thereof. Third, and related to the previous goal, to examine the strength or weakness of these industries' capability to forecast/explain the stock market during the COVID-19 period. Using a sentiment index, the results pointed to different sensitivities among industries but most of them were negatively impacted by the pandemic.

Fourth, to test the evidence that firms in highly concentrated industries earn lower returns after controlling for firm characteristics and other macro variables. To this end, a Herfindhal-type concentration index was constructed and evaluated. Results found were weak. The existing body of literature pertinent to industry-level factors is not as wide as firm-level factors. Fifth, to investigate the impact of the 2007 financial crisis on industry returns and the real economy. A breakdown in the dynamic interactions among the stock market and economic fundamentals, consistent with prior evidence, was detected. Finally, to study the linkages among industries themselves and between each industry and the stock market at the volatility level. As there is very little research on the volatility spillovers between industries and the aggregate stock market, studying how a given industry's volatility impacts upon another industry's risk and return (or the extent to which an industry's risk can explain other industries' risk-return profiles), is warranted. The results indicated that about one third of the industries examined (six out of seventeen), notably *Oil* and *Financials,* significantly impacted the volatility of the aggregate market. This finding makes good economic sense given the weight of these industries in the US economy.

This paper extends the paper by Laopodis (2016), who also examined a similar issue, but it differs from it in the following respects. First, this version includes a short literature review section so as to make it more comprehensive. Second, the examination of the global financial crisis of 2007 and the COVID-19 period are new to this paper. Third, the methodological design employed in this paper includes the volatility linkages between the stock market and the fundamentals. Fourth, this paper additionally examines the relationship between an industry's returns with the concentration of firms in that industry. Finally, the sample period is different and extended on both sides (start and end) in this paper.

The contribution of this paper to the literature is clear. First, understanding how industries interact with the macroeconomic fundamentals is essential to not only investors and portfolio managers but also to policy-makers so as to design proper monetary and fiscal policies. Second, it is important to know the different sensitivities of each industry to major global events – financial and otherwise – so as to construct more resilient investment portfolios for global investors as well as assist managers navigate through such turbulent times. Third, knowing how market volatility impacts an industry and vice versa is essential to all market participants. For example, consumers would like to know how high market turbulence would affect industries' production of goods and services, investors would like to be informed about the change in the value of their portfolios and firm managers would be interested to know how much the cost of credit would be affected when they plan raising new capital or investing.

The rest of the paper proceeds as follows. Section 2 summarizes the relevant literature. Section 3 lays out theoretical considerations and testable hypotheses. The section concludes with data sources and variable construction. Section 4 presents both the preliminary statistical results on the main series as well as the main empirical findings. Section 5 contains further analysis of dynamic relationships among industries including the crisis of 2007, the period of the pandemic as well as volatility spillovers. This section ends with some additional robustness tests. Concluding remarks and suggestions for further research are given in Section 6.

2. Short Literature Review

The relationships between macroeconomic fundamentals and stock market returns have long attracted the attention of scholars in investment research. However, evidence on the existence linkages between fundamentals and stock market returns is mixed. Keim and Stambaugh (1986), Fama and French (1989), Balvers et *al.* (1990) and Chen (1991) showed that macro variables such as default and term spreads, industrial production and dividend yields forecasted stock returns. Along the same lines, Fama (1990), Schwert (1990) and Barro (1990) reported that the stock market and several economic variables are closely linked. For example, Fama (1990) examined whether fundamentals such as expected cash flows and discount rates explained stock returns in the US and found a positive and a negative relationship, respectively. Work was also done for international stock markets such as that by Chan et *al.* (1991) and Mukherjee and Naka (1995) on the Japanese stock market, and Mookerjee and Yu (1997) on Singapore's stock market. In all cases, the examined macro variables and the stock market were closely linked

However, since the 1990s the nature and extent of the relationship between the stock market and economic fundamentals changed drastically. Campbell and Shiller (1988), Carlson and Sargent (1997), and Shiller (2000) indicated that non-fundamental factors, such as excessive speculation and irrational exuberance, were causing turbulence in major stock markets worldwide. Lee (1998) noted that earnings, dividends, and industrial production – all fundamental variables themselves – failed to explain stock prices. Similarly, Chan et *al*. (1998, p. 175) argued that macroeconomic fundamentals make a 'poor showing' in explaining equity returns and that the authors themselves could not explain this poor performance. Finally, Flannery and Protopapadakis (2002) examined seventeen macro announcements and found only six of them to be significant risk factors.

In a number of papers, Binswanger (2000, 2004) and Laopodis (2011, 2016) noticed a decoupling between the financial and economic (real) sectors of major economies and this disconnection had started as early as the mid1990s. Along the same vein, Hong et *al*. (2007) investigated the lead-lag relationships among industries, the stock market, and several macroeconomic magnitudes. The authors find that *Metal*, *Retail* and *Financial* services industries lead both the stock market, as well as certain economic indicators. Thus, it can be said that significant economic information in certain influential industries gradually diffuses into the market. Tse (2015) reexamined the Hong et *al*. (2007) results using an extended period (1946–2013) and data (48 industries) and found that only one to seven industries had significant predictive power for the stock market, depending on the significance level and the models used. However, he did find some evidence of the opposite direction from the stock market to industries as the stock market performs better than industries in predicting economic growth.

Lee et *al.* (2013), which examined the dynamic causal relation between industry returns and stock market returns by considering multiple structural breaks for ten major eastern and southern Asia countries, found that finance and consumer service industry returns have significant power in explaining the movements of market returns. Wu and Shamsuddin (2014) using 1700 Australian stocks over the 1990-2009 period investigated whether industry portfolio returns could predict the aggregate market. The authors found that a few industries significantly lead the market, after controlling for well-known market predictors. However, contrary to studies for the US, they did not find that an industry's ability to predict the market was closely related to its propensity to forecast economic growth but governed by proxies for investor attention.

Finally, more recent research by Peiró (2016) investigated the dynamic linkages among stock prices, interest rates and macroeconomic activity in selected European countries for the 1969-2012 period and found that interest rates were important determinants of industrial production during the first years but not in the later years. Cine (2018) examined the predictive ability of industry returns for the stock market and applied it to the US. Using a new statistical methodology, the random forest method which accounts for both linear and nonlinear dynamics, she found that industry returns indeed contain significant out of sample forecasting power for the market index return.

3. Methodology and Data

3.1. Data sources and Variable construction

The dataset contains seventeen, value-weighted, monthly industry portfolios retrieved from K. French's website. These industry portfolios are: *Food, Mining, Oil, Clothing, Durables, Chemicals, Consumer, Construction, Steel, Fabricated Products*, *Machinery, Cars, Transport, Utilities, Retail, Financial*, and *Other*. Appendix A describes briefly each industry. The portfolios' values are collected from January 1960 to December 2021 period.

The fundamental variables used in the study are the unemployment rate, industrial production, AAA- and BBB-rated bond yields, the 10-year Treasury note, the 3-month Treasury bill, and the consumer price index (CPI). I constructed nominal, continuously compounded returns for the stock market index (SP) and real returns by subtracting the rate of inflation, derived from CPI. Using the corporate bonds' and government bond yields' data, I constructed a credit spread, BAA-bond yields *minus* the T-note, and a term spread, 10-year Treasury note yield *minus* the federal funds rate. Credit and term spreads have been found to predict real economic activity (see Estrella and Hardouvelis, 1991).

All fundamental variables are taken from the Federal Reserve of St. Louis' *FRED* website. The stock market proxy is the NYSE and the S&P 500 dividend yield were collected from *Bloomberg*.

3.2. Methodological design

Drawing on Laopodis (2016), we begin by exploring whether a given industry's returns can explain economic fundamentals. The relevant regression specification is below:

$$y_t = \delta_i + \sum_{j=1}^{n} \eta_{it}\, r_{i,t-j} + \upsilon_{it} \qquad (1)$$

where y_t is a fundamental variable at time t, $r_{i,t-j}$ is the industry's lagged, return i at time $t - j$ (j = 1 to n lags) and υ_{it} is the disturbance term. This equation will be applied to each industry.

The focus here is on parameter η_{it} because, if statistically significant, it will indicate the extent and nature of the prediction of a specific industry on the specific fundamental variable. To obtain an idea about the inter-temporal significance of this parameter for each industry, the rolling regression methodology will be used. A persistently statistically-significant coefficient (for many years or decades) would suggest that a particular industry showed up as a significant explanatory variable to the particular fundamental variable.

Next, we examine presence of dynamic interactions among all industries and the market simultaneously given the fundamental variables. This is tested with a vector autoregressive (VAR) model, expressed as follows:

$$r_t = B_0 + \Sigma^{n}_{l=1} B_l\, r_{t-l} + A\, F_t + u_t \qquad (2)$$

where r_t is a vector of the returns of the specific industries, with and without the stock market, B_l is the autoregressive part of an industry's returns at lag l, where $l = 1, \ldots, n$, and A the matrix of coefficients describing the vector of fundamental variables, F. The optimal lag length (l) will be determined by the Schwartz information criterion (SIC).

The third and final hypothesis to be investigated refers to the manner in which return volatility transmits from an industry to the stock market and vice versa. The standard methodology to address this issue is the bivariate GARCH(p,q) model. Let r_t be the continuously compounded return of an $n \times 1$ vector of returns at time t for each market:

$$r_t = \mu + \varepsilon_t \qquad (3a)$$

$$\varepsilon_t / \Omega_{t-1} \sim N\,(0, H_t) \qquad (3b)$$

where the $n \times 1$ vector of disturbances, ε_t, represents the innovation (news) for each market (each industry and the stock market) at time t, H_t is the $n \times n$ variance-covariance matrix, Ω_{t-1} is the information available to each market at time $t\text{-}1$. Following Engle and Kroner (1995), the conditional covariance matrix can be expressed as

$$H_t = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$$
$$+ \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}' H_{t-1} \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \qquad (3c)$$

The coefficients of interest here are g_{12} and g_{21} which measure the volatility impacts of one market to the other. For example, a statistically significant g_{12} would imply that the volatility of the stock market affects a given industry's volatility. The maximum likelihood estimation procedure of Berndt et *al*. (1974) is employed to derive the coefficients' values. To ensure that the bivariate GARCH (p,q) is correctly specified, we use the Ljung-Box Q-statistics to test for white noise in the residuals.

The next obvious question is whether stock market volatility affects the conditional mean of each industry's returns. If such an important relationship exists it would imply a proportional (expected) return–volatility tradeoff. This relationship can be conveniently modeled by adding the market's contemporaneous conditional standard deviation (volatility) into each industry's conditional mean equation (equation 3a). The model then becomes a modified ARCH-in-Mean (GARCH-M, in our case) or volatility-in-mean (or volatility feedback) model, as suggested by Engle et *al*. (1987). It is modified in the sense that a given industry's conditional mean does not include its own volatility but that of the aggregate stock market. We can always include a lagged conditional standard deviation in equation (3) to reflect consumer expectations. Hence, we have equation (4) as follows:

$$r_t = \mu + \lambda_1 \, sdm_t + \lambda_2 \, sdm_{t-1} + \varepsilon_t \qquad (4)$$

where sdm_t is the market conditional standard deviation, sdm_{t-1} is its lag and λ_1 and λ_2 are their coefficients. A positive λ means that risk-averse investors would require a higher expected return (that is, a higher risk premium) from the industry's returns for bearing more market risk. The conditional mean's error term has the usual properties of being *i.i.d.* (identically and independently distributed) with zero mean and unit variance.

Finally, to ensure that all above specifications do not suffer from typical econometric problems such as residual serial correlation and heteroskedasticity, I perform a battery of diagnostic tests on each estimated model and report them along with the estimates.

4. Preliminary and Main Empirical Results

4.1. Summary statistics

Descriptive statistics on the industries and the stock market nominal returns are shown in Panel A of Table 1. The industries' returns range from a low of 0.667 (*Steel* industry) to a high of 1.075 (*Food* industry) The mean return of all industries is 0.958 relative to 0.510 and 0.466 for the NYSE and SP500 indices, respectively. The *Steel* and *Mining* industries had the highest volatility, which was well above 7%, while the *Utilities* industry had the lowest standard deviation (3.913%), as expected. In all industries (except for of *Oil* and *Consumer*), negative skewness and statistically significant kurtosis are detected. A negative skewness implies that industries tend to have a higher probability of producing large negative returns relative to the normal distribution. High kurtosis (or leptokurtosis) suggests that there is a higher probability of extreme outcomes. Finally, all industries including the stock market display non-normality as evidenced by the statistical significance of the Jarque-Bera (JB) statistic's values.

Panel B of the table depicts the number of firms in each industry per decade. As seen from the numbers, there has been robust growth in all industries from the 1960s to the mid1990s, despite some slowdowns by some of them (*Mining*, *Oil*, *Construction*, *FabPr*, and *Utilities*) but the sharp decline in all industries surfaced since late 1990s and most notable in the 2010s. For example, the *Oil*, *Construction*, *Utilities*, *Retail* industries lost almost half of their firms beginning in the 2000s, while industries such as *Cars* and *Chemicals* remained roughly at the same levels over the decades. Thus, all industries went through the cycles of economic expansions and contractions over the five decades with some having experienced spectacular growth in the 1990s (e.g., *Machinery, Financials*, and *Other*).

4.2. Rolling regressions of industry returns and fundamental variables

Equation (1) is first estimated with all five fundamental variables: industrial production growth, the inflation rate, the credit spread, the (changes in the) dividend yield, and (the changes in) the unemployment rate.[1]

[1] Taking the changes in these variables was necessary to make them stationary. The remaining variables were stationary.

Table 1. Summary statistics on industries and stock market returns

Panel A: Descriptive Statistics

Industry	Mean	Median	St. Dev.	Skewness	Kurtosis	JB stat
1. Food	1.075	1.0600	4.268	-0.121	5.475*	142.22*
2. Mining	1.015	0.8400	7.220	-0.245	4.636*	131.33*
3. Oil	1.014	1.1100	5.346	0.066	4.225*	151.44*
4. Clothing	1.052	1.0760	6.009	-0.237	5.613*	208.33*
5. Durables	0.805	0.9100	5.556	-0.185	5.635*	212.13*
6. Chemicals	0.928	1.0190	5.539	-0.007	5.321*	164.32*
7. Consumer	1.068	1.2900	4.572	0.029	5.655*	153.97*
8. Construction	0.892	0.8900	5.845	-0.094	4.864*	114.44*
9. Steel	0.667	0.6500	7.248	-0.165	5.234*	155.32*
10. FabPr	0.968	1.1100	5.204	-0.476	5.637*	224.65*
11. Machinery	0.970	1.0800	6.274	-0.385	5.030*	160.56*
12. Cars	0.897	0.6000	6.149	-0.007	5.310*	154.77*
13. Transport	1.021	1.2800	5.531	-0.357	4.696*	181.31*
14. Utilities	0.870	0.9900	3.913	-0.121	4.197*	134.65*
15. Retail	1.038	0.9500	5.181	-0.224	3.322*	141.87*
16. Financials	1.005	1.2500	5.371	-0.376	5.694*	132.43*
17. Other	0.897	1.1300	4.738	-0.443	4.418*	112.48*
Average	*0.958*					
NYSE	0.5103	0.8800	4.364	-0.759*	6.082*	307.75*
SP500	0.466	0.6450	4.291	-0.949*	3.872*	312.75*

Panel B: No. of firms in each industry

Industry	1960s	1970s	1980s	1990s	2000s	2010s
1. Food	109	167	154	166	115	90
2. Mining	53	56	80	57	34	44
3. Oil	92	137	289	220	154	148
4. Clothing	108	169	136	136	79	46
5. Durables	115	164	182	188	104	57
6. Chemicals	66	75	81	92	77	71
7. Consumer	69	91	137	193	197	157
8. Construction	129	215	235	198	125	97
9. Steel	93	88	77	84	53	39
10. FabPr	37	66	70	57	37	26
11. Machinery	261	414	698	811	628	439
12. Cars	54	76	66	84	54	50
13. Transport	137	151	150	174	139	111
14. Utilities	123	169	192	184	114	91
15. Retail	147	258	290	365	272	188
16. Financials	116	463	890	1221	955	697
17. Other	308	1005	1407	1875	1675	1240

*Notes: St. Dev. is the standard deviation of the returns and JB stat is the Jarque-Bera statistic for normality; * denotes statistical significance at the 5% level; sample is from January 1960 to December 2021.*

The task in this analysis is to investigate the predictive ability of each of the seventeen industries on the five fundamental variables to see if any of these industries have surfaced as information leaders, decade by decade. Rolling regressions were run (with a twelve-month interval) for all five fundamental variables and all industries starting with January 1961 (since the first year is lost due to the initial estimation) and ending December 2021. I experimented also with 2 years as the initial sample but the results did not change significantly. The yearly results from each regression were averaged for each decade. The optimal lag length, based on the SIC, was two (months). To account for heteroskedasticity, the Newey-West (Newey and West, 1987) heteroskedasticity-correction approach was used. The results are depicted in Table 2, Panels A to E, corresponding to the five fundamental variables used.

Table 2. Fundamental variables and industry leaders by decade, 1960 – 2021

Panel A: *industrial production growth*	
Decade	*Industry leaders*
1960s	Steel*, Machinery, Cars
1970s	Food, Clothing, Chemicals, FabPr, Transport
1980s	Mining*, Oil, Clothing, Consumer*, Construction, Machinery, Utilities*, Financials*, Other*
1990s	Chemicals, FabPr, Transport, Financials
2000s	Clothing, Durables, Chemicals, Steel, Machinery, Transport, Retail*, Financials*, Other*
2010s	Construction*, Food***, Retail*, Utilities***
Panel B: *unemployment rate*	
1960s	Transport
1970s	Clothing, Construction, Cars
1980s	Construction, Steel, Transport
1990s	Steel, Cars, Transport
2000s	None
2010s	None
Panel C: *inflation*	
1960s	none
1970s	Mining, Oil*
1980s	Mining*, Oil,*
1990s	Oil
2000s	None
2010s	Chemicals*, Construction***, Retail*, Utilities***
Panel D: *spreads*	
1960s	Food*, Oil, Durables*, FabPr, Financials*, Other, Cars
1970s	Food, Oil, Durables*, Construction*, Machinery*, Retail, Financials
1980s	Steel*, Machinery*, Utilities
1990s	Mining, Clothing, Chemicals*, Steel*, Cars
2000s	Food, Oil*, Steel*, Financials*
2010s	Cars***, Clothing***, Mining*, Oil***, Steel***, Utilities*
Panel E: *dividend yield*	
1960s	Food, Oil, Consumer, Construction, Steel, Machinery, Cars, Financials, Other
1970s	Food, Mining, Oil, Clothing, Durables, Chemicals, Consumer, Construction, Steel, FabPr, Machinery, Cars, Transport, Retail, Other
1980s	Food, Clothing, Durables, Chemicals, Consumer, Construction, FabPr, Cars, Transport, Retail, Financials, Other
1990s	Consumer, Other

2000s	Mining, Clothing, Construction, Cars, Retail, Financials, Other
2010s	Clothing***, Financials*, Food***, Oil*

*Notes: The spreads variables are the difference between the BAA yields and the 10-year T-note and the 10-yr T-note and the fed funds rate; *, **, *** denote statistical significance at the 1%, 5% and 10%, respectively; two lags in all regressions.*

A number of comments can be made on these results. First, the manufacturing, construction and durable products sectors seem to provide significant explanatory power during each decade on the three of the five fundamental variables, namely the industrial production growth, dividend yield and the credit (or term) spreads. Second, a handful of industries are seen to provide news about the unemployment rate and inflation in the economy. Finally, while the *Mining* and *Oil* industries surfaced as recurrent information leaders in inflation, *Financials* did not emerge as such in either the unemployment or inflation rates. Therefore, it appears that not all industries have the ability to provide information leadership for some macro variables. However, to the extent that these specific industries pay attention to news about the fundamentals in the economy, it can be argued that they deserve having the dominant role in the information propagation mechanism.

4.3. Dynamic interactions among industries and market returns

In this section, I look at the dynamic linkages among the industry returns, the stock market and the macro fundamentals in each decade. I begin with the dynamic interactions among each industry's returns, continue by including the stock market returns and finally, repeat these estimations with the fundamentals as exogenous variables. In other words, equation (2) was estimated in a number of ways. In all instances, a two-month lag specification was again the optimal one for each industry's returns based on the SIC. The fundamental variables, however, entered the model with one lag.[2]

The variance decompositions for each industry and the market, for each decade, with the fundamentals are only presented.[3] The variance decompositions are shown in Table 3.[4] The main takeaways from the table are as follows. First, there appears to be no short-run interactions (linkages) among the industries' returns in any decade despite some of them (e.g., *Cars*, *Chemicals*, and *Construction* and, to some extent, *Consumer*) having emerged as significant predictors of most of the industries' returns. Second, there seems to be persistence in the variance decompositions (innovations) of own returns for many industries in the 1980s and 1990s, which diminished thereafter. Third, stock market returns do not surface as significant contributor to all industries' variances in any decade. Thus, one can conclude that the market's returns do not add anything substantial to the variance of an industry's returns, a result in agreement with prior findings that the market trails movements from the industries.

When observing the variance decompositions of nominal stock market returns (see Table 4) using the S&P500 index returns, I note that the *Cars*, *Chemicals*, *Construction*, *Consumer* industries and, to a lesser extent, the *Financials*, *Machinery* and *Oil* industries surface as important components in their variance decompositions over time.[5] However, their explanatory power appears to be different in each decade. Finally, I repeated this analysis using real returns, for both the industries and the stock market, but did not detect any statistically significant changes from the main results.

[2] There was no evidence of cointegration among the variables and thus a VAR specification was used.
[3] No qualitative change was detected without the fundamentals. In any case, all VAR outputs are available upon request.
[4] I used a 12-month lag period but report only the values corresponding to the lag beyond which there was no change in the values (increases or decreases). Typically, that lag was two months.
[5] I have also used the NYSE index but the results were essentially the same.

Table 3. Variance decompositions for each industry by decade (1960- 2021)

1960s

	Cars	Chem	Cloth	Const	Cons	Dur	FabP	Fin	Food	Mach	Mini	Oil
	Ret	Steel	Trans	Util	Other	NSR						
Cars	94%	0%	0%	1%	0%	0%	0%	0%	2%	0%	2%	0%
	0%	1%	0%	0%	0%	0%						
Chem	54	39	0	0	0	0	1	0	2	0	0	0
	3	0	1	0	0	0						
Cloth	50	13	28	0	0	0	0	0	2	0	0	0
	3	0	0	0	2	0						
Const	43	22	11	17	0	0	0	0	1	0	0	0
	5	0	0	0	0	1						
Cons	37	21	5	0	29	0	0	0	1	0	0	0
	2	0	0	3	0	1						
Dur	0	3	2	0	1	85	2	0	2	1	1	0
	1	1	2	0	0	0						
FabP	38	11	6	2	2	1	32	0	1	0	0	0
	1	0	0	0	1	0						
Fin	36	21	7	5	2	1	0	23	0	0	0	0
	3	0	0	1	0	1						
Food	38	22	6	4	11	1	0	2	11	0	0	0
	1	0	0	1	9	0						
Mach	37	17	6	2	8	0	0	1	2	17	0	0
	6	1	0	1	0	0						
Mini	38	12	12	0	0	1	2	0	0	0	26	0
	5	0	0	1	0	0						
Oil	30	14	2	2	0	0	3	6	0	0	0	40
	0	1	0	0	0	0						
Ret	44	14	3	3	1	0	0	3	0	1	0	1
	22	2	0	0	0	0						
Steel	44	19	4	3	1	2	2	0	0	0	1	0
	3	18	0	1	0	0						
Trans	37	15	11	2	0	0	2	0	0	2	2	0
	7	1	17	1	3	0						
Util	25	17	2	0	8	2	1	11	2	2	1	2
	1	0	0	25	0	0						
Other	43	25	3	2	4	0	0	2	0	0	0	1
	2	0	0	0	14	0						

1970s

Cars	88%	1%	2%	0%	0%	0%	1%	1%	0%	0%	0%	0%
	0%	2%	1%	0%	0%	0%						
Chem	36	47	3	0	0	3	1	1	0	0	0	0
	1	2	0	0	0	2						
Cloth	62	6	21	0	0	1	0	2	0	0	2	0
	2	2	0	0	0	0						
Const	58	12	8	8	0	2	2	4	0	0	1	0
	1	3	0	0	0	1						
Cons	15	21	1	6	39	2	0	4	1	0	3	0
	1	0	2	0	0	1						

Dur	9	1	2	4	12	67	0	0	0	1	0	0
	0	0	0	0	0	0						
FabP	35	18	9	6	0	1	17	4	0	0	0	0
	0	4	0	0	0	0						
Fin	42	11	5	9	2	1	4	16	0	0	2	0
	0	0	3	0	0	1						
Food	39	14	5	4	11	3	3	2	4	9	0	2
	0	1	1	0	0	0						
Mach	38	17	7	5	8	2	3	3	0	12	2	0
	0	2	0	0	0	0						
Mini	18	28	6	6	0	3	7	0	0	0	21	0
	2	2	0	0	1	1						
Oil	15	14	2	6	2	3	6	3	0	1	6	30
	1	4	0	0	0	4						
Ret	58	7	5	3	5	1	1	2	2	0	3	0
	8	2	0	1	0	0						
Steel	35	21	3	2	5	3	5	2	1	1	1	0
	0	15	0	0	0	0						
Trans	46	13	8	3	0	1	3	4	0	1	3	1
	0	2	11	0	3	1						
Util	32	5	6	5	1	2	5	10	3	0	2	6
	0	0	0	17	0	0						
Other	50	13	8	4	2	2	3	5	0	0	0	3
	0	0	1	0	3	0						
1980s												
Cars	85	0	2	0	0	0	0	0	0	0	1	2
	0	0	0	0	0	2						
Chem	55	35	3	0	0	0	0	1	0	0	0	0
	0	0	0	0	1	0						
Cloth	53	8	26	0	0	1	0	3	0	0	3	1
	0	0	0	0	1	0						
Const	58	15	5	11	0	1	0	4	0	0	1	1
	0	1	0	0	0	1						
Cons	44	11	8	0	26	1	0	1	0	0	4	0
	0	0	0	0	0	2						
Dur	0	0	7	3	4	70	1	2	0	0	0	4
	0	0	0	0	0	2						
FabP	48	18	6	3	0	0	14	3	0	0	0	0
	0	0	0	0	1	1						
Fin	44	12	10	2	6	0	0	18	0	0	3	2
	0	0	0	0	0	0						
Food	37	7	9	0	17	0	0	3	16	0	4	2
	0	0	0	0	0	1						
Mach	60	13	2	4	0	0	2	2	1	10	0	0
	0	0	0	0	0	1						
Mini	26	12	2	12	5	2	0	2	1	1	33	0
	0	0	0	0	1	0						
Oil	12	20	3	3	3	2	1	0	0	1	7	38
	0	0	3	1	1	0						
Ret	57	4	17	0	2	2	0	2	1	0	3	1
	6	0	0	0	0	1						

Steel	42	15	0	6	2	0	1	5	0	0	5	1
	0	16	0	0	2	0						
Trans	51	10	6	3	1	0	5	3	0	0	1	1
	0	0	12	0	0	0						
Util	25	8	1	5	13	0	0	10	1	2	3	8
	0	1	0	19	0	0						
Other	53	15	9	2	3	0	1	2	0	0	1	1
	0	0	0	0	4	2						
1990s												
Cars	87	0	0	0	2	1	0	0	0	0	0	0
	0	1	3	0	0	0						
Chem	38	48	0	0	0	2	2	0	0	0	0	2
	0	2	0	0	0	0						
Cloth	24	11	53	0	0	0	0	0	0	0	0	4
	0	1	0	0	0	1						
Const	41	6	17	28	0	0	0	0	0	0	0	2
	1	0	0	0	0	3						
Cons	14	9	7	10	46	0	0	0	1	2	4	0
	0	1	0	1	0	0						
Dur	0	0	0	2	1	91	0	1	0	0	0	0
	0	0	0	0	0	0						
FabP	38	12	12	5	2	0	21	0	0	1	0	0
	0	0	1	1	1	0						
Fin	31	4	3	15	0	0	0	31	1	0	0	3
	2	0	1	0	0	3						
Food	22	7	13	10	15	0	0	0	21	0	0	0
	0	0	0	0	1	3						
Mach	18	19	0	3	0	1	4	1	0	0	1	39
	0	3	0	0	2	4						
Mini	12	6	1	2	2	0	0	0	7	0	61	0
	0	2	0	0	0	3						
Oil	18	19	0	4	0	1	4	2	0	0	2	40
	0	2	0	0	3	4						
Ret	33	5	25	7	1	0	2	0	0	1	0	3
	17	0	0	0	0	0						
Steel	38	20	0	4	2	1	1	0	2	3	4	1
	0	18	0	0	0	2						
Trans	41	22	4	1	1	1	4	1	0	1	0	2
	0	1	13	0	0	2						
Util	8	4	2	6	4	0	0	6	3	3	3	10
	1	1	1	44	0	0						
Other	33	7	9	14	1	0	0	1	1	4	0	3
	2	1	0	1	13	4						
2000s												
Cars	82	2	2	1	0	0	1	1	0	0	0	0
	1	2	1	3	0	0						
Chem	50	43	0	0	0	0	0	0	0	0	0	1
	0	0	0	0	1	0						
Cloth	51	10	28	1	1	0	0	0	0	0	0	0
	0	2	0	0	0	0						

Const	43	5	8	30	1	0	0	1	1	0	0	0
	0	2	0	2	0	1						
Cons	12	9	0	0	70	0	0	0	0	0	1	1
	0	0	0	1	0	0						
Dur	4	0	0	0	3	82	0	0	1	0	0	0
	0	3	2	0	0	1						
FabP	55	8	5	2	0	2	17	0	0	0	0	1
	1	1	0	2	0	0						
Fin	47	7	7	2	3	1	0	25	0	0	0	0
	1	0	0	2	0	0						
Food	22	9	6	0	20	1	1	0	27	0	1	0
	1	0	0	1	3	1						
Mach	34	6	0	1	6	3	4	0	0	40	0	0
	0	0	1	1	0	0						
Mini	20	19	4	3	0	0	2	0	0	1	39	3
	1	0	0	1	0	0						
Oil	18	16	0	0	0	3	4	0	0	0	6	43
	0	0	0	3	0	0						
Ret	50	8	9	1	1	0	0	0	2	0	1	0
	18	5	0	1	0	0						
Steel	40	13	0	3	1	1	5	1	1	11	2	0
	0	14	0	3	1	0						
Trans	49	12	5	1	0	1	0	2	0	0	0	0
	1	3	20	1	0	1						
Util	25	8	0	2	4	2	4	0	0	2	1	7
	3	3	1	33	0	1						
Other	40	9	0	3	4	1	2	1	1	18	0	0
	1	1	1	1	13	0						
2010s												
Cars	78	3	0	1	1	0	0	0	5	0	1	1
	4	0	1	0	0	2						
Chem	47	36	1	0	0	0	0	1	3	0	0	5
	1	0	1	0	0	0						
Cloth	38	3	45	0	4	0	0	0	5	0	1	0
	0	0	1	0	0	0						
Const	41	11	2	33	0	0	0	0	5	1	0	0
	0	0	1	0	0	2						
Cons	15	14	1	11	42	0	0	0	3	0	2	3
	0	0	4	1	0	0						
Dur	0	1	10	10	0	70	1	0	0	0	0	1
	0	1	1	0	2	0						
FabP	66	8	0	1	1	0	12	0	5	0	0	1
	0	0	2	0	0	1						
Fin	51	11	0	4	0	3	0	19	3	0	0	0
	0	0	1	1	0	0						
Food	13	9	2	12	15	0	0	0	30	0	0	4
	1	0	7	0	0	2						
Mach	56	12	2	3	0	0	1	1	3	14	0	1
	1	0	1	0	0	0						
Mini	29	12	1	1	2	0	5	1	1	0	32	4
	0	0	1	2	0	5						

Oil	36	14	3	1	0	0	5	0	0	0	3	29
	1	0	0	0	1	1						
Ret	37	5	15	9	9	1	0	0	6	1	0	0
	11	0	2	0	0	0						
Steel	47	10	0	0	0	0	1	3	1	1	10	2
	0	17	1	0	1	2						
Trans	56	12	0	2	0	0	0	2	4	0	0	1
	1	2	13	0	0	0						
Util	5	1	0	9	14	1	4	10	6	1	1	6
	0	1	5	28	0	2						
Other	47	18	1	8	5	0	0	1	4	2	0	1
	3	0	2	0	5	0						

Note: 2010s spans until 2021.

Table 4. Variance decompositions of nominal market returns, 1960 – 2021, by decade

Cars	Chem	Cloth	Const	Cons	Dur	FabP	Fin	Food	Mach	Mini	Oil	Retail	Steel	Trans	Util	Other
1960s																
40	10	3	1	11	0	0	2	0	0	0	1	3	0	0	1	1
1970s																
42	12	5	2	5	4	2	4	1	1	0	1	1	0	1	0	0
1980s																
48	18	6	2	3	0	0	3	0	0	0	2	0	0	1	0	0
1990s																
27	9	6	9	5	2	1	4	0	3	1	6	1	1	0	1	2
2000s																
38	16	0	1	8	0	4	1	0	7	0	0	0	0	0	0	0
2010s																
43	6	3	5	3	4	2	8	0	3	0	4	0	2	1	0	0

Note: stock returns' own variance decompositions ignored.

5. Further Evidence on the Industries – Market Linkages

5.1. The Impact of the 2007 financial crisis

The 2007 global financial crisis has altered the business and economic landscape of major economies. Hence, it is important to examine the extent and nature of the impact of this crisis on the industries. In addition, given the heterogeneity among and extent of concentration within each industry, all market agents would be interested in determining the magnitude of the impact of the financial crisis. Finally, the analysis will be informative for global investors and portfolio managers with respect to whether potential gains from portfolio diversification are more likely to be achieved by diversifying across industries in times of severe financial stress. Consequently, in this subsection, I present some results on how the industries were linked among themselves, the economic fundamentals and with the market during the 2007 global financial crisis. The financial crisis subperiod is defined here from 2007 to 2010. I compare the findings with the previous and subsequent decades.

Figure 1 displays the simple correlations in each decade without the market (1st graph) and with it (2nd graph). From the first graph, it is evident that the industries' returns were more strongly linked among themselves, reaching a high correlation of 0.737 during the crisis, and a second highest correlation of 0.7331 during the 1970s. From the second graph, I see that the industries – market correlations were lower in each decade, reaching a high value of 0.6558 during the crisis and a low value of 0.3097 during the 1990s. These results are in line with the findings of Laopodis (2011) who found that since the 1990s there has been a disconnection between the stock market and the real economy.

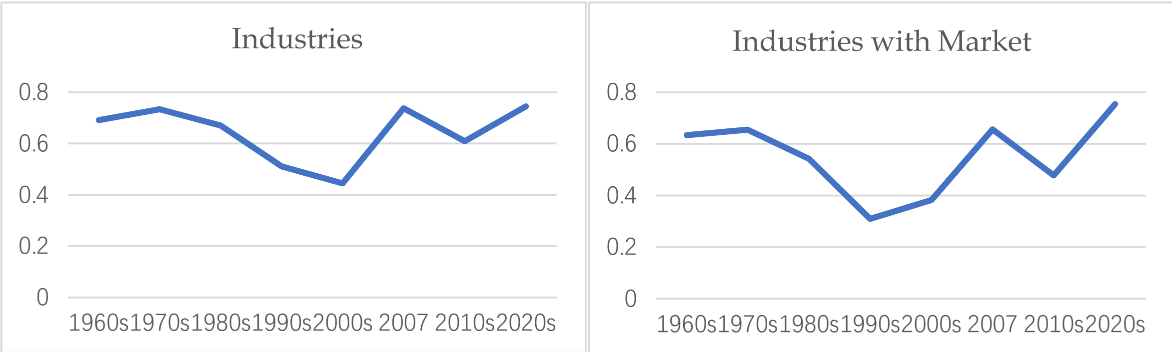
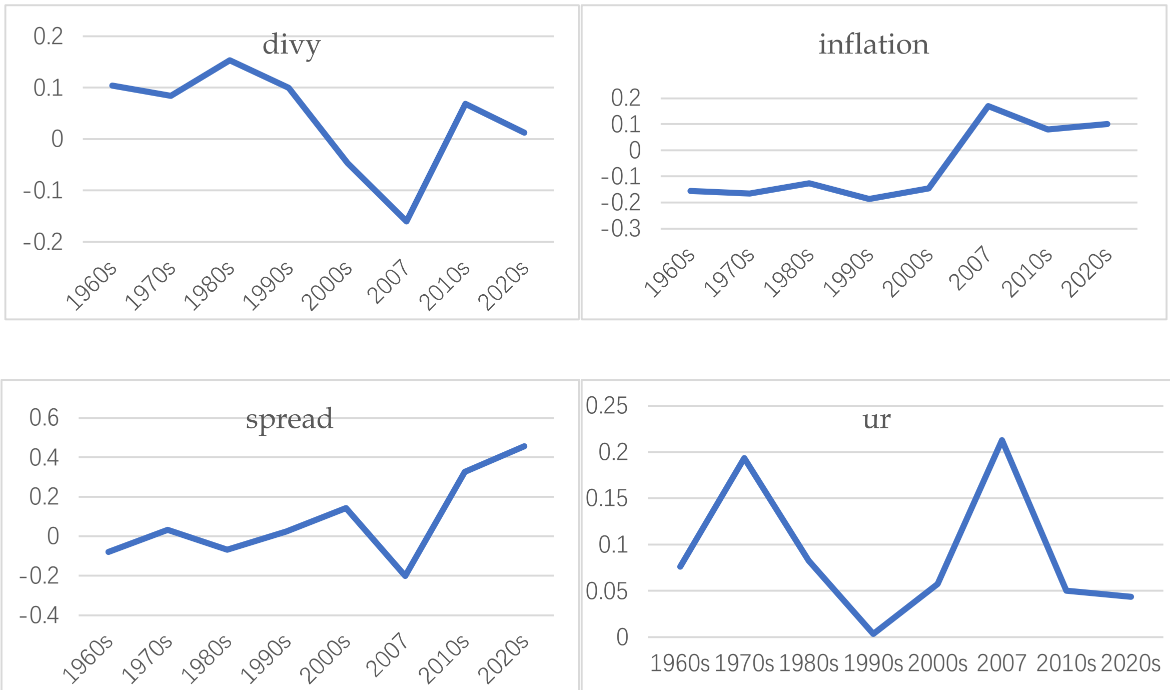


Figure 1. Correlations among industries with and without the stock market

Notes: the 2000s period refers to 2000 – 2006; the 2007 year corresponds to the 2007 – 2010 crisis period.

Figure 2 shows the correlations between all industries' average returns and each of the economic fundaments, decade by decade. The first graph displays the average industry returns correlations with the dividend yield (*divy*). I observe that during the 1960s to 1990s, the correlations were weak, positive and declining (having become negative in 2007), before reverting to being positive (and weak) again in the 2010s. As far as inflation (*inf*) is concerned (2nd graph), I see a negative correlation until the financial crisis, during which it turned positive albeit weak. The correlation with the *spread* (either the term or the credit spread) appears to be variable over the decades, alternating between positive and negative, but its dip during the financial crisis is notable.



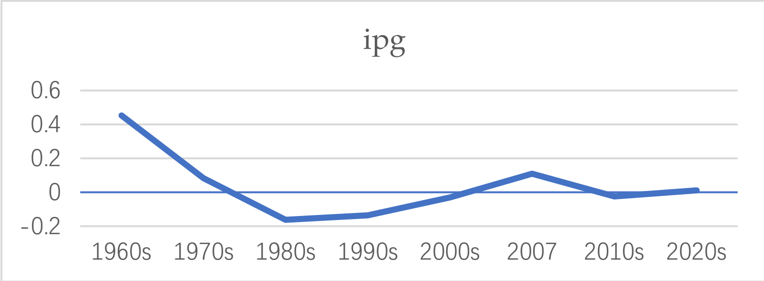


Figure 2. Correlations among industries and fundamentals

Notes: divy refers to the divided yield; spread is the difference between the 10-year Treasury note yield and the federal funds rate; ipg is the growth rate in industrial production and ur is the unemployment rate.

The correlations between the industrial production growth (*ipg*) and those of the industries started as positive in the 1960s and 1970s, then turned sharply negative in the 1980s to 2000s reverting back to being positive during the 2007 crisis, only to become negative again in the 2010s. Finally, the industries' returns correlations with the unemployment rate (*ur*) remained always positive over the six decades.

In all, what is the message from these results? These simple findings highlight a number of important insights about the general linkages between the United States' real and financial sectors. First, I conclude that there have been weak correlations between the industries' returns and economic fundamentals in each decade. This finding corroborates our earlier findings of little linkages between the magnitudes. Second, some correlations are counter-intuitive given the extant evidence. For example, the empirical literature has documented a strong linkage between stock returns, the dividend yield and industrial production growth (Schwert, 1990, and Fama, 1990). Third, the negative correlations between industry returns and inflation (Boudoukh and Richardson, 1993 and Schotman and Schweitzer, 2000) and the unemployment rate (Gonzalo and Taamouli, 2017) are well-documented in the literature.

The final point to make on these findings is that the 2007 global financial crisis has greatly changed the nature and extent of interactions between the real and financial economy. Many of the economic variables appear to have altered their relationship to industry returns due to the elevated risk levels of the 2007 financial situation. Thus, the breakdown in the dynamic interactions among the market and economic fundamentals (Laopodis, 2011), which began in the 1990s, became more pronounced during the financial crisis.

5.2. Stock market and industry returns volatility linkages

In this subsection, I explore the dynamic linkages among industry returns and the stock market at the volatility level. To that end, I employ the bivariate GARCH-in Mean (GARCH-M) specification.

Table 5 contains the empirical results from the bivariate GARCH-M (1,1) model.[6] The optimal lag length was one lag (month) for all industries and the market based on SIC. I begin with the question of whether stock market volatility affects the conditional mean of each industry's returns. As mentioned in the methodology section, if such an important relationship exists it would imply a proportional return–market volatility tradeoff. The model was run both with the assumptions of normality and generalized error distribution (GED). All results presented in the table pertain to those with the GED assumption (in all cases, the GED parameter was statistically significant).

Unfortunately, following the relevant literature the evidence on the relationship between stock returns' conditional mean and volatility is, at best, inconclusive. For example, French et *al*. (1987) and Campbell and Hentschel (1992) find a positive correlation between the two, while Nelson (1991) and Glosten et *al*. (1993) note a negative correlation. Finally, Harvey (2001) using exogenous predictors, finds that the relationship depends on the

[6] The results for the volatility linkages among the industries are not presented but are available upon request.

model selected as well as the conditioning information on both the mean and variance specifications. In this paper, I take the simplified view of examining the impact of market's volatility on each industry's returns and vice versa, *ceteris paribus*. The first two columns of the table show the impacts of the contemporaneous and lagged conditional standard deviation from the stock market (*sdm*) to each of the industries' returns, while the fourth and fifth columns show the impacts of the contemporaneous and lagged conditional standard deviation from each industry (*sd*) to the stock market's returns, respectively. The table displays each coefficient with its corresponding t-statistic.

Table 5. Industry and Stock Market Volatility Spillovers

Industry	From the market (*sdm*)			From an industry (*sd*)		
	To industry mean		To industry variance	To market mean		To market variance
	sdm_t	**sdm_{t-1}**	**sdm_t**	**sd_t**	**sd_{t-1}**	**sd_t**
Food	0.1242	0.2478	-0.1673	0.1587	0.3094*	0.1756
	(1.062)	(1.464)	(-0.607)	(1.056)	(2.467)	(0.699)
Mining	0.4712	0.5601*	0.1311	0.0089	0.1302	0.1513**
	(1.472)	(1.987)	(0.122)	(0.056)	(1.034)	(2.786)
Oil	0.0071	0.0876	0.0970	-0.1699	-0.0174	0.3444**
	(0.093)	(0.299)	(0.163)	(-1.228)	(-0.107)	(3.287)
Clothing	0.5014	0.7886*	0.2215*	0.0277	0.1469	0.1727
	(1.235)	(2.277)	(2.348)	(0.218)	(1.319)	(0.645)
Durables	0.0608	0.3361	1.8271**	0.2136	0.4022**	-0.1254
	(0.173)	(0.897)	(2.867)	(1.127)	(3.171)	(-0.339)
Chemicals	0.2785	0.6091*	1.1086*	0.1213	0.3015*	0.1006
	(0.756)	(1.901)	(2.297)	(0.657)	(2.398)	(0.276)
Consumer	0.0697	0.1391	0.0441	0.1603	0.3671*	0.0589
	(0.365)	(0.717)	(0.110)	(0.963)	(2.745)	(0.195)
Construction	0.5002	0.7013*	1.866**	0.0508	0.1561	0.3378**
	(1.534)	(2.071)	(6.357)	(0.403)	(1.331)	(3.476)
Steel	0.1978	0.3712	1.1198	-0.0942	-0.0031	0.4789
	(0.489)	(1.161)	(1.141)	(-0.744)	(-0.030)	(1.304)
FabPr	0.3936	0.5316*	0.9701	0.0572	0.3249	0.4236
	(1.581)	(2.110)	(1.786)	(0.238)	(1.746)	(0.787)
Machinery	0.3682	0.5335*	0.5221*	-0.0611	0.0766	0.6545
	(1.114)	(1.867)	(2.261)	(-0.513)	(0.671)	(1.276)
Cars	04538	0.8336*	0.4791*	-0.0320	0.1065	0.0286
	(1.272)	(2.451)	(1.850)	(-0.186)	(0.709)	(0.100)
Transport	0.2208	0.4816	0.4521*	0.0171	0.2456*	0.7114
	(0.650)	(1.481)	(1.813)	(0.106)	(1.821)	(1.412)
Utilities	0.1283	0.0971	-0.0233	-0.2828	-0.0368	0.5334**
	(0.583)	(0.412)	(-0.064)	(-0.964)	(-0.136)	(4.478)
Retail	0.4879	0.6341*	0.1038	0.1169	0.2467*	0.2457
	(1.612)	(2.406)	(1.248)	(0.750)	(2.245)	(0.834)
Financials	0.1024	0.3561	0.1287	0.0246	0.1845	0.3534**
	(0.255)	(0.951)	(0.934)	(0.147)	(1.511)	(4.645)
Other	0.3141	0.3910	0.5233	-0.0367	0.1591	0.3311**
	(1.023)	(1.651)	(0.697)	(-0.208)	(1.167)	(5.176)

***Notes**: This table contains the results from a GARCH-M(1,1) with each industry's and the market's returns, as conditional means and their corresponding conditional standard deviations; the model was estimated with the assumptions of a generalized error distribution; t-ratios are in parentheses; *,** denote statistical significance at the 5% and 1% levels, respectively; values below the sdm_t and sdm_{t-1} columns indicate the coefficients of the market's contemporaneous and one-month lagged conditional standard deviation on each industry's conditional mean,* *respectively; similarly, the values below sd_t and sd_{t-1} columns refer to the coefficients of each industry's contemporaneous and one-month lagged conditional standard deviation on the market's conditional mean, respectively; values below the column labeled 'To industry variance' pertain to the coefficients measuring the contemporaneous impact of the market's conditional standard deviation (sdm_t) on each industry's conditional variance; similarly, the values below the last column labeled 'To market variance' denote the coefficients measuring the contemporaneous impact of each industry's conditional standard deviation (sd_t) on the market's conditional variance.*

The results reveal insignificant but positive contemporaneous volatility spillovers from the market to all industries. Similarly, there are no significant (yet mostly positive) volatility spillovers from any industry to the market. However, when trying the one-month lagged conditional standard deviations of each industry and the market, the results showed strong statistical significance. Specifically, the one-month, lagged market conditional standard deviation surfaced as significant for eight (*Mining, Clothing, Chemicals, Construction, FabPr, Machinery*, *Cars* and *Retail*) out of the seventeen industries. The finding that the market's volatility affects the above industries makes economic sense if one realizes that these industries comprise most of the goods-producing super sector of the US economy. Next, six (*Food, Durables, Consumer, Transport* and *Retail*) out of the seventeen industries' lagged conditional standard deviations revealed strong statistical significance in affecting the market's returns. The service-producing sector, which includes the *Food* and the *Transport* industries, was also found to add to market volatility. In general, these findings are in accordance, in part, with the earlier findings that the industries and the aggregate stock market affect each other (albeit at the mean level).

Taken together from these findings, it can be inferred that investors in those industries might be rewarded for their exposure to higher levels of volatility coming from the aggregate stock market. Such reward, however, may not be felt immediately for those investors but with a delay. This finding is in line with our earlier evidence that stock market returns may not significantly affect all industries' returns. In general, movements in the stock market's volatility may not always be important in explaining many U.S. industries' returns and that other variables might be relevant to investors when attempting to formulate expected returns (see also Baillie and DeGennaro, 1990).

The next question is whether an industry's conditional volatility affects the market's volatility and vice versa. The third column of the table pertains to market volatility spillovers to each industry's conditional variance, whereas the last column refers to the spillovers from each industry's volatility to the market's conditional volatility. In none of the cases, a second lag of the market's conditional standard deviation was statistically significant. From the results, it can be seen that market volatility contemporaneously affects the *Clothing, Durables, Chemicals*, *Construction, Machinery, Cars* and *Transport* industries' conditional variances. Furthermore, the *Mining, Oil, Construction, Utilities, Financials* and *Other* industries' volatility significantly impact the market's volatility. The fact the *Oil, Utilities* and *Financials* industries' volatilities are seen to affect market volatility makes good economic sense in view of their special status within the economy. The finding that oil price volatility affects market volatility is intuitive because stock returns of firms (and, by extension, industries) fall due to lower expected profitability (Alaali, 2020; Joo and Park, 2021). Similarly, when financial volatility is high corporations may have to pay higher rates to raise capital. Consequently, they will be less likely to undertake new capital investments thereby depressing the entire industry. Finally, the utilities sector can affect industries because higher volatility in energy and other necessary services lead to higher costs of production and thus reduced production. In all, these negative impacts on all industries will be reflected in the stock market.

To further shed light on these industries' significance within the economy and impact on the general stock market, it is instructive to view their conditional variances (or standard deviations). Figure 3 exhibits the conditional standard deviations of the some of the above-mentioned industries (*Durables, Construction, Cars, Mining, Oil, Utilities, Financials* and *Other*) for the entire period. As is evident from these graphs, each industry has its own conditional volatility pattern. For example, the *Durables*, *Cars* and *Mining* industries exhibited higher volatility only since the late 2000s, while the *Construction, Financials* and *Other* industries experienced high volatility throughout the 1957–2014 period. By contrast, some industries such as *Utilities*, despite being the one with the lowest volatility, exhibited higher volatility (but still lower than that of the above industries in the 2000s) during the mid-1970s and/or mid 1980s and not much in subsequent years. Finally, the *Oil* industry had highly volatile periods during some years in the 1970s and in the late 2000s.

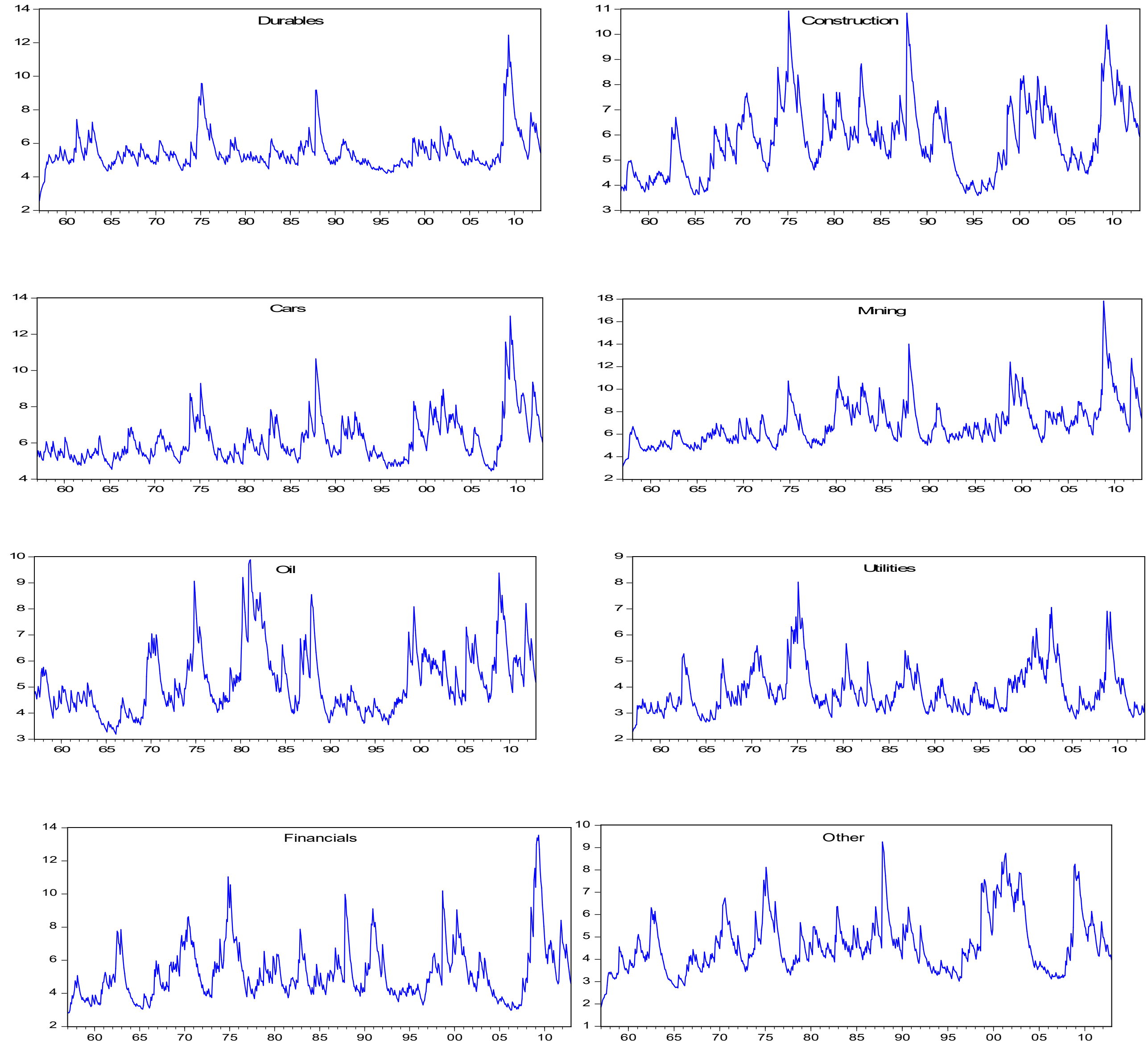


Figure 3. Conditional standard deviations of selected industries, 1960 – 2021

Therefore, it is important to highlight that the size of volatility of some of the above industries was much larger during the 2000s and/or during the 1970s and 1980s compared to the previous years, as seen from the graphs. Finally, since it may be suspected that these higher volatility subperiods may drive these results, the GARCH model was rerun with each of these sub-periods in assessing each industry's volatility impact on market volatility. The ensuing results, in general, showed that they were not (statistically) significantly influencing the general results obtained above.

5.3. Industry returns and market structure

In this section, I examine the relationship between an industry's returns with the concentration of firms in that industry. Evidence suggests that firms in highly concentrated industries earn lower returns after controlling for firm characteristics such as size and book-to-market and other macro variables (Hou and Robinson, 2006). It is also possible for highly concentrated industries to have a high(er) correlation with economic fundamentals than for low concentration industries. As a result, these industries' returns may follow (be correlated with) market returns.

To test the above conjectures, I construct a Herfindhal-type index (along the lines of Hou and Robinson, 2006), H_{ij}, as follows:

$$H_{ij} = \sum_{i=1}^{n} s^2_{ij} \qquad (5)$$

where s_{ij} is the number of firms in industry i relative to the seventeen industries' total number of firms, j (seventeen in our sample). This ratio is computed for every month in order to create a series of such ratios for all industries and for all the months from 1960 to 2021. Small values of the index imply that the industry is comprised of many competing firms, while large values that the industry is concentrated in the hands of a few firms. An alternative measure would be to take the log of each industry's number of firms for every month creating a proxy for size (S) in an industry.

Thus, I set up a regression of the following form with the above variables (H and S) included one at a time:

$$R_i = a_i + \beta_m R_m + \beta_c Z_i + \varepsilon_i \qquad (6)$$

where R_i is an industry's return, R_m is the market return and Z_i the concentration ratio or the size variable.

Table 6 contains selected statistics on the concentration ratios of each industry for the entire sample period. As seen from the table, the industries with the highest concentration ratios (looking at the means for the full sample period) are *Financials*, *Machinery*, *Other* and *Oil*. The lowest concentration industries are *Cars*, *FabrPr*, and *Food*.

The regression results are shown in Table 7. Instead of reporting coefficients and their related statistics, I ran rolling regressions and computed the p-values of the concentration ratio and the size variables for every decade. The regressions had an estimation window (starting point) of one year (January 1960 to December 1961) and the estimation step was 12 months each time. If the variable's p-values were equal to or lower than 0.05 (corresponding to the 5% level of significance) I designated as significant (*yes*) and not significant (*no*). From the results, it appears that there was no statistical significance of the Herfindhal index across industries and decades. Similar results were obtained using the size variable (but these are not reported, although available upon request). Thus, the general tentative conclusion is that concentration ratios and/or the size of an industry do not impact an industry's returns (at least, as examined within this specification).

Table 6. Selected statistics on industry concentration ratios, 1960 - 2021

Statistic	Industry								
	Cars	Chemicals	Clothing	Construction	Consumer	Durables	FabPr	Financials	
Mean	0.0171	0.0203	0.0296	0.0429	0.0336	0.0331	0.0124	0.1536	
Median	0.0142	0.0177	0.0236	0.0398	0.0334	0.0325	0.0109	0.1862	
Max	0.0349	0.0388	0.0634	0.0668	0.0477	0.0605	0.0201	0.2218	
Min	0.0098	0.0130	0.0107	0.0234	0.0213	0.0148	0.0063	0.0356	
	Food	Machinery	Mining	Oil	Other	Retail	Steel	Transport	Utilities
Mean	0.0124	0.1536	0.0358	0.1263	0.2745	0.0412	0.0222	0.0407	0.0402
Median	0.0280	0.1284	0.0134	0.0396	0.2920	0.0596	0.0139	0.0305	0.0354
Max	0.0811	0.1539	0.0311	0.0797	0.3819	0.0839	0.0704	0.1094	0.0981
Min	0.0215	0.1044	0.0052	0.0272	0.1137	0.0492	0.0086	0.0255	0.0204

Table 7. Statistical significance of concentration ratios

Industry	Decade					
	1960s	1970s	1980s	1990s	2000s	2010s
			Statistical significance			
Cars	yes	no	no	no	yes	no
Chemicals	yes	no	no	yes	yes	no
Clothing	no	yes	no	yes	no	no
Construction	no	no	no	no	yes	no
Consumer	no	no	no	no	no	no
Durables	yes	no	no	no	no	no
FabPr	yes	no	no	no	no	no
Financials	no	yes	no	no	no	no
Food	no	no	no	no	yes	no
Machinery	no	no	no	no	no	no
Mining	no	no	no	no	no	no
Oil	no	yes	no	no	no	no
Other	no	no	no	no	no	no
Retail	no	yes	yes	yes	no	no
Steel	no	no	no	no	no	no
Transport	no	no	no	yes	yes	no
Utilities	no	no	yes	yes	no	no

Notes: this table shows the p-values of the Herfindhal index (H) coefficient; 'yes' means statistical significant and 'no' means no statistical significance.

Early research by Brozen (1971) found that high returns are not persistent in the high-stable concentration industries. Later research by Chang et al. (2010) examining the Taiwan-listed companies into 85 industries found that firms in more concentrated industries are relatively experiencing lower stock returns, among other findings. Finally, Grullon et al. (2019) indicated that over 1990s and 2000s firms in industries experiencing increases in concentration levels have achieved higher profitability.

5.4. The impact of COVID-19

There are various ways that one can test the impact of the pandemic period on stock returns. For example, one can use a dummy variable for the period in a regression or use the actual number of COVID-19 cases. In this subsection, I use regression analysis with the Daily News Sentiment Index (DNSI), which is a high-frequency measure of economic sentiment based on actual words on economics-related news articles from 24 major U.S. newspapers. The index is described in Buckman et *al*. (2020) and its methodology in Shapiro et *al.* (2020). Figure 4 shows the monthly changes in the index from January 2019 to December 2021. As is clearly evident, the index dropped significantly during 2020 but began rising thereafter, which implies recovery and a better consumer sentiment. Thus, I examine the nature and extent of the impact of the changes in DNSI on these US industry returns during that period.

I estimate a time-series regression model with returns of industry as the dependent variable and DNSI as the independent variable, with and without the stock market, as follows:

$$R_{it} = \alpha_i + \beta_1 \, DNSI_{t-1} + \gamma_i \, R_{i,t-1} + \delta \, MR_t + \varepsilon_{it} \qquad (7)$$

where R_{it} is the returns for each of the seventeen industries, *DNSI* is the monthly change in the index (used with a lag) and *MR* is the stock market return (measured by the NYSE and/or the SP500 index). The main interest is on the coefficient β_1, which specifies the effect of a change in (the lagged) DNSI on R_{it}. Finally, I employ the Newey-West approach to correct standard errors for autocorrelation and heteroskedasticity.

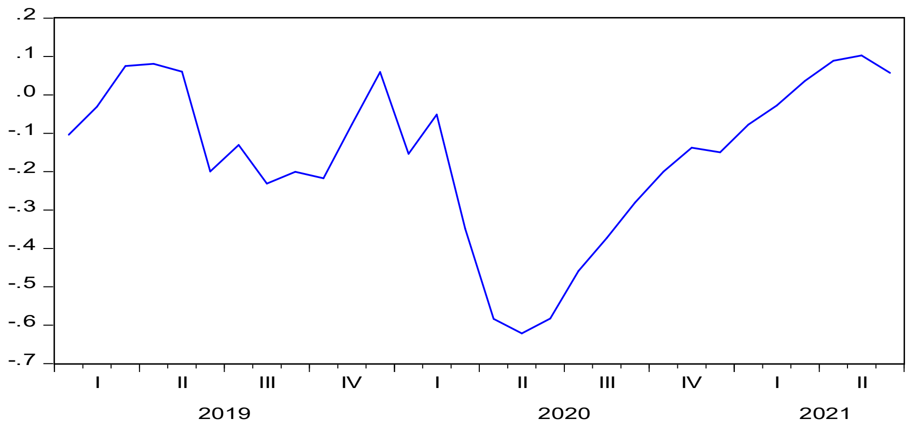


Figure 4. Monthly changes in the Daily News Sentiment Index (DNSI)

Table 8 contains the results from the regressions for each industry with the stock market. The R-squared values ranged from a low of 3% to a high of 20%. From the results, it can be seen that fourteen out of the seventeen industries suffered from past movements in the sentiment index and six of them in a highly statistically significant manner. Also, the high values of the estimated coefficients attest to the greater impact to the stock returns of these industries during the pandemic period. For example, a one-unit increase in the sentiment index resulted in a 31% decline in the *car* industry, 11% in the *clothing* industry but only 2% in *consumer* spending.

Let us discuss this 'counter-intuitive' finding. At first, it is important to mention that a vast literature on the impact of consumer (and investor) sentiment on stock and industry returns exists. Baker and Wurgler (2006, 2007) analyzed the impact of sentiment over the cross-section of returns. The study reported that at the time of high (low) sentiment, speculative and optimistic stocks give low (high) returns. Put differently, when investor sentiment is low, subsequent returns are much higher for some industries characterized by low capitalization, highly volatile, unprofitable, non-dividend-paying, with extreme growth potential or distressed stocks. When sentiment is high, such categories of stock earn relatively low subsequent returns. Verma et al. (2008) and Kumari and Mahakud (2015) studied the sentiment in rational (institutional) and irrational (retail) investors and reported that the impact of irrational sentiment on stock returns was immediate and distinct, among other findings. There is also asymmetry in sentiment changes where high/low sentiment is stronger/weaker in impact. Hence, periods of higher investor optimism tend to be followed by lower future returns, which are more pronounced for industries that are hard to price and during a global crisis such as the health pandemic.

Interestingly, there were some industries (*Financials*, *Oil* and *Utilities*) whose stock returns were boosted by declines in market sentiment. This finding makes sense because these entail staple products for people and it is hard to drastically cut down on them, even during severe global crises. In addition, pair this conclusion with the fact that consumer spending was one of the industries which had the smallest negative impact, as mentioned above.

In sum, the COVID-19 pandemic indeed affected most industries in the US albeit in a different manner. Perhaps, the short-lived, negative sentiment index was responsible for these results that were statistically insignificant for some industries. Nonetheless, the world pandemic's impact was serious and strong, and many industries worldwide suffered from it. Szczygielski et al. (2022) found that the COVID-19 pandemic has affected all industries worldwide and lead to higher volatility. Beak et al. (2020) reported that they documented significant increases in systematic risk for defensive industries, such as telecom and utilities, but decreases in systematic risk for aggressive industries, such as automobiles and business equipment.

Table 8. Impact of COVID-19 on US industry returns

Industry	constant	$DNSI_{t-1}$	RNYSE	R_{t-1}	R^2
Cars	0.2779	-31.623***	0.8490	-0.3415*	0.1978
	(0.389)	(0.176)	(0.543)	(0.171)	
Chemicals	0.2586	-6.574	-0.2763	0.2206	0.0567
	(1.879)	(5.125)	(0.288)	(0.278)	
Clothing	0.4383	-11.277***	1.0671***	-0.7061***	0.1678
	(1.078)	(2.767)	(0.296)	(0.225)	
Construction	1.0921	-12.456	0.5116	-0.3410	0.1168
	(1.118)	(7.567)	(0.421)	(0.287)	
Consumer	0.7841	-2.2645	-0.1708	0.1816	0.0567
	(0.798)	(2.001)	(0.262)	(0.187)	
Durables	0.6610	-7.436**	-0.6160	0.5864	0.1733
	(0.778)	(4.041)	(0.567)	(0.487)	
FabPr	1.4191	-5.911*	0.2646	-0.1619	0.0500
	(0.867)	(2.301)	(0.345)	(0.176)	
Financials	2.1167	1.3920	0.2628	-0.1817	0.0501
	(2.001)	(2.889)	(0.345)	(0.234)	
Food	1.0801	-1.2291	0.0413	-0.0517	0.0034
	(1.001)	(1.878)	(0.109)	(0.102)	
Machinery	1.8230	-7.6915**	0.3692	-0.3558	0.0678
	(1.501)	(3.912)	(0.528)	(0.401)	
Mining	1.9448	-3.9852	-0.3838	0.2931	0.0508
	(1.890)	(3.987)	(0.342)	(0.223)	
Oil	2.8789	5.2581	-1.3978*	0.4660*	0.0889
	(2.889)	(5.123)	(0.728)	(0.230)	
Other	1.6042	-9.9481***	0.6349	-0.6542	0.1201
	(1.021)	(3.210)	(0.399)	(0.368)	
Retail	0.9565	-7.6521***	-0.2805	0.0778	0.2035
	(0.998)	(2.901)	(0.254)	(0.089)	
Steel	1.8451	-1.5063	-0.7531	0.4729*	0.0720
	(1.987)	(2.223)	(0.451)	(0.201)	
Transport	0.6382	-3.4171	1.1456*	-0.7556*	0.0989
	(0.778)	(3.117)	(0.512)	(0.345)	
Utilities	0.9589	1.1201	0.2078	-0.1878	0.0302
	(1.001)	(1.889)	(0.342)	(0.197)	

*Notes: $DNSI_{t-1}$ is the lagged Daily News Sentiment Index, R is the market return proxied by the NYSE; R_{t-1} is the industry's lagged return; *, **, *** denote statistical significance at the 10%, 5% and 1%, respectively.*

5.5. Robustness tests

In this subsection, some implicit robustness tests are carried out in the previous empirical analyses and then some additional ones (based on alternative specifications) are done in order to validate the above findings. These robustness tests, however, did not qualitatively change our results. First, both the SP500 and the NYSE market indices were employed but there were not any statistically significant changes in the results reported earlier. In addition, the real stock returns were used instead but, again, the results were essentially the same. Second, different spreads, a credit and a term spread, were used but again these did not exert any differential impacts on the main results. Regarding the volatility model, it was again estimated with the normality assumption, but the overall results did not indicate statistically significant deviations. Finally, the volatility model was rerun for some subperiods, but the results did not imply any deviations from the main findings.

As an additional robustness test, the Exponential GARCH-M specification was estimated but no significant changes from the reported results above were detected. The only noteworthy result to mention is that the one-month lag of the stock market (sdm_{t-1}) coefficient was more often statistically significant than with the GARCH-M specification. Also, the model was re-estimated decade by decade but, on average, these results corresponded to those reported above (in terms of statistical significances and average sizes of the estimated coefficients).

Finally, when estimating equation (7) without the stock market (SP500 or NYSE), the results were much weaker compared to the ones with the stock market and so only the former results were reported. The NYSE index was a bit better (in terms of the R-squared values) than the SP500 in the regressions.

6. Conclusions

This paper investigated industry returns as a source of information to other industries. I hypothesized that an industry's ability to forecast stock market returns depends upon its capacity to efficiently interpret and disseminate information emanating from the macroeconomic fundamentals. With that in mind, I set out to examine the lead-lag interactions among seventeen large industry portfolio returns, the aggregate stock market and a number of leading fundamental variables, namely (term and credit) spreads, the stock market's dividend yield, the rates of inflation and unemployment, and industrial production growth, for the United States, from 1960 to 2021.

The results indicate that the above-mentioned macroeconomic variables offered significant explanatory power for most of the industry portfolios examined, albeit to varying degrees. A number of leading industries provided valuable information to the stock market as early as one or even two months ahead. In addition, certain industries' returns, particularly *Oil* and *Financials*, entailed an important source of information that could be exploited by the other industries. This result was asserted via the deployment of alternative econometric methodologies. Further examination of the dynamics among industries and the stock market, with and without controlling for the fundamental variables, revealed that stock market movements did not surface as significant contributors to the industries' variances in any decade.

When considering the dynamic interactions between each industry and the stock market at the volatility level, I observed that stock market and industry volatilities did not always affect each other's returns. Thus, it can be inferred that a market risk–return profile for investors in these industries may not always be economically significant and timely. Similarly, when the impact of each industry's volatility on market volatility is assessed, results are mixed, with *Oil* and *Financials* exhibiting a strong relationship. The 2007 global financial crisis appears to have altered the linkages between the fundamentals and the financial market and hence, the disconnection between the market and economic fundamentals, which began in the 1990s, became more pronounced during that period. Further, the COVID-19 period also negatively impacted almost all the industries albeit to differing extent. Finally, when examining the industries' dynamics with concentration ratios, via a Herfindhal-type index, it was found that concentration ratios and/or the size of an industry did not impact an industry's returns.

The implications of these results are clear. First, portfolio traders can use industry returns, instead of firm returns, in their portfolios so as to take advantage of inter-industry information flows. Second, understanding the feedback of information between the industries and the stock market would greatly enrich trading agents' valuations of industries. Finally, given that financial and other crises do affect industries, although at varying degrees, managers of companies in these industries need to know the sensitivity of their company to such extraordinary events and react accordingly.

Funding Statement

This research received no external funding.

Acknowledgments

The author is indebted to two reviewers whose comments greatly improved the paper. Any errors are his own.

Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

Appendix: Industry descriptions

Food	Foods
Mines	Mining and Minerals
Oil	Oil and Petroleum Products
Clths	Textiles, Apparel & Footware
Durbl	Consumer Durables
Chems	Chemicals
Cnsum	Drugs, Soap, Perfumes, Tobacco
Cnstr	Construction and Construction Materials
Steel	Steel Works Etc
FabPr	Fabricated Products
Machn	Machinery and Business Equipment
Cars	Automobiles
Trans	Transportation
Utils	Utilities
Rtail	Retail Stores
Finan	Banks, Insurance Companies, and Other Financials
Other	Other

Source: K. French's website.

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