Distribution Agreement

Sichen Zhu April 13, 2020

Stock Price Comovement and Location Effect

by

Sichen Zhu

Zhanwei Yue
Adviser

Economics

Zhanwei Yue

Adviser

Zha Tao

Committee Member

Yifeng Zhu

Committee Member

Davide Fossati

Committee Member

Le Chen

Committee Member

2020

Stock Price Comovement and Location Effect

By

Sichen Zhu

Zhanwei Yue

Adviser

An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
Bachelor of Arts with Honors

Economics

2020

Abstract

Stock Price Comovement and Location Effect
By Sichen Zhu

I investigate stock return comovement based on locations over the period from 1988 to 2018. It is found that while the comovement effect is significant in the first half of the sample, it gradually declines to zero over years. Two possible factors, the Great Recession and market efficiency, that may have caused this gradual decline are also tested. I argue that the Great Recession is not the key reason that explains this decline in comovement effect. Furthermore, a qualitative study on asset values managed by operating hedge funds suggests that the growing trend for hedge funds increases the overall market efficiency, thus contributing to this decline.

Stock Price Comovement and Location Effect

By

Sichen Zhu

Zhanwei Yue

Adviser

A thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
Bachelor of Arts with Honors

Economics

2020

Table of Contents

Introduction and Literature Review…..…………………………………………………..1

Data Availability …………………………………………………..……………..3

Methodology and Results …………….………………………………………………..8

Conclusion …………….……………………………………………………………11

Appendix …………….……………………………………………...………………15

I. Introduction and Literature Review

Stock return comovement has long been a topic central to economic research. Scholars have studied the comovement pattern in different segments of the world and tried to investigate the reasonings behind the correlation patterns in stock market. As among the first to discover such comovement behavior, Pindyck and Rotemberg argued that stock prices tend to move together due to changes in current or expected future economic fundamentals such as macroeconomic conditions (1993). From then on, many scholars were working on verifying stock price comovement around the world. For instance, Brooks and Negro noticed clear evidence on international stock market comovement and further developed a factor model containing country factors (2003). Jang and Sul, from a different perspective, limited the scope from global to Asian financial market and proved that the strength of stock return comovement was very strong in some periods (2002). Brooks and Negro further shifted their focus from global to national stock market in United States, as a much stronger pattern of firm-level stock return comovement could be well observed present during mid 1990s. They also concluded that the comovement pattern was not permanent due to the IT bubble shock.

Nevertheless, even if Brooks and Negro pioneered to study comovement effect in domestic market opposed to international financial market, a highly limited amount of literature has explored the domestic comovement pattern across regions. This study, yet, should be desirable because a great number of research papers have discussed the correlation between firm location and stock returns. There are some earlier literature investigating the effects of locality on firms in light of investors' decisions. Coval and Moskowitz documented the tendency for investors to overweight portfolios that contain proximate firms due to information asymmetry, causing a significant issue of asset mispricing (1999). It was one of the earliest literatures that revealed the fact that geographical factors could have a profound impact on firms. The more recent literature supported this geographical perspective by focusing on how particular geographical attributes influence firm decisions. Moretti and Wilson discovered that state taxes have big effects on the distribution of labor supply and on the ability for firms to attract high skilled workers. Dougal, Parsons and Titman gave another thorough study with an emphasis on uncovering how demographic features, particularly education level and pleasant weather, could explain firms' value creation (2006). Furthermore, they evaluated whether this effect differs across firms with different levels of human capital. The discussion of firms and geographical areas could well give rise to a deeper understanding of labor supply, asset pricing as well as regional economy. It could also contribute to some meaningful implications for firms' business decisions.

Therefore, it is natural to justify that firms in the same geographical regions tend to operate and move together, causing a strong stock price return comovement. Pirinsky and Wang tested for the 1988-2002 period and validated that strong stock return comovement across states (2003). I plan to extend this sample period to 2018 and examine if the comovement pattern persists and if the economic development in the past fifteen years has any influence on this pattern. My study measures the strength of comovement by evaluating the relationship between individual stock return and returns of the stocks in the same region. The second section illustrates the source of data, such as geographical, economic and financial data, utilized in the study. The third section discusses the methodologies and displays the results from OLS regressions. In this section, it is confirmed that the stock return comovement pattern was strong prior to the year of 2003. It is also suggested that the period after the year of 2003 does not experience a significant comovement effect, driving the overall comovement effect in the entire sample period to be extremely small. The third section furthers seeks explanation why there exists a change in comovement effect around the year of 2002. Two possible explanations, recessions and market efficiency, are carried out and examined. A quantitative approach is adopted for examining the recession hypothesis and it is concluded that the Great Recession does not contribute to such decline in comovement effect. A qualitative methodology is utilized for evaluating the market efficiency perspective, as it is very difficult to quantify market efficiency by numeric data. I consider the growing trend for hedge funds as a key driving force for increasing market efficiency due to how hedge funds typically trade. It is observed that there could exist a relationship between the time when hedge funds start soaring in financial market and the time when the comovement effect begins declining.

II. Data Availability

Following Christo Pirinsky and Qinghai Wang, my study also investigates all domestic common stocks traded on NYSE, AMEX, and NASDAQ, excluding REITs, closed-end funds, and ADRs over the period from 1988 to 2018. Firms' corresponding zip codes are obtained from the Compustat dataset. The U.S. Census website provides the one-to-many relationship between zip codes and Federal Information Processing Standards codes (FIPS) which identifies state and county. With this information, the FIPS codes for each firm could be obtained by merging the two datasets. Using the FIPS codes of firms, I further merge the dataset with the Metropolitan Areas and Components data defined by the Office of Management and Budget (OMB). This particular dataset defines several Metropolitan Statistical Area (MSA) by assigning a set of FIPS to each MSA. MSA refers to geographical regions with comparatively high population density and intense socioeconomic activities at the core. Because of such good economic properties of MSAs, I define a firm's location as the Metropolitan Statistical Area (MSA) of its headquarters, as what Christo Pirinsky and Qinghai Wang did. Some of the MSA are very well-known. For instance, the New

York-Newark-Jersey City and Los Angeles-Long Beach-Anaheim are two largest MSAs defined by OMB. Some are not as well-known as them, so in order to reduce undesired bias, I set the minimum number of firms within an MSA to be 5. All regions that have less than five publicly traded firms are dropped from the sample. Moreover, apart from firm locations, the data on firm monthly return and industry classification using Standard Industry Classification Code are also available in the Compustat dataset for further robustness tests. Also, in order to measure monthly returns in terms of excess returns, the monthly return data are further adjusted against risk-free interest rates. By tradition, risk-free interest rate is measured by the interest rate of one-month Treasury bills. Apart from firm-level data, Compustat dataset also have information on the asset values managed by operating hedge funds over years. This data would be utilized to further explore the relationship between market efficiency and stock return comovement.

The economic data on market condition such as recession indicators are available on the economic data website of Federal Reserve Bank of St. Louis. The recession indicator variable is derived from the GDP-based recession indicator index, which measures the likelihood that the given period is in recession. If the index rises above 67%, then the period is determined to be a recession, and thus the recession indicator variable would assume the value of 1. It would assume the value of 0 otherwise.

Table I Panel A presents some basic statistics about the distribution of firms and MSAs according to the MSA classification in 1993. As shown, the number of firms and MSAs slightly change over years. The number of firms first reaches a peak around 2002 and then gradually declines. Also, because I only keep the MSAs where there are at least 5 firms, the minimum number of firms in an MSA is consistently 5, while the maximum is around 750. This is because a very large group of publicly traded firms is clustered in the New York region, which is known as the most essential financial hub of the nation. Table I Panel B presents the statistics regarding the distribution of firms and MSAs according to the MSA classification in 2018. By comparison to Table I, the basic distribution does not change much. The only difference is that the number of MSAs increases causing a decline in the average number of firms in each MSA, because economy evolved, and OMB classified more MSAs in 2018. Since some MSAs defined in 2018 might not be defined in 1993, but most of the MSAs defined in 1993 are still in the 2018 classification, I choose to refer to the 1993 classification for my study.

III. Methodology and Results

1. Local comovement of stock returns

Comovement of stock returns measures the extent to which the return of an individual stock is correlated with that of the stocks belonging to the same geographical location. Following Christo Pirinsky and Qinghai Wang, my study measures the comovement effect by the following regression model:

$$R_{i,t} = \alpha_i + \beta^{LOC} * R_{LOC,t} + \beta^{MKT} * R_{MKT,t} + \varepsilon_{i,t} \quad (1)$$

In the equation (1), $R_{i,t}$ is the monthly return for the individual stock i at time t. $R_{LOC,t}$ is the location index, which represents the monthly return of the local portfolio at time t. The local portfolio consists of all of the stocks in the same region as stock i. Then $R_{LOC,t}$ measures the monthly excess return of the portfolio. The excess return of the portfolio is equal-weighted, which is simply the average of the returns of all stocks in the portfolio. The value-weighted approach is not adopted here in order to avoid the unintended interaction with market capitalization factor. However, for some regions with relative few stocks, this regression is problematic because each stock could have a misleadingly high correlation with the location index, which incurs a biased estimation of the comovement effect. As a result, a slightly adjusted methodology for deriving the location index is warranted. I instead construct the location index by first taking the individual stock i out of the local portfolio and then applying the same method mentioned before. Therefore, for each individual stock in the same geographical region, the corresponding location index is also slightly different. In this way, the issue of spurious relationship could be largely avoided, as Christo Pirinsky and Qinghai Wang claimed. In this model (1), the strength of the comovement effect is simply estimated by the coefficient, β^{LOC}.

Model (2) is almost identical to model (1) except that it adds another control variable in order to ensure that the explanatory power of $R_{LOC,t}$ does not come from that of other possible factors, such as industry clusters. In model (2), the industry factor serves as a control variable, as in some circumstances, stocks in the same industry tend to cluster in a similar region and thus also tend to behave similarly. For example, the San Francisco Metropolitan area has more than half of its publicly traded firms in computer related industries, while nearly half of all publicly traded firms in the Houston area are in the Oil industry (Pirinsky and Wang (2003)). In order to mitigate the issue incurred by industry clusters, I add a similar index for industry into the model. The resulting model (2) is as followed:

$$R_{i,t} = \alpha_i + \beta^{LOC} * R_{LOC,t} + \beta^{MKT} * R_{MKT,t} + \beta^{IND} * R_{IND,t} + \varepsilon_{i,t} \qquad (2)$$

$R_{i,t}$ denotes industry index, which is computed similarly as the location index. For any individual stock i, an industry portfolio is constructed, which contains all of the stocks that are in the same industry as that of the individual stock i. Then the individual stock i is excluded from the portfolio and the equal-weighted portfolio return is computed. The coefficient β^{LOC} then represents the strength of the comovement effect after the industry factor is controlled.

Table II summarizes the test results for the pooled OLS regression outputs for model (1) and (2). As the table reveals, I split the full sample into two periods, from 1988 to 2002 and from 2003 to 2018. As previous literature has confirmed, in the period prior to 2002, the comovement effect was very strong. However, for the period from 2003 to 2018, the coefficient β^{LOC} becomes insignificant with the t-statistics as small as 0.43. It turns out that the post-2002 period differs severely from the pre-2002 period. The difference of the strength of comovement effect in two periods causes the overall comovement effect in the full sample to be very small. While the t-statistics for the coefficient β^{LOC} is greater than 1.96, the magnitude of the coefficient is very negligible compared to β^{MKT}.

After I add the industry control variable, the result basically remains unchanged. The magnitude of the coefficient β^{LOC} goes down very slightly, for instance, from 0.130 to 0.109 for the period 1988 – 2002, and similar things happen to t-statistics as well. The major pattern, however, is the same. The comovement coefficient β^{LOC} is still statistically significant for the pre 2002 period, while for the post-2002 period it is dropped to be insignificant. The almost identical result for model (1) and model (2) suggests that the explanatory power of location factor does not come from the effect of industry clusters in the nation.

For the sake of robustness, I also control for time fixed effect because each individual stock is pooled over years. There well could be a time-series component in the data. The regression result for model (2) after I control for time fixed effect is reported in the panel A in Table III. Moreover, in cross-section level, I further control for two other factors, size (SMB) and value (HML), in the Fama-French Three Factor Model. These two factors capture how the cross-section of stock returns could be explained by the differences in firm size and firm value. The corresponding test result is displayed in the panel B of Table III. The major results remain the same for the above-mentioned four regressions. The consistency in all of the above robustness tests reveals the need to further investigate the reasons that contribute to this structural break.

2. Comovement of stock returns and economic conditions

Some literature has pointed out the relationship between financial crisis and stock comovement and argued that stock market behavior during the Great Recession should be evaluated separately. For example, Jang and Sul took financial crisis into consideration when evaluating stock return comovement in Asian financial market (2002). Didier et al. also demonstrated that the Great Recession displays some new features such as financial linkage that distinguishes between the period before and after the collapse of Lehman Brothers (2012). Consequently, stock market correlation might appear differently during the Great Recession, which is included in the second half of the sample. While this fact might more or less explain the drop in comovement effect, market efficiency could also have an influence on the degree of diversification in financial market (Calluzzo, Moneta, Topaloglu (2019)). According to the efficient market theory, the more efficient the financial market is, the less stock anomalies will be present, directly decreasing the stock return comovement within the same regions. As a result, the market being driven to a higher efficiency might also explain the inconsistency between the two time periods in the sample. Hence, in the following text, the two possible explanations would be evaluated using quantitative and qualitative approaches.

In order to investigate whether the Great Recession could account for this drop in the significance of comovement effect, I take advantage of recession indicator data. Recession index, documented by St. Louis Fed Research, measures the probability that the U.S. economy is in a recession during the indicated period. As mentioned by the data availability session, the recession index data is further transformed to a binary variable, $\gamma_{recession}$. If the probability as indicated by the recession index is above 67%, then the period is defined as a recession period and thus $\gamma_{recession}$ assumes the value of 1. Otherwise, Figure I visualizes the recession dummy variable, $\gamma_{recession}$. As shown by Figure I, the first half of the sample, from 1988 to 2002, has two shorter recession periods, while the second half, from 2003 to 2018, has a longer recession period, the Great Recession. In order to see the comovement effect after excluding the Great Recession period, I construct the following regression model:

$$R_{i,t} = \alpha_i + \beta^{LOC} * R_{LOC,t} + \beta^{MKT} * R_{MKT,t} + \beta^{IND} * R_{IND,t} + \beta * \gamma + \varepsilon_{i,t} \quad (3)$$

γ denotes a binary interaction term that involves $\gamma_{recession}$, the recession indicator variable, and the location index, $R_{LOC,t}$. Due to the nature of binary interaction terms, if β is statistically different from zero, then one could argue that the Great Recession period has an impact on the explanatory power of the local index. Table IV displays the regression result for model (3). It could be observed that the t-statistics for the coefficient β is statistically insignificant, meaning that the Great Recession does not contribute to an increase or decrease in the comovement effect in the second half of the sample. When the industry control variable is included, as the regression result suggests, the significance of each variable almost remains unchanged. These results show that the Great Recession is not the key reason that could justify the decline in the comovement effect after the year of 2003.

In order to explore the effect of market efficiency, I take advantage of the fact that hedge funds are part of the main forces that drive up financial market efficiency. Because hedge funds typically develop trading algorithms by detecting stock anomalies and asset mispricing attributed to some sources of market under-diversification, the more operating hedge funds there are in the market, the more efficient the market tends to be. This phenomenon is what Calluzzo, Moneta, Topaloglu characterized as anomaly-based trading in 2019. Consequently, to test if market efficiency could contribute to the inconsistency in comovement effect, I plot the asset values managed by operating hedge funds over the sample years, and the result is displayed in Figure II. As indicated, while the trend for the number of hedge funds is generally increasing, the growth speed begins to accelerate around the year of 2003. Although the number of hedge funds sharply went down around 2002 – 2003, it immediately rebounded again after the Great Recession.

To compare the trend of hedge funds and that of stock return comovement effect, I also estimate the comovement coefficient, β^{LOC}, for each year. In order to more accurately estimate the coefficient by years, I make full use of the sample data by computing the comovement coefficient in a rolling window basis with a one-year window length. For each sub-sample with the length of one year, I apply the model (2) to compute the comovement coefficient and finally average over the 12 estimated coefficients for each year to transform the monthly coefficient series into a yearly series. The time-series comovement coefficients after smoothing are plotted in Figure III. The 95% confidence intervals for the coefficients over year are plotted in Figure IV. As Figure III and Figure IV illustrate, comovement coefficients gradually go down and approach to zero across the sample years. Although the comovement coefficients temporarily go up around 2012, they are immediately back to the previous level after the peak. While these plots also confirm that the comovement effect in the first half of the sample was much stronger than the comovement effect in the second half of the sample, they also show that the comovement effect begins to be insignificant around 2004 – 2005. By comparing Figure II and Figure III, one can tell that comovement effect starts to become insignificant approximately after the number of operating hedge funds soared. This discovery is consistent with the view that a growing number of hedge funds tends to increase the diversification in the market, thus making the market more efficient.

IV. Conclusion

This paper investigates stock return comovement based on location. Following the methodology utilized by Christo Pirinsky and Qinghai Wang in 2002, I first confirm that a strong stock return comovement existed prior to the very beginning of 21st century. The paper further extends the sample period to 2018 to examine if the stock return comovement pattern becomes different as the world has been developing economically. It is discovered that the comovement effect gradually becomes insignificant as the sample period is prolonged. More specifically, hardly any comovement patterns could be observed in the second half of the sample. Two possible explanations for this shift are evaluated in this study. The first explanation is based on the findings by Jang and Sul who claimed that stock market correlation behaves differently during the Great Recession, which is included in the second half of the sample. By excluding the Great Recession from the second half of the sample, it is verified that the recession does not change the explanatory power of the location index in the second half of the sample. As a result, the Great Recession could not be the key force that drives down the comovement effect after the year of 2003. Secondly, as Calluzzo, Moneta, Topaloglu pointed out in 2019, institutional investors, especially those with high turnover such as hedge funds, play an important role in arbitrage processes and in improving market efficiency. As market efficiency improves, there is less under-diversification in the market, and the stock return comovement could be consequently mitigated. This hypothesis is tested using a qualitative approach in this paper. By comparing the time-series graphs for operating hedge fund values and for yearly comovement coefficient series, one could tell that comovement effect was decreased to close to zero right after the number of hedge funds soared, which happened roughly around the year of 2003.

Because a better understanding of stock return comovement could have direct implications on asset allocation and social welfare, this upgraded study of stock return comovement indicates that geography gradually becomes a less important consideration for achieving efficient market diversification. At the meantime, the local bias of investors and the social costs of market under-diversification is diminishing (Benartzi (2001)). However, while the two possible explanations could help understand the potential reasonings that might lead to this gradual decline in comovement patterns, more time is needed to really validate the decline. Moreover, more studies involving integrated realms of economics need to be conducted in order to formally justify the above hypothesis and investigate the decline in comovement.

Reference

Akbas, Ferhat, et al. "Smart money, dumb money, and capital market anomalies." Journal of Financial Economics 118.2 (2015): 355-382.

Brooks, Robin, and Marco Del Negro. "Firm-level evidence on international stock market comovement." Review of Finance 10.1 (2006): 69-98.

Brooks, Robin, and Marco Del Negro. "The rise in comovement across national stock markets: market integration or IT bubble?." Journal of Empirical Finance 11.5 (2004): 659-680.

Calluzzo, Paul, Fabio Moneta, and Selim Topaloglu. "When Anomalies Are Publicized Broadly, Do Institutions Trade Accordingly?." Management Science (2019).

Coval, Joshua D., and Tobias J. Moskowitz. "Home bias at home: Local equity preference in domestic portfolios." The Journal of Finance 54.6 (1999): 2045- 2073.

Dougal, Casey, Christopher A. Parsons, and Sheridan Titman. "Urban Vibrancy and Firm Value Creation." (2018).

Dougal, Casey, Christopher A. Parsons, and Sheridan Titman. "Urban vibrancy and corporate growth." The Journal of Finance 70.1 (2015): 163-210.

Gohar, Raheel, Syed Zulfiqar Ali Shah, and Habib Ahmad. "Economic Integration and Stock Market Comovement: An Empirical Study Pairing Pakistan's Stock Exchange with 21 other Markets." Journal of Reviews on Global Economics 7 (2018): 28-36.

Griliches, Zvi. "Education, human capital, and growth: a personal perspective." Journal of Labor Economics 15.1, Part 2 (1997): S330-S344.

Huyghebaert, Nancy, and Lihong Wang. "The co-movement of stock markets in East Asia: Did the 1997–1998 Asian financial crisis really strengthen stock market integration?." China Economic Review 21.1 (2010): 98-112.

Jang, Hoyoon, and Wonsik Sul. "The Asian financial crisis and the co-movement of Asian stock markets." Journal of Asian Economics 13.1 (2002): 94-104.

Jiang, Yonghong, Mengmeng Yu, and Shabir Hashmi. "The financial crisis and co-movement of global stock markets—a case of six major economies." Sustainability 9.2 (2017): 260.

Moretti, Enrico, and Daniel J. Wilson. "The effect of state taxes on the geographical location of top earners: evidence from star scientists." American Economic Review 107.7 (2017): 1858-1903.

Pirinsky, Christo, and Qinghai Wang. "Does corporate headquarters location matter for stock returns?" The Journal of Finance 61.4 (2006): 1991-2015.

Weisbrod, Burton A. "Education and investment in human capital." Journal of political Economy 70.5, Part 2 (1962): 106-123.

Appendix

Table I
Summary Statistics

Panel A

			Num. of Firms per MSA		
Year	Num. of Firms	Num. of MSA	Median	Min.	Max.
1988	3726	97	30	5	799
1995	5540	124	37	5	834
2003	4949	111	36	5	821
2010	4500	101	33	5	809
2018	4500	103	33	5	813

Panel B

			Num. of Firms per MSA		
Year	Num. of Firms	Num. of MSA	Median	Min.	Max.
1988	3641	153	25	5	799
1995	5340	181	31	5	833
2003	4789	194	31	5	818
2010	4310	185	27	5	806
2018	4297	164	27	5	810

Table II
Comovement Effect

	β^{LOC}	β^{MKT}	β^{IND}
Model 1			
1988 – 2002	0.130	0.280	
t-stat	*(72.71)*	*(86.36)*	
2003 – 2018	-0.001	1.670	
t-stat	*(-0.04)*	*(3.23)*	
1988 – 2018	0.002	0.530	
t-stat	*(22.4)*	*(330.02)*	
Model 2			
1988 – 2002	0.109	0.258	0.052
t-stat	*(57.54)*	*(79.26)*	*(47.80)*
2003 – 2018	-0.001	1.669	0.002
t-stat	*(-0.05)*	*(3.19)*	*(0.11)*
1988 – 2018	0.002	0.525	0.003
t-stat	*(19.09)*	*(326.52)*	*(32.16)*

Table III
Robustness Tests for Comovement Effect

Panel A

	β^{LOC}	β^{MKT}	β^{IND}
1988 – 2002	0.106	0.267	0.051
t-stat	*(55.66)*	*(80.88)*	*(46.44)*
2003 – 2018	-0.007	1.720	0.004
t-stat	*(-0.40)*	*(3.32)*	*(0.21)*
1988 – 2018	0.001	0.531	0.029
t-stat	*(15.65)*	*(332.16)*	*(29.33)*

Panel B

	β^{LOC}	β^{MKT}	β^{IND}	*SMB*	*HML*
1988 – 2002	0.07	0.391	0.045	0.231	0.312
t-stat	*(36.78)*	*(104.54)*	*(41.50)*	*(60.07)*	*(66.25)*
2003 – 2018	-0.003	1.640	0.00006	2.505	0.600
t-stat	*(-0.17)*	*(1.80)*	*(0.00)*	*(2.61)*	*(0.68)*
1988 – 2018	0.001	0.514	0.003	0.313	0.237
t-stat	*(12.45)*	*(312.45)*	*(25.53)*	*(146.25)*	*(101.20)*

Figure I

Figure I shows the recession indicator series over the sample year. The value of 1 represents that the given period is defined as a recession period, and the value of 0 means that the given period is a non-recession period. As indicated, there are three recession periods in the entire sample.

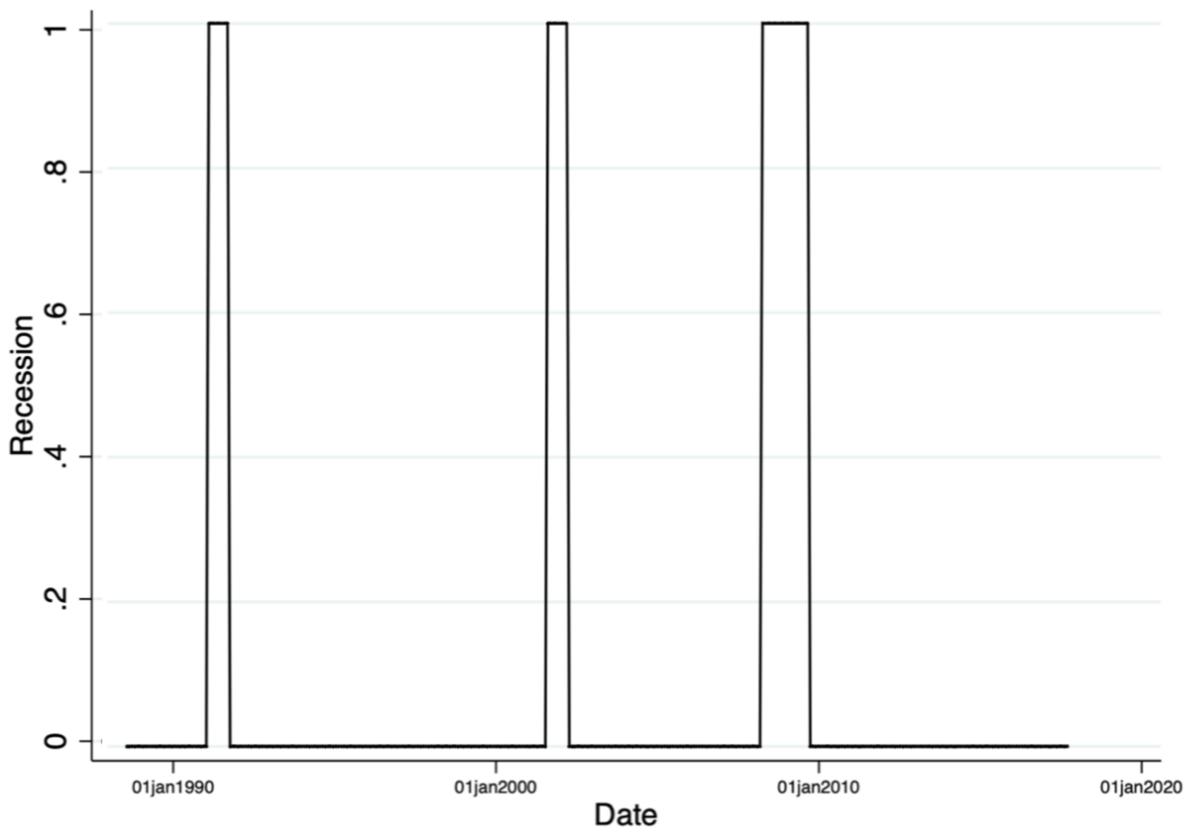

Table IV
Comovement Effect and Economic Conditions

	β^{LOC}	β^{MKT}	β^{IND}	β
Model 1				
2003 – 2018	-0.0003	1.675		-0.012
t-stat	*(-0.02)*	*(3.22)*		*(-0.12)*
Model 2				
2003 – 2018	-0.0005	1.673	0.002	-0.012
t-stat	*(-0.03)*	*(3.20)*	*(0.11)*	*(-0.12)*

Figure II

This figure displays the asset values managed by operating hedge funds over years. As indicated, the number of hedge funds begins soaring at around 2003.

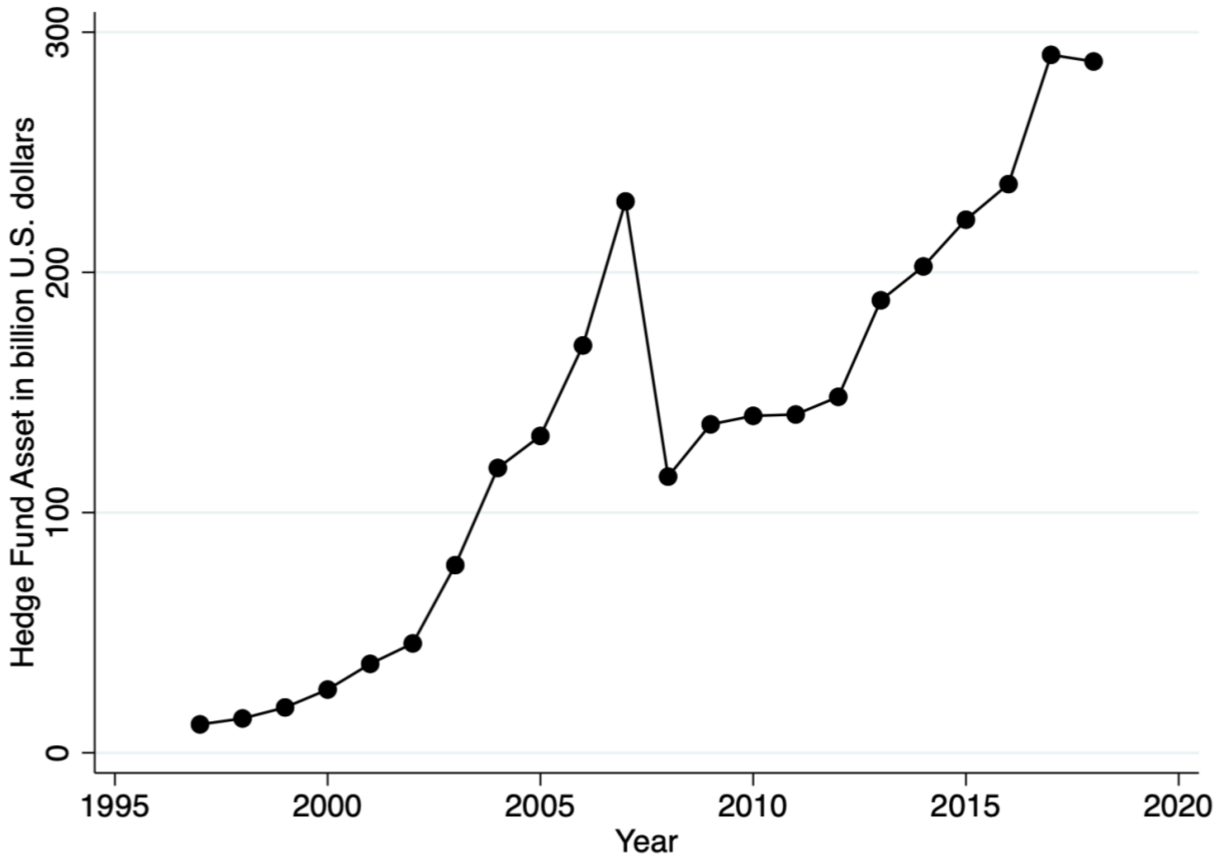

Figure III

This figure displays how the strength of comovement effect, characterized by comovement coefficients, changes over years. The comovement coefficients series is obtained by running the regression model (1) in a rolling window basis and then averaging the resulted coefficients over months for each year. The plotted series is the aforementioned coefficient series after smoothing.

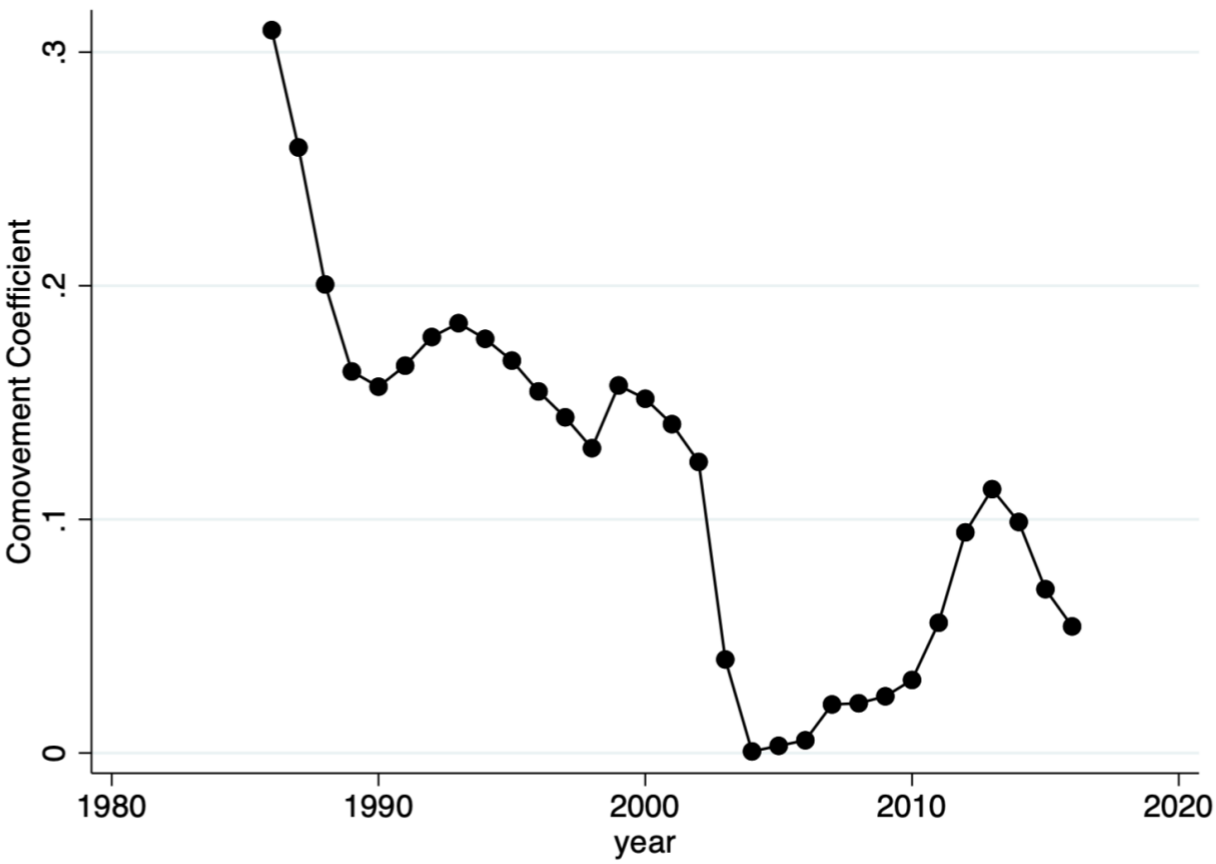

Figure IV

This figure displays how the confidence intervals of yearly comovement coefficients over year. It could be observed that comovement coefficients start to become insignificant around 2004.