Comovement, Passive Institutional Ownership and Price Informativeness**

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Abstract
Between September 1992 and December 2011 the average US market model R^2 increased consistently from 0.17 to 0.47. We propose and show that this rise was primarily driven by the increasing equity ownership of financial institutions following passive investment strategies. Passive investing increases comovement by neither performing fundamental research nor trading around firm-specific news. In addition, by not monitoring management, passive investing allows corporate managers to disclose less. As a result, passive institutional ownership reduces firm-specific volatility and increases comovement. Our results provide support for the hypothesized negative relation between R^2 and price informativeness.

Keywords: comovement, volatility, informed trading, correlated trading, passive investors, institutional ownership

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1. Introduction

Investment scholars and practitioners have shown great interest in the measurement and forecast of stock return correlations, or comovement, since the development of quantitative risk analysis and the Capital Asset Pricing model. In an influential paper, Campbell, Lettau, Malkiel, and Xu (2001) show a steady decline in average correlations in the decades between 1960 and 1990. However, evidence in recent studies suggest that comovement is no longer declining but has been rising over the past 20 years or so (Kamara, Lou, and Sadka, 2010; Bradley and Litan, 2011; and Sullivan and Xiong, 2012). Although this reversal has been the subject of much speculation in the popular press it has remained surprisingly unexplored by academics. To our knowledge, no rigorous tests have been performed to determine whether this reversal constitutes a temporary deviation of the times-series or a structural break. Without this distinction, understanding its underlying causes becomes a difficult undertaking. This study investigates the nature and cause(s) of this reversal and discusses potential market efficiency implications.

Our study has two objectives. Our first objective is to understand the nature of comovement's trend reversal. We want to know with as much precision as possible when this shift took place and whether it is a temporary deviation in the series or a permanent break. To answer this question, we implement the Bai and Perron (1998, 2003) structural break model to the average R^2 series, a commonly used comovement proxy. Our estimation results suggest that average R^2 trend went through a structural break with approximate date of September 1992. Parting from this result we formulate a second objective, which is to determine the underlying cause(s) of this break. Given that we know from our analysis that we are dealing with a structural break, we look for major changes in capital markets as potential explanations.

The inflection point of the average R^2 series in September 1992 coincides with major technological and regulatory changes in capital markets and the financial services industry. There are at least two avenues fostered by these changes that have the potential to contribute to higher comovement. First, a decline in transaction and information acquisition costs could have increased comovement by reducing market frictions (Rajan and Zingales, 2003; Shiller, 2003; Rajan, 2005; Hendershott, Jones, and Menkveld, 2011; Chordia, Roll, and Subrahmanyam, 2011). Second, an increase in passive portfolio management strategies could have also increased comovement by reducing informed trading. While both of these conditions could lead to higher comovement, they have opposite effects on price informativeness. Lower market frictions result in more informative prices because of the removal of idiosyncratic noise. Alternatively, passive institutional ownership results in less informative prices because it reduces fundamentals-based trading and discourages corporate disclosure.

[Figure 1 around here]

Even though institutional ownership of common stocks has been growing for several decades, the growth observed since the early 1990s responds only to increases in ownership by passive institutional investors such as index and exchange-traded funds (ETFs). As Figure 1 shows, institutional ownership has been growing steadily since 1983. The onset of the series coincides with changes in tax legislation that made defined contribution (i.e. 401k) plans attractive to retail investors,[1] discouraging direct participation in equity

[1] These regulatory changes occurred between 1981 and 1986. Although 401k plans were already part of the tax code since 1978, their use became widespread once the IRS proposed that employees could contribute to 401k plans via employee salary reductions, in 1981, and the modifications to the Tax Reform Act in 1984 and 1986. The Tax Reform Act of 1984 modified the rules for 401k plans to ensure contributions did not discriminate in favor of high income employees while the Tax Reform Act of 1986 tightened these rules and increased the before-tax maximum contributions employees can make to these plans to more than 6% of annual gross salary (EBRI, 2005).

markets and encouraging institutional investing. A closer examination of institutional ownership however, reveals that while the active and passive portions of institutional ownership grew at similar rates until the mid-1990s, their paths began to diverge at that time. Since then, passive institutional ownership has continued to rise while active ownership has declined. As of September 1992, passive investors owned about 30% of the total market capitalization of the NYSE, Amex, and Nasdaq[2]. By December 2010, their ownership had risen to about 50%, or 72% of all institutional shares. We attribute this growth to the introduction of technologies designed to reduce portfolio rebalancing costs and tracking error in index and Exchange Traded Funds (ETFs). Consider as an example the effect that just one of these technologies, the Financial Information eXchange (FIX) Protocol, has had on portfolio rebalancing costs. Invented in 1994 by three large investment banks to manage their internal trades, FIX has become the standard protocol to match and execute institutional block orders. Because of its flexible design, FIX allows financial institutions to access each other's books, fill block orders, and trade entire baskets of stocks at one time (SEC, 1997). In this way, instead of making hundreds of phone calls and separate buy and sell orders to rebalance a fund that tracks a broad index, the task can now be accomplished by a single person in a few transactions.

Although lower transaction and information acquisition costs have had an effect on both active and passive investors, the cost gap between passive versus active strategies has widened, giving passive institutional investors the ability to compete against active

[2] We identify passive institutional investors as those that meet the *quasi-indexer* definition in Bushee (1998). *Quasi-indexers* are passive investors that use indexing or buy-and-hold strategies; their portfolios are well diversified and have low turnovers. A list of quasi-indexers current to December 2010 was obtained from Brian Bushee's Institutional Investor classification website, (http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html). All other financial institutions are classified as active.

investors based on fees and attract clients to their funds.[3] Because of their nature, passive portfolios are typically diversified and tend to have low turnovers with trades limited to periodic rebalancing and accommodating net fund flows. As a result, passive investors have little incentive to trade on firm-specific news, perform fundamental research or monitor management (Porter, 1992; Bushee, 1998, 2001; Wermers and Yao, 2010). Hence, with more shares controlled by passive financial institutions, less costly information would be impounded into asset prices, making prices less informative. In addition, with more shares controlled by passive institutions there is less monitoring and with it, there are more opportunities for corporate insiders to extract private-control benefits by disclosing less (Jin and Myers, 2006). Lower fundamental-based trading and corporate disclosure increase comovement because they cause idiosyncratic volatility to decline relative to the volatility of systematic factors. Consistent with this prediction we find that the fraction of total stock return volatility attributable to firm-specific news has plummeted during the period in which passive institutional ownership has risen. Figure 2 decomposes total volatility into market, industry, and firm-specific following Campbell, Lettau, Malkiel, and Xu (2001). Panel B in Figure 2 shows that at its peak, in April 1995, firm-specific volatility made up the lion's share of total volatility and was about 7 times the size of market and industry volatilities combined. By December 2010, this ratio had shrunk to virtually one-to-one.

[Figure 2 around here]

[3] This "fee war" between active and passive institutional investors has gained the attention in the financial press in recent years. The "war" reached a high point in September 2012, when Charles Schwab announced it was lowering fees in its US Broad Market ETF from 6 bps to 4 (Financial Times, 2013). In addition to the distinct low-cost of passive investments, active institutional investors might have also lost clients because they are unable to demonstrate that their higher fees translate ability to outperform their own benchmarks. According to research performed by Gerstein Fisher for the period 1998-2013, actively-managed mutual funds in the highest performing quintile were in the second highest quintile based on fees. Further, the worst performing funds were the most expensive and funds in the second cheapest quintile were twice as likely to outperform the most expensive funds (Forbes, 2013).

Consistent with a passive investment explanation of comovement's rise, we find a positive relation between market model R^2 trends of individual stocks and changes in passive institutional ownership. For instance, stocks in the highest quintile in passive institutional ownership change (corresponding to an average growth of 37% between 1993 and 2010) had an R^2 growth of 12.2 basis points (bps) per month after controlling for other factors such as increases in correlated trading, increases in correlated cash flows, and lower market frictions. In contrast, R^2s from firms in the lowest quintile of the distribution (corresponding to an average reduction of 5.7%) did not change significantly. In addition, we also demonstrate that passive institutional ownership is an economically more important determinant of R^2 change than any of the competing factors mentioned above.

Besides contributing to better understand the nature of comovement's trend reversal, our study contributes to the literature in two additional ways. First, we provide empirical evidence of a positive relation between passive institutional ownership and comovement. Although this relation had been hypothesized before in academic and practitioner literature (e.g. Kamara, Lou, and Sadka, 2010; Wurgler, 2010; Bradley and Litan, 2011; Sullivan and Xiong, 2012), no supporting evidence had been presented until now. Second, and perhaps more importantly, using several correlated trading proxies,[4] we find no evidence to support the commonly held assumption that comovement has risen because of correlated trading by open-ended index-funds and ETFs (Sullivan and Xiong, 2012; Da and Shive, 2012; and Staer, 2012). This leads us to conclude that comovement has increased because of a decline in informed trading. In this way, the results in our study support the existence of a negative relation between R^2 and price informativeness (Roll, 1988; Morck, Yeung, and Yu,

[4] These proxies are ETF ownership, number of indexes a stock belongs to, and several dummy variables that indicate when stocks have been added or deleted from certain popular Standard & Poor's indexes and to the "low-priced" stock asset class.

2000; Wurgler, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; Durnev, Morck, and Yeung, 2004). Multiple studies find evidence supporting the existence of this negative relation, while many others find evidence opposing it. Thus, this issue remains highly controversial.

Grossman and Stiglitz (1980) stress the importance of a balance between informed and uninformed trading for informational efficiency. In their model, speculators and passive investors provide liquidity, while active investors carry out the task of acquiring costly information, learning from it, and transmitting this knowledge through informed trades. Active investors are rewarded with arbitrage profits while the market benefits with informational efficient prices, a positive externality of arbitrage. Grossman and Stiglitz note that "How informative the price system is depends on the number of individuals who are informed; but the number of individuals who are informed is itself an endogenous variable in the model" (page 393). In other words, the number of informed investors is not only a function of the arbitrage profits available but of structural factors which in turn determine the size of these profits. Under current technology, it is substantially less costly and less risky to use passive strategies than to actively manage a portfolio compared to 20 years ago. As a result, the arbitrage profits necessary to entice investors to gather and process costly information are now higher than they were prior to program trading. In addition to higher comovement, this could also explain the presence of larger and more sustained mispricings and higher fragility in capital markets (Kamara, Lou, and Sadka, 2010).

Taking all evidence together, we conclude that while lower market frictions might have had a positive effect on comovement through faster information diffusion, the effect of passive investing has been even greater, with negative implications for market efficiency. As more financial institutions have switched their focus from fundamental research to index-tracking, the amount of firm-specific information incorporated into stock prices might have declined. This might seem ironic, as firm-specific news has never been so plentiful, accessible, and inexpensive.

The remainder of this article is organized as follows. Section 2 provides an analysis of comovement's trend reversal. Section 3 describes the sample and variables used in our empirical analysis. Section 4 explores the influence of passive institutional ownership on comovement's trend. Section 5 evaluates the economic significance of changes in passive institutional ownership on comovement relative to other factors. We also consider two alternative explanations of comovement unrelated to information: changes in the composition of publicly traded stocks and temporary comovement surges during speculative periods. Results from these tests are summarized in the Appendix. Section 6 concludes.

2. Statistical characteristics of US comovement's trend reversal: 1962-2011

2.1. Measuring comovement

We design an appropriate comovement measure to perform times series and cross sectional analyses. Our measure is a modified version of the comovement measure in Campbell, Lettau, Malkiel and Xu (2001); it is the coefficient of determination (R^2) from a market model regression in which returns are a function of value-weighted market and industry indexes. Our procedure fits the market model to all common and ordinary stocks in the University of Chicago's Center for Research in Securities Prices (CRSP) database. We modify the original R^2 estimation for the following statistical and economic reasons:

(i) The use of rolling windows in the original R^2 estimation introduces serial correlation to the series. Serial correlation impedes accurate break point identification and reduces standard errors, yielding artificially inflated trend estimates. To control for built-in serial correlation, we estimate individual R^2s by fitting the market model on non-overlapping periods. Although this modification reduces serial correlation at the expense of the stability derived from long averaging periods, this is a minor concern because the added variability affects the high frequency component of the series, but not its trend.

(ii) Changes in the number of stocks in a given month could produce spurious changes in average R^2. In a market or industry with few securities, each individual stock represents a high proportion of the index, causing correlation between individual stocks and market and industry indexes to be high (Morck, Yeung and Yu, 2000). To avoid spurious correlations, we exclude the individual firm from the calculation of market and industry indexes on that firm's market model (Durnev, Morck, Yeung, and Zarowin, 2003).

(iii) Trend and structural change estimates of comovement could depend on the market model specification used. As a robustness measure, we repeat our time-series tests on an alternative beta-free measure of comovement derived from the volatility decomposition in Campbell, Lettau, Malkiel, and Xu (2001) and calculated as 1-(firm volatility/total volatility).[5] Structural break dates and trend estimates are very similar to those obtained using average R^2.

[Figure 3 around here]

Figure 3 shows that the natural logarithm of comovement remained relatively flat during the 1960s, 1970s, and 1980s, followed by a sharp upward trend during the 1990s and 2000s. As expected, the use of non-overlapping periods results in a large high-

[5] This measure is used in Brockman, Liebenberg and Schutte (2010). The volatility decomposition in Campbell, Lettau, Malkiel, and Xu (2001) does not require the estimation of industry or firm betas and for this reason, this measure and the average R^2 might differ at high frequencies. In the volatility decomposition, daily data is used to construct monthly sample variances without imposing a parametric structure to describe the times-series behavior of the variances (similar to Merton, 1980; Poterba and Summers, 1986; French, Schwert, and Stambaugh, 1987; Schwert, 1989; and Schwert and Seguin, 1990). Since a parametric structure is more important to produce accurate forecasts than to describe historical movements, and because all models tend to produce similar historical fitted volatilities ex-post, both measures are expected to yield consistent estimates of comovement's trend.

frequency variation in the series. However, the series' first-order autocorrelations are small which improves the accuracy of the structural break tests. Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1979; Said and Dickey, 1984, 1985) strongly reject the null of a unit root.[6] Hence, we assume that comovement is stationary and that the shift in Figure 3 is endogenous to the series (Perron, 1989).

2.2 Structural break point identification

We identify structural break dates using the Bai and Perron's (1998, 2003) dynamic programming algorithm, chosen from the extensive structural break literature because of its validity under fairly general assumptions. These include the use of autoregressive parameters in the residuals (Kramer, Ploberger, and Alt, 1988; Bai, 1997). These parameters are necessary because comovement measures remain somewhat serially correlated even with non-overlapping periods. Unlike Perron (1989) who determines break points visually, possibly introducing subjective biases (Christiano, 1992; Zivot and Andrews, 1992), the Bai and Perron algorithm is entirely data driven. Also, the limiting distribution for estimators and test statistics in Bai and Perron (1998) is useful to determine the relative strength of the break(s) and build confidence intervals around the estimated break date(s). To distinguish between global and local minima, we fit the Bai and Perron algorithm to the longest possible series obtainable with CRSP data, January 1926 to December 2011. For the average R^2 measure, the algorithm strongly rejects the null hypothesis of series stability, and identifies three breaks: September 1947, February 1966,

[6] The ADF regression equation includes drift, trend, and up to 24 lags of the series' first-difference.

and September 1992, the latter being the strongest. The 95% confidence interval for the September 1992 break is very narrow, ranging between July and October 1992.[7]

[Table 1 around here]

Panel A of Table 1 summarizes the statistical properties of average R^2 values during the January 1962 to December 2011 period and the sub periods up to and after September 1992. Panel B repeats the analysis on our robustness measure. Average and median R^2 values are respectively 0.22 and 0.20. This means that in a typical month, about 20% of the return variation in stocks responds to pervasive factors while the remaining 80% is firm-specific. These proportions are consistent with those presented in Roll (1988) for the period September 1982 to August 1987 (average CAPM R^2 of 0.18). Average R^2 varies widely through time, its monthly standard deviation is 0.09. Autocorrelation coefficients remain significant up to the fifth lag before and after September 1992.

The Bai and Perron algorithm identifies the timing of changes in the relation between comovement and time, but it does not provide details on the magnitude of the trends. To determine the economic importance of the break, we regress the natural logarithm of comovement on time and break dummies. Our dummy variables are built in the style of Perron (1989) and Zivot and Andrews (1992) and capture changes in the series' level and growth rates. To control for serial correlation we impose an AR(5) specification on the residuals. We test three model specifications:

$$y_t = \mu + \theta DU_t(\lambda) + \beta t + \mu_t; \ \mu_t = \sum_{i=1}^{5} \phi_i \, \mu_{t-i} + e_t \qquad (1)$$

$$y_t = \mu + \beta t + \gamma DT_t^*(\lambda) + \mu_t; \ \mu_t = \sum_{i=1}^{5} \phi_i \, \mu_{t-i} + e_t \qquad (2)$$

$$y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \mu_t; \ \mu_t = \sum_{i=1}^{5} \phi_i \, \mu_{t-i} + e_t \qquad (3)$$

[7]The confidence intervals for earlier breaks are wider, which is consistent with them being weaker. For the September 1947 break, the 95% confidence interval ranges between June 1947 and May 1948. For the February 1966 break, the 95% confidence interval is even wider; it ranges between January 1966 and February 1968.

where μ is the equation's intercept. $DU_t(\lambda)$ is an indicator that takes the value of one if $t>T\lambda$, the structural break date. Its associated coefficient, θ, captures the magnitude of the change in the series' intercept. t is a count variable for time, and its associated coefficient, β, captures the series' trend up to the structural break date. $DT_t^*(\lambda)$ is a count variable for the post-break period, and its associated coefficient, γ, represents the magnitude of the change in the series' slope. ϕ_i are autoregressive parameters.

Model (1) is the "crash" model in Perron (1989), which allows for a one-time change in the intercept of the trend function. Model (2) is Perron's "changing growth" model, which allows for a change in the magnitude and sign of the series' growth. Model (3) combines models (1) and (2) and allows for changes in both level and growth. Coefficient estimates for these models appear in Table 2. Panel A reports estimates for the average R^2 while Panel B reports estimates for our robustness measure.

[Table 2 around here]

Panel A of Table 2 shows that, based on AIC, the model that best fits the data is Model (3). According to Model (3), in September 1992, average R^2 experienced a one-time decline in the series' level and a gradual, positive change in its growth. The changing growth coefficient (γ) is 54.36 (t=9.64). This means that during the period October 1992 to December 2011 average R^2 grew at an average 0.53% [(-1.57+54.36)/100] per month.

3. Sample and variable construction

3.1 Sample construction

We conduct two separate empirical tests to determine the validity of our hypothesis. Each test uses a different sample covering the period 1993-2010. The period of study is limited by the availability of institutional ownership classification data, which ends in

2010. In addition to requiring return and passive institutional ownership data, to be part of the sample, a stock must have data available to calculate proxies for cash flow comovement, correlated trading, presence of informed market participants, and market frictions. We explain the construction of each of these proxies in section 3.1. For the tests of passive institutional ownership changes on individual R^2 trends, described in Section 4, we use a pooled sample of 720 securities (i.e. unique PERMNOs) for a total of 12,944 observations. We denote this sample as the *survivor sample* because to calculate passive institutional changes we require that firms remain listed during the entire 1993-2010 period. For the tests of annual changes in passive institutional ownership on annual changes in individual R^2s, described in Section 5, we use the *full sample* of 6,151 securities for a total of 46,318 observations. Descriptive statistics for the two samples are in Tables 3 and 4.

A potential concern with testing the relation between changes in passive institutional ownership and R^2 trends on stocks listed during the *entire* sample period is the possibility of a survivor bias in our coefficient estimates. In other words, there is a possibility that our regression coefficients might not hold in stocks that became publicly traded after 1993 and/or were delisted before 2010. To account for this possibility we repeat our tests using only stocks listed for the entirety of other sample periods: 1993-2009, 1994-2010, and 1994-2009. Coefficient estimates from these alternate samples are similar to those shown in tables 5 and 6. In addition, we conduct a separate test on the relation between annual changes in passive institutional ownership and annual changes in market model R^2 values using the *full* and *survivor samples*. This second set of tests measures the economic significance of the relation between passive institutional ownership and R^2, in comparison to other potential explanations for comovement's rise. Results from these tests are qualitatively the same in both samples. We summarize the results from tests conducted on the *full sample* in Table 7 and discuss them in Section 5. For brevity, results from tests using the *survivor sample* are not reported but are available upon request.

3.2 Variables used in the analysis

Tables 3 and 4 report descriptive statistics of the variables used in our analysis for the *full* and *survivor* samples. We winsorize each variable's distribution at the 0.5% and 99.5% levels to limit the effect of outliers. Variables used in our study are: stock return comovement (the dependent variable), passive institutional ownership (the independent variable) and proxies for four additional determinants of comovement: correlated trading, correlated cash flows, information production, and market frictions.

We include *Market Capitalization* as a control variable that proxies for several determinants of comovement. *Market Capitalization* has been traditionally used as a proxy for information supply. Crawford, Roulstone and So (2012) explain that *Market Capitalization* proxies for "various dimensions of the firm's information environment, including media exposure and the overall level of investor interest." (p. 1536). At the same time, the size of the firm's equity is also related to market frictions and correlated trading, as stock from large firms tend to be more liquid and belong to multiple indexes and ETFs. The average (median) firm in the *full sample* has capitalization of $3,068 ($293.29) million while the average firm in the *survivor sample* is about twice that size, with average (median) capitalization of $6,279 ($865.2) million. The difference between means and medians in both samples reveals the presence of some very large firms that skew the distribution. Market Capitalization in our sample varies widely, from $2.19 ($2.54) million to $162.7 billion in the *full (survivor) sample.*

[Table 3 around here]

3.2.1 Stock return comovement

Stock return comovement is the market model R^2 of daily individual stock returns over the past calendar year. To control for the effects of firm turnover within the year, we only include stocks listed for a minimum of 250 trading days over the prior 12 months. As in the times series portion of our analysis, we estimate the market model by regressing individual stock returns on value weighted market and industry indexes. Average (median) annual R^2 values are 0.17 (0.09) for the *full sample* and 0.22 (0.16) for the *survivor sample*. The cross sectional dispersion of annual R^2s is much higher than the time-series dispersion of monthly R^2s in Table 1. The standard deviation of the annual R^2s is 0.18 (0.20) for the *full (survivor) sample* and its range fluctuates between near zero and 0.85.

3.2.2 Passive institutional ownership

We define passive institutional ownership as the percent of common and ordinary shares owned by institutional investors following passive investment strategies, and it is an independent variable. Quarterly institutional ownership data is from the Thomson Financial 13(f) database. [8] We identify passive financial institutions by their manager's behavior following Bushee (1998, 2001) and Bushee and Noe (2000). Bushee classifies financial institutions into quasi-indexers, transient, and dedicated. A list of quasi-indexer, transient and dedicated financial institutions current to December 2010 is available at

[8] Institutional holdings data is public information. Institutional investors operating in the US with portfolios of $100 million or more are required to file 13(f) reports with the SEC within 45 days of the end of each calendar quarter. The reports contain information on all equity positions greater than 10,000 shares or $200,000 in market value. The stock holdings in the 13(f) reports constitute the dominant majority of true institutional holdings. According to Sias, Starks and Titman (2006), the total market value of the equity holdings of institutions filing 13(f) reports (and thus included in the database) accounts for about 90% of the Conference Board estimate of total equity holdings by institutional investors.

Professor Brian Bushee's Institutional Investor classification website. Portfolios of quasi-indexers have low turnovers and diversified holdings consistent with a passive buy-and-hold strategy of investing in a broad set of firms. Alternatively, transient and dedicated institutions follow more active investment styles. Our proxy for passive institutional ownership is the common and ordinary equity shares owned by quasi-indexers as a percent of the total common and ordinary equity shares outstanding in all firms in the CRSP database. All financial institutions not classified as quasi-indexers by Bushee are assumed to follow active investment styles, either as fundamental-based or speculative traders. Non-passive institutional ownership is also calculated and included into our analysis as an information production proxy.

Average and median passive institutional ownership for the *full sample* is 29% while average (median) passive institutional ownership for the *survivor sample* is 35% (37%). The range of passive ownership varies widely from zero to 92%, providing ample opportunity to examine how passive institutional ownership influences comovement.

3.2.3 Correlated Trading

There are at least three different mechanisms through which correlated trades may be generated by open-ended index-funds and ETFs. When these trades are unrelated to information, they cause excess comovement. First, correlated trades might arise when open-ended index fund managers buy and sell shares of all stocks in their portfolios to accommodate net fund flows (Wurgler, 2010; Bradley and Littan, 2011; Sullivan and Xiong, 2012). The buying or selling of all stocks in an index-fund should not cause excess comovement unless they also occur in other stocks. However, as the number of publicly available indexes and index-funds has increased, many stocks no longer belong to just one index, but are part of multiple indexes. The larger the number of indexes a stock belongs to, the higher the likelihood that a stock will be bought or sold alongside many other stocks in the market, and the higher the possibility that its returns will commove with the returns of other stocks.

Second, correlated trading arises through the "in kind" creation/redemption process of ETFs (Da and Shive, 2012; Staer, 2012; Broman, 2013). This mechanism gives certain large institutional investors, called Authorized Participants (or APs) the right to buy or redeem ETF shares in bundles directly from the ETF sponsor. In this way APs can arbitrage mispricings between ETF shares and their underlying portfolios. When the ETF price is lower than the portfolio's Net Asset Value (NAV), an AP can buy ETF shares on the secondary market and redeem them for the underlying basket of securities directly from the ETF sponsor. Then, the AP can sell these securities at the current market price, producing a synchronized sale of all securities contained in the ETF. Alternatively, when the ETF price is higher than the NAV, an AP can purchase a portfolio of securities that matches the composition of the ETF, exchange the securities for ETF shares directly from the sponsor, and sell these newly created ETF shares in the secondary market. Just like with open-ended funds, the synchronized purchase or sale of securities in a single ETF should not have an effect on comovement at the market level. However, Broman (2013) documents a common component in equity ETF mispricing that makes synchronized ETF creations and redemptions likely. Therefore, with more shares owned by ETFs, there is a stronger possibility of synchronized "in-kind" redemptions/creations in multiple ETFs and an increased chance for correlated trading.

Finally, correlated trading can arise because of style and habitat investing. Style and habitat investing occurs when investors focus their attention on certain assets while neglecting others. Style investing refers to limiting a portfolio to stocks with common characteristics such as industry affiliation, size, price, market-to-book, and momentum

(Barberis and Shleifer, 2003; Barberis, Shleifer, and Wurgler, 2005). Alternatively, habitat investing refers to limiting a portfolio to a publicly available index, such as the Dow Jones Industrial Average or the S&P500. These indexes are often built to serve as market benchmarks with stocks that might not share common characteristics. The excess comovement from style and habitat investing has been documented extensively, particularly as stocks move in and out of habitats and asset classes. When a stock is added (dropped) to (from) an index or asset class, comovement with other index or asset class constituents increases (declines) while comovement with the market declines (increases) (Lynch and Mendenhall, 1997; Wurgler and Zhuravskaya, 2002; Barberis, Shleifer, and Wurgler, 2005; Kaul, Mehrotra, and Morck, 2000; Vijh, 1994; Greenwood and Sosner, 2007; Greenwood, 2008).

Throughout our empirical tests we control for correlated trading using three proxies:

(i) *Number of index memberships:* This is the number of indexes to which a stock belongs in a given year. This variable is a proxy for correlated trading but its relation with R^2 can be interpreted in two ways. First, there might be a positive relation between *number of index memberships* and R^2 because the more broad-based indexes a stock belongs to, the higher is the likelihood that correlated purchases and redemptions of index-fund shares will involve a large cross-section of stocks. Second, there might be a negative relation between *number of index memberships* and R^2 because, the more style-based indexes a stock belongs to, the higher the correlation with other stocks in the same investment style (i.e. style effects), and the lower the correlation with all other stocks in the market. We use constituencies of all Standard & Poor's indexes to construct this variable. We expect a positive relation between number of index constituencies and R^2.

(ii) *ETF ownership*: This is a proxy for correlated trading produced by the "in kind" creation/redemption process of ETFs. This variable is the proportion of common and ordinary stocks owned by ETFs. We obtain ETF ownership data from the CRSP Mutual Fund Database. ETF holdings do not appear in this data set until 2003, presumably because they were negligible before this year. We expect that stocks more heavily owned by ETFs will be subject to more correlated trading because of more "in kind" creation/redemption of ETF shares. Therefore, we expect a positive relation between ETF ownership and R^2.

(iii) *Index and investment style addition/deletion indicators:* We use an indicator that denotes additions into and deletions from the set of "low-priced" stocks. This indicator is a proxy for correlated trading arising from style investing. Additions (deletions) into "low-priced" stock indicators take the value of one when the average price over the past twelve months declines below (climbs above) $10 per share. In addition, we use a set of indicators that denote additions into and deletions from popular indexes. These variables proxy for correlated trading arising from habitat effects. Our indicators take values of one when stocks are added into or deleted from any large-cap, mid-cap, or small-cap Standard & Poor's indexes during the year.[9] Based on the habitat and style investing literature we expect that stocks added to an index and the "low-priced" stock category will start to commove more strongly with other stocks in the same index or asset class, and less with the rest of the market. Therefore, we expect a negative (positive) relation between addition (deletions) indicators and R^2.

[9] Standard & Poor's index constituents are available from Compustat. We recognize that there are many indices other than those of Standard & Poor's. However, membership in a characteristic Standard & Poor's index will be highly correlated with membership in the same characteristic index sponsored by different entity.

Careful examination of our correlated trading proxies reveals that the effects suggested to have triggered comovement's rise in prior literature only exist in a small number of firms. Tables 3 and 4 report descriptive statistics for the correlated trading proxies used in our analysis. Table 3 reports summary statistics for the continuous variables while Table 4 reports frequency counts for the indicators. The average stock in our *full (survivor)* sample is part of about five (eight) indexes. In contrast, the median stock in our *full sample* belongs to no index while the median stock our *survivor sample* belongs to 11 indexes. The large discrepancy between means and medians in the *full sample* reveals skewness. Over half of the firms in the *full sample* do not belong to any index. In contrast, the firm that marks the 75th percentile of the sample belongs to 12 indexes. In the case of the *survivor sample*, the difference between mean and median is not as large. This suggests that most stocks that belong to multiple indexes have been listed for quite some time and that multiple index memberships do not extend to the entire market. Without index memberships extending throughout the market, it is unlikely that correlated trading from open-ended index funds following broad-based indexes would have the strength to cause a two-decade-long increase in stock correlations as suggested by Sullivan and Xiong (2012).

Similar to index-fund memberships, ETF ownership is also quite small, but growing. The breadth of ETF ownership has increased dramatically since 2003. In 2003, 25.62% of stocks had some form of ETF ownership. By 2010, 91.29% of stocks were owned by ETFs to some degree. Despite this extraordinary growth, the number of shares controlled by ETFs remains relatively small. In 2003, ETF ownership represented 0.002% of total market capitalization. By 2010, this proportion had grown to 3.87% of total market capitalization, an impressive growth, but still a comparatively small portion of the market. Average (median) ETF ownership for the stocks in our sample is 1% (0%) and 2% (0%) for the *full* and *survivor* samples, respectively. ETF ownership ranges between 0% and 13%.

Table 4 shows the number of additions into and deletions from large-cap, mid-cap and small-cap Standard & Poor's indexes and the "low-priced" stock category. The number of additions and deletions involve a small number of firms in our samples. In total, there are 5,489 additions and deletions among the stocks in the *full sample*, which represents 11.85% of all firms. From these 2,129 belong to indexes while the remaining 3,360 are "low-priced" stocks. Because the number of publicly available indexes has increased, the number of additions into indexes (1,437 additions, involving 3.01% of firms) has exceeded the number of deletions (692 deletions, involving 1.49% of firms). Alternatively, the number of additions and deletions into the "low-priced" stock category are almost matched (1,869 additions vs. 1,491 deletions). Frequency counts for the *survivor sample* reveal similar patterns than those described for the *full sample*. Although it has been widely documented that habitat and style investing can influence comovement, only deletions from habitats or investment styles would be consistent with a positive comovement trend. Table 4 shows that the number of deletions in our sample is very small.

3.2.4 Correlated Cash Flows

Standard finance theory establishes a one to one relation between equity prices and discounted cash flows in the absence of market frictions. Hence, assuming even a minimum of efficiency, there should be a positive association between cash flow comovement and R^2. We measure cash flow comovement as the R^2 from the regression of unanticipated cash flow shocks on unanticipated shocks to market and industry cash flow indexes. The cash flow proxies used are quarterly earnings, free cash flow, and sales per share. We use cash flow shocks to control for the persistency of cash flow levels. We measure these shocks as the residuals from the following pooled regression:

$$E_{it} - E_{it-4} = \propto + \beta_1(E_{it-1} - E_{it-5}) + \beta_2(E_{it-2} - E_{it-6}) + \beta_{13}(E_{it-3} - E_{it-7}) + \mathrm{e_{it}} \quad (4)$$

Where E_{it} represents cash flow per share of firm *i* in quarter *t*. The residual e_{it} represents unexpected innovations to cash flow per share. The dependent variable is the difference between cash flow per share in quarter *t* and cash flow per share in quarter *t-4*, a year earlier. Cash flow shocks are standardized by dividing them by price at the end of the previous quarter. We create quarterly market and industry indexes of cash flow shock to price ratios by computing weighted average cash flow shocks for the market and Fama and French (1997) 48 industries. Finally, in the fourth quarter of each year, we regress quarterly individual cash flow shocks on contemporaneous shocks to market and industry indexes over the past five years.

We estimate unanticipated shocks to cash flow per share on the fourth quarter of each year following Irvine and Pontiff (2009). For brevity, from these three proxies we only report the results for sales per share. Results using the other two proxies (earnings per share and free cash flow per share) are similar to those in Tables 5 through 8 and are available upon request. Table 3 reports an average (median) sales per share comovement of 0.15 (0.10) for the *full sample* with a range of variation between 0.00 and 0.93. Summary cash flow comovement statistics for the *survivor sample* are not very different. These values are similar to those obtained for the average and median return comovement (average of 0.17, median of 0.09, and range between 0 and 0.85).

3.2.5 Information production

Piotroski and Roulstone (2004) examine how economic agents might have an effect on comovement by incorporating different types of information into stock prices. They find that corporate insiders and institutional investors (those that follow active trading strategies) have a negative effect on comovement by incorporating firm-specific information. Alternatively, other studies demonstrate that analyst coverage has a positive effect on comovement which results from reducing uncertainty while interpreting firm-specific information (Schutte and Unlu, 2009) and providing market and industry information (Crawford, Roulstone and So, 2012).

As with passive institutional ownership, we identify active financial institutions following Brian Bushee's Institutional Investor Classification. Active institutional ownership is the common and ordinary equity shares owned by transient and dedicated institutions as a percent of the total common and ordinary equity shares in CRSP. In general, active ownership is smaller than passive ownership in both, the *full and survivor samples*. Average active ownership for the *full* and *survivor samples* is 17% (14% and 16% for the medians, respectively) and takes values between zero and 71%.

Following Chang, Dasgupta and Hilary (2006), analyst coverage is the maximum number of analysts to issue annual earnings forecasts over the past 12 months. Analyst forecast data comes from *I/B/E/S*. Following standard practice, we assume that firms not in *I/B/E/S* have no analyst following. Mean and median analyst coverage is 5.96 and 3 for the *full sample,* and 7.89 and 5 for the *survivor sample*. The number of analysts covering a stock ranges from zero to 40.

3.2.6 Market Frictions

Formally defined, market frictions are those market conditions that violate the CAPM's perfect market assumptions. These assumptions are: perfect divisibility of investment (Markowitz, 1952, 1959); zero transaction, information gathering, and portfolio management costs (Levy, 1978); no market segmentation (Merton, 1987); no investor so large as to exert a sizable effect on security returns or the risk-free rate; and no short-sale restrictions (Markowitz 1987, 1990). Market frictions impede the fast incorporation of firm-specific information into prices and causes prices movements unrelated to fundamentals, a phenomenon to which Black (1986) refers as noise. Therefore, noise should reduce comovement to levels lower than those justified by firms' fundamentals.

We use a parsimonious measure, which we call *Noise*, to capture the impact of information and liquidity-based frictions on price formation. This variable, constructed in the spirit of Boehmer and Kelley (2009), measures the extent to which stock prices deviate from a random walk. We define *Noise* as the autocorrelation coefficient of daily market model residuals. We calculate this variable in annual frequencies using daily returns from July through the following June. To obtain our measure, we regress returns of individuals stocks on day t with market returns on day t, extract the model estimation residuals, and calculate the correlation between residuals on day t and residuals on day t-1. Given that deviations from a random walk can produce either positive or negative autocorrelations, we define *Noise* as the absolute value of the autocorrelation coefficient. Thus, a *Noise* of zero indicates that unexplained returns follow a random walk while large values show that unexplained returns depart substantially from a random walk. Average *Noise* is 0.12 (median of 0.09) and it ranges from zero to 0.54.

In addition to *Noise,* we include liquidity variables to proxy for market frictions. Boehmer and Kelley (2009) find a strong relation between random walk deviations and stock liquidity. Liquid stocks not only adjust faster to news because of faster execution speeds but also because investors recognize them more easily (Grullon, Kanatas, and Weston, 2004; Frieder and Subrahmanyam, 2005; Cronqvist, 2006). Using standard methods, we compute the following five liquidity variables: stock turnover, dollar volume, the inverse of the Amihud (2002) illiquidity measure, and number of days traded during the past twelve months. The mean turnover (1.64) is significantly higher than its median (0.67).

Similar discrepancies are evident between means and medians in dollar volume (average of $626 million and median of $65.35 million) and the inverse Amihud measure (average of 44.10x10^{-7} and median of 0.30x10^{-7}). This suggests a strong tilt in the sample towards liquid stocks. Despite this tilt, there is still enough variation in the data to differentiate between liquid and illiquid stocks. The number of trading days in a year ranges widely from 29 to 254, but average and median trading days are quite high (mean of 240.20 and median of 252) relative to the standard deviation (31.38 days). This implies that the vast majority of sample stocks are actively traded.

4. Influence of passive institutional ownership on individual R^2 trends

Our hypothesis is that passive institutional ownership reduces the proportion of trades motivated by firm-specific information. Based on this hypothesis we propose that increases in passive institutional ownership explain the positive trend in average comovement since the early 1990s.

To test this hypothesis, we examine the comovement trends of individual stocks while controlling for changes in their determinants other than passive institutional ownership. We calculate trend coefficients for securities in the *survivor sample* sorted on passive institutional ownership growth between 1993 and 2010. Results from these tests are presented in Figure 4 and Table 6. To test the robustness of our results, we also examine R^2 trends of securities sorted on changes in two alternative variables, firm size and *noise* (i.e. return autocorrelation). Results from robustness checks are presented in Table 7. The results presented in this section suggest that increasing comovement since the early 1990s is primarily the result of increasing passive institutional ownership.

4.1 Cross-correlations

Table 5 shows pairwise Pearson correlations for all variables in the *full* and *survivor* samples. We winsorize each variable's distribution at the 0.5% and 99.5% levels and take natural logs to reduce the influence of outliers. The resulting distributions more closely resemble the normal. Additionally, taking the natural log of the variables allows the estimated coefficients from regression analyses to be interpreted as elasticities. The correlation coefficient of 0.62 (0.60) between R^2 and *passive institutional ownership* for the *full (survivor) sample* is consistent with our hypothesis. We also find strong correlations between R^2s and other variables such as *active institutional ownership* (0.50), *ETF ownership* (0.40), *number of index memberships* (0.57), *firm size* (0.74), *analyst coverage* (0.59), *share volume* (0.71), *turnover* (0.62), and the *Inverse Amihud* measure (0.79). There is also a strong negative correlation between R^2 and *Noise* (-0.49). With the exception of *active institutional ownership*, which according to theory should be negative, the sign of all coefficients conform to prior literature. As expected, we find positive correlations between R^2 and correlated trading and R^2 and *analyst coverage*, and negative correlations between R^2 and market friction proxies.

Table 5 also reveals some very strong correlations between *passive institutional ownership*, our independent variable, and controls such as *active institutional ownership* (0.58), *number of index memberships* (0.64), *firm size* (0.67), *analyst coverage* (0.61), *share volume* (0.62), *turnover* (0.56), and the *Inverse Amihud* measure (0.73). This suggests dependence on common omitted factors such as financial deregulation and institutional change, the range of financial products, and risk sharing opportunities, which started to emerge since the 1980s (Rajan and Zingales, 2003; Shiller, 2003; Rajan, 2005).

In general, R^2 is highly correlated with all treatment variables and controls except for *cash flow comovement*. Average correlations between *cash flow comovement* and all other variables are also very low.

Although these coefficients largely support our hypothesis, it is possible that their magnitude may be overstated because of common omitted factors. In addition, pairwise correlations support multiple potential explanations for the positive comovement trend. To better understand which of these factor(s) better explains comovement's trend reversal we examine the effect of passive institutional ownership on comovement's trend in a multivariate setting. In an additional test, we evaluate the influence of *passive institutional ownership* changes on R^2 changes in comparison to changes in other factors: correlated trading, correlated cash flows, information production, and market frictions. At this point we do not rule out the possibility that the sustained increase in R^2 might have been a consequence of a combination of factors but want to know if *passive institutional ownership* is indeed the most important.

4.2 R^2 trends and changes in passive institutional ownership

We calculate the change in passive institutional ownership between 1993 and 2010 on each security in our *survivor sample*. We then sort securities into quintiles according to this change. Table 6 reports the average change in passive institutional ownership for all stocks and each quintile in the *survivor sample*. On average, passive institutional ownership grew by 14.4% between 1993 and 2010. Stocks in the top passive institutional ownership growth quintile increased by an average 37%, while institutional ownership in the lowest quintile declined by an average 5.7%. Figure 4 tracks the evolution of equally-weighted average R^2 for each of these groups. It is evident from looking at this figure that stocks in the top two quintiles have experienced much faster increases in their average R^2s than the rest of stocks in the sample, and that the slope of average R^2 becomes steeper as we move across quintiles, from low to high.

We take a closer look at R^2 trends across quintiles of passive institutional ownership growth using pooled regressions. Table 6 shows coefficients from pooled regressions of individual R^2s on a time dummy and controls. We fit three different model specifications. In Model 1, individual R^2s are regressed on year (t) and firm dummies, to account for firm-specific factors that might have resulted in higher market correlations. For example, increases in market share might have turned a firm into a bellweather firm that investors use to price other stocks in the same industry (Hou, 2007). The error term in model one is assumed to follow a standard normal:

$$R^2_{it} = b_0 + b_1 * t + b_2 * firm\ dummy_i + \varepsilon_{it} \tag{5}$$

The average R^2 trend is captured by b_1. Average trend for securities in the *survivor sample* is 12.2 bps per month (t=47.27). R^2 trend increases monotonically across stocks sorted on *passive institutional ownership* growth. Stocks in the lowest quintile have an average trend of 8.8 bps per month (t=12.81). This coefficient increases as we move across quintiles from lowest to highest and reaches 17.7 bps (t=38.31) in the top quintile.

The increase in trend coefficients across *passive institutional ownership* growth quintiles in Model 1 fully supports our hypothesis. However, we are concerned that the dynamics of this model's residuals might be misspecified, causing standard errors to be understated. More specifically, we are concerned that serial correlation in the R^2s of individual stocks would make OLS estimators inefficient. Model 2 addresses the potential effect of serial correlation on our test statistics by imposing an AR(1) structure on the residuals:

$$R^2_{it} = b_0 + b_1 * t + b_2 * firm\ dummy_i + \delta_{it} \text{ where } \delta_{it} = AR(1)_i * \delta_{it-1} + \varepsilon_{it} \tag{6}$$

According to Model 2, the average trend for *survivor sample* securities is 17.9 bps per month (t=5.42). Although still statistically significant at the 1% level, the test statistic for this coefficient is much smaller than that obtained in Model 1. Securities in the lowest *passive institutional ownership* growth quintile have average trend of 13.9 bps per month (t=3.07). This coefficient increases across quintiles, but not monotonically. In addition, the average AR(1) coefficients are highly significant, suggesting that this specification effectively removes the effect of serial correlation from the standard errors.

In Model 3, we estimate the average trend of securities in passive institutional ownership growth quintiles while imposing an AR(1) structure on the residuals and controling for firm-specific-factors and other determinants of comovement's growth:

$$\begin{aligned} R^2_{it} = {} & b_0 + b_1 * t + b_2 * \text{firm dummy}_i + b_3 \ln(\text{active institutional ownership})_{it} \\ & + b_4 * \ln(\text{num.S\&P index memberships})_{it} + b_5 * \ln(\text{salescomov.})_{it} \\ & + b_6 * \ln(\text{market cap.})_{it} + b_7 * \ln(\text{num.analysts})_{it} + b_8 * \ln(\text{noise})_{it} \\ & + b_9 * \ln(\text{share volume})_{it} + b_{10} * \ln(\text{turnover})_{it} + b_{11} * \ln(\text{inv. Amihud measure})_{it} \\ & + b_{12} * \ln(\text{num. trading days})_{it} + \delta_{it} \quad \text{where} \quad \delta_{it} = AR(1)_i * \delta_{it-1} + \varepsilon_{it} \end{aligned} \tag{7}$$

As in models 1 and 2, the coefficient of interest is b_1. The average trend for securities in the *survivor sample* is 8.8 bps per month (t=1.72), statistically significant at the 10% level. As in prior specifications, the trend coefficient increases across quintiles of passive institutional ownership growth. For the first two quintiles, average R^2 trend is statistically insignificant but grows monotonically in the third (7.3 bps per month; t=1.82), fourth (7.6 bps per month; t=1.96), and fifth (12.0 bps per month; t=3.55). This increase in the R^2 trend coefficients fully supports our hypothesis and suggests that the primary cause for the sustained increase in average R^2 since the early 1990s is the rise of *passive institutional ownership*.

4.3 Robustness checks

We put the inference drawn from Table 6 to the test by fitting Model 3 on securities sorted on variables other than passive institutional ownership. Specifically, we sort securities on *market capitalization* and *noise* (i.e. autocorrelation coefficient). In doing this we are testing the alternative that comovement has risen because of sustained increases in correlated trading and/or sustained reductions in market frictions.[10]

4.3.1 R^2 trends and changes in market capitalization

We sort securities on *market capitalization* because its correlation with R^2 (0.73 in the *survivor sample*) is the highest among all regressors. *Market capitalization* is a proxy for information production (Crawford, Roulstone, and So, 2012), market frictions, and correlated trading. *Market capitalization* can be used to proxy for correlated trading because large firms are more likely to belong to multiple open-ended index funds and ETFs and because firm size is a very popular investment style. The pairwise correlation between market capitalization and number of index memberships in Table 5 is very high. It is 0.70 in the *full sample* and 0.74 in the *survivor sample.*

Panel A of Table 7 reports average changes in *market capitalization* for all stocks and each quintile in the *survivor sample* between 1993 and 2010. On average, *market capitalization* grew by $5.8 billion. Stocks in the top *market capitalization* growth quintile increased by an average $26.6 billion, while market capitalization in the lowest quintile declined by an average $579.8 million.

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[10] We rule out the possibility that comovement's trend could also respond to sustained increases in cash flow comovement in additional, unreported tests. Irvine and Pontiff (2009) and Chun, Kim, Morck and Yeung (2008) contend that cash flow comovement responds primarily to long run dynamics in product market competition. The more competitive the environment, the more likely it is that cash flows will respond to idiosyncratic factors (e.g. introduction of innovative management and business practices). Therefore, for the trend in return comovement to be explained by a similar trend in cash flow comovement, the US economy should have lost competitiveness since the 1990s. This is not what happened. There is ample empirical evidence of increasing competitiveness in US businesses via higher labor productivity growth from the mid-1990s to the mid-2000s, possibly tied to the adoption of new information technologies (Delong, 2002; Rogoff, 2004; Fernald, Thipphavong, Bharat, 2007). In a separate analysis and consistent with the economic data, we find that various cash flow comovement measures do not show the same pattern we observe in stock return comovement. Cash flow comovement declines steadily since the mid-1960s, but it does not increase in the 1990s. Results from this supplemental analysis are available to interested readers upon request.

Panel A of Table 7 shows the result of fitting a modified version of Model 3 on securities in the *survivor sample* and market capitalization growth quintiles. This model specification controls for firm-specific factors, imposes an AR(1) structure on the residuals, and controls for all determinants of comovement's growth other than *market capitalization*:

$$R^2_{it} = b_0 + b_1{*}t + b_2{*}firm\ dummy_i + b_3{*}\ln(passive\ institutional\ ownership) + b_4{*}\ln(active\ institutional\ ownership)_{it} + b_5{*}\ln(num.S\&P\ index\ memberships)_{it} + b_6{*}\ln(salescomov.)_{it} + b_7{*}\ln(num.analysts)_{it} + b_8{*}\ln(noise)_{it} + b_9{*}\ln(share\ volume)_{it} + b_{10}{*}\ln(turnover)_{it} + b_{11}{*}\ln(inv.\ Amihud\ measure)_{it} + b_{12}{*}\ln(num.\ trading\ days)_{it} + \delta_{it} \quad (8)$$

Where $\delta_{it} = AR(1)_i{*}\delta_{it-1} + \varepsilon_{it}$

As in the original Model 3 specification, the coefficient of interest is b_1. The average trend coefficient for securities in the *survivor sample* in this specification is 7.2 bps per month (t=1.41), statistically insignificant. This suggests that when passive institutional ownership and market friction proxies are included in the regression, together they explain the entirety of comovement's positive trend. Unlike securities sorted on passive institutional ownership growth, the trend coefficients of securities sorted on market capitalization growth does not increase monotonically across quintiles. Average R^2 trend increases from the first (5.1 bps per month; t=1.15) to the third quintile (13.6 bps per month; t=3.86), but then declines in the fourth (10.7 bps per month; t=2.84) and fifth (7.7 bps per month; t=1.99). This pattern is inconsistent with an alternative hypothesis in which the primary cause for the sustained increase in average R^2 is related to factors prevalent in large firms, such as correlated trading from open-ended index fund and ETFs or having very liquid security markets and low information acquisition costs.

4.3.2 R^2 trends and changes in noise

In addition to sorting securities on *market capitalization*, we sort variables on *noise,* a proxy for the effects of market frictions on security returns. The increase in average R^2 since 1993 coincides with profound technological and regulatory changes in capital markets.

As a result, we have witnessed an unprecedented decline in transaction and information acquisition costs (Chordia, Roll, and Subrahmanyam, 2011; Hendershott, Jones, and Menkveld, 2011). The emergence of online discount brokers and the vast resources deposited into mutual funds have increased market participation and depths. In addition, automated trading has had a positive effect on liquidity by narrowing down spreads, and reducing adverse selection costs (Hendershott, Jones, and Menkveld, 2011). Hence, it is possible that increasing comovement is a consequence of faster information diffusion derived from lower market frictions.

To test this hypothesis we repeat the same test described in sections 4.2 and 4.3.1 but this time we sort all securities in the *survivor sample* into quintiles based on *noise.* Panel B of Table 7 reports average changes in our *noise* variable for all stocks and each quintile in the *survivor sample*. There is an overall reduction in noise between 1993 and 2010 (-0.054). The noise measure declines in the first (-0.27), second (-0.09), and third (-0.03) quintiles of the distribution, but increases in the fourth (0.02) and fifth (0.10). This implies that about two-fifths of the firms in our sample saw their returns become more negatively autocorrelated and dispels the idea that the past two decades have been marked by lower market frictions for securities across the board. Market frictions seem to have eased for a large number of securities, but some have seen either very little improvement or even deterioration from their pre-1990s levels.

Panel A of Table 7 shows the result of fitting a modified version of Model 3 on securities in the *survivor sample* and change in *noise* quintiles. This model specification controls for firm-specific factors, imposes an AR(1) structure on the residuals, and includes all controls except those related to market frictions:

$$\begin{aligned} R^2_{it} = {} & b_0 + b_1 * t + b_2 * \mathit{firm\ dummy}_i + b_3 * \ln(\mathit{passive\ institutional\ ownership}) \\ & + b_4 * \ln(\mathit{active\ institutional\ ownership})_{it} + b_5 * \ln(\mathit{num.S\&P\ index\ memberships})_{it} \\ & + b_6 * \ln(\mathit{salescomov.})_{it} + b_7 * \ln(\mathit{num.analysts})_{it} + b_8 * \ln(\mathit{market\ cap.})_{it} + \delta_{it} \end{aligned} \tag{9}$$

Where $\delta_{it} = AR(1)_i * \delta_{it-1} + \varepsilon_{it}$

Once again, the coefficient of interest is b_1. The average trend coefficient for securities in the *survivor sample* in this specification is 9.0 bps per month (t=2.42). Just as it was observed using *market capitalization* as the sorting variable, the trend coefficients of securities sorted on *noise* changes do not increase monotonically across quintiles. The behavior of the trend coefficient across quintiles is erratic and no pattern can be identified. Average R^2 trend declines from the first (13.6 bps per month; t=4.44) to the second quintile (5.3 bp per month; t=1.91), just to increase again between the second, third (8.2 bp per month; t=3.24) and fourth (9.0 bps per month; t=3.22), and to decline again between the fourth and fifth (4.7 bps per month; t=1.55). This pattern is inconsistent with market frictions being responsible for comovement's increasing trend.

5. Influence of passive institutional ownership on comovement

In addition to our main tests on the average trend of individual R^2s, we design a supplementary test in which annual changes in *passive institutional ownership* are regressed on annual changes in R^2. This test serves two purposes. First, it determines the influence of passive institutional ownership increases on R^2 increases in comparison to changes in other variables. Second, it provides an opportunity to test the relation between *passive institutional ownership* increases and R^2 increases that could be implemented on both, *full* and *survivor* samples. In this way, we mitigate effects of a possible survivor bias in our main results which, by construction, only include securities listed during the entire 1993-2010 period.

To determine the sensitivity of R^2 increases to *passive institutional ownership* increases we conduct first-difference pooled regressions with two-way fixed-effects, two-way standard error clustering (Petersen, 2009; Thompson, 2011), and White (1980) heteroskedasticity-consistent standard errors. We choose first-difference as opposed to level regressions for two reasons. First, because first-differences are more appropriate to answer our research question. Given that our interest is to understand what might have caused comovement's secular increase, it is more appropriate to look at how R^2 increases respond to increases in passive institutional ownership and other factors than at levels of these variables. Second, because by taking first-differences we render the individual R^2 series stationary, making them fit for cross-sectional analysis. Fu (2009) conducts unit-root tests on the idiosyncratic volatility (i.e. 1-R^2) series of 26,000 stocks in the CRSP universe and rejects the null of a random-walk in about 90% of these. Based on this result we conclude that there is a strong possibility that a sizable portion of our individual R^2s is not stationary.

Table 8 reports coefficients and corresponding t-statistics from first-difference regressions of the natural logarithm of individual R^2s on the natural logarithm of *passive institutional ownership* and controls for observations in the *full sample*. Columns (1), (2), and (3) in Table 8 report regression coefficients and test statistics of model specifications that exclude ETF ownership. These regressions are fit on the entire 1993-2010 period. Columns (4), (5), and (6) in Table 8 report coefficients and test statistics including ETF ownership. Because change in ETF ownership data is only available since 2004, regression coefficients in these columns only apply to the 2004-2010 period.

Given that the continuous variables in our analysis are first-differenced and log-transformed, and that annual changes are small, we interpret coefficient estimates of these variables as elasticities. Therefore, with the exception of index and investment style addition and deletion dummies, the coefficients in Table 8 show the percentage change in R^2 associated with a 1% increase in each independent variable.

[Table 8 about here]

The regression coefficients and test statistics in Table 8 are consistent with a passive institutional ownership explanation of the shift in comovement's trend. Coefficient estimates for changes in passive institutional ownership are by far the largest and most significant of all. Annual changes in *passive institutional ownership* are positively related to annual R^2 changes in all model specifications. Consider the change in *passive institutional ownership* in columns (1), (2), and (3). The response of R^2 to a one percent increase in *passive institutional ownership* is 1.19, 1.12, and 1.10 percent (t=3.83, 3.82, and 3.77). During the most recent period, 2004-2010, the response is even stronger. It is, 1.85, 1.67, and 1.66 percent (t=7.52, 5.24, and 5.33).

Coefficient estimates in columns (4), (5), and (6) show that, although positive, the effect of *ETF ownership* changes on R^2 changes is economically and statistically insignificant. This might happen because the ETF industry is still in its infancy and very small relative to the size of the equity markets.

Coefficient estimates for correlated trading proxies are, for the most part, statistically significant and bear the expected signs, suggesting that increases in correlated trading are important determinants of R^2 increases. Coefficient estimates for *number of index memberships* are negative and significant. The coefficient estimate for this variable in Column (3) suggests that a 1% increase in index memberships results in a 5 bp (t=4.86) reduction in R^2. Put it in a different way, a unit-increase in index memberships relative to the mean (5.04) results in a 0.25% (5.04x-0.05) reduction in R^2. This implies that correlated trading from multiple index memberships is primarily the result of investors' focusing on certain indexes that fit their investment styles and not of open-ended index-fund managers' accommodating net fund flows.

Just like with *number of index memberships*, index-fund addition and deletion dummies also suggest significant habitat and style-investing effects on R^2. For example, Column (1) shows that between 1993 and 2010, deletions from large-cap indexes, mid-cap indexes, and the "low-priced" stock category, which occurs when prices increase above $10 per share, result in R^2 increases of 0.17 (t=2.03), 0.08 (t=2.08), and 0.18 (t=4.13) percent, respectively. On the other hand, additions into large-cap and small-cap indexes result in R^2 reductions of 0.15 (t=4.34) and 0.13 (t=4.56) percent. It is important to note that while the order of magnitude of additions and deletions for large-cap indexes is similar, index additions have surpassed deletions in 16 of the 18 sample period years. This is a natural consequence of the rapid increase in publicly available indexes documented in Wurgler (2010). With R^2-reducing additions being the dominant force, correlated trading from habitat effects should have been a hindrance, and not a cause, for comovement's positive trend.

The effect of informed market participants on R^2 changes is captured by changes in *active institutional ownership* and *number of analysts.* There is a positive and significant relation between *active institutional ownership* changes and R^2 changes in columns (1), (2) and (3) of Table 8. This relation is inconsistent with prior literature. According to Chakravarty (2001), institutional ownership changes convey information as long as institutional investment decisions are motivated by firm-specific information. When this happens, institutional trading should accelerate the incorporation of firm-specific news into prices (Piotroski and Roulstone, 2004). Therefore, changes in *active institutional ownership* should increase firm-specific volatility and reduce R^2. This is not what we observe in the data. In column (1) of Table 8, a 1% increase in *active institutional ownership* results in a 0.49% increase in R^2 (t=2.79). This positive relation might respond to herding, which in turn might be the result of structural changes in the compensation scheme of financial managers (Rajan, 2005). Rajan posits that a shift in compensation, from fixed to return-based, has caused a separation between financial manager incentives and those of their clients.Until the 1970s the incentive of financial managers, who worked mostly for banks, was to keep their client's money safe. Afterwards, with the rise of mutual funds, this incentive shifted from fulfilling fiduciary duties to outperforming other fund managers. According to Rajan (2005), the downside of more intense competition in portfolio management has been an increased incentive by financial managers to avoid penalties tied to underperformance. In this environment, many financial managers choose to herd rather than compete, thus failing to perform fundamental analysis. Coefficient estimates for *analyst coverage* are all statistically insignificant.

Coefficient estimates for most market friction proxies are statistically insignificant as well, except for noise and the Amihud measure in the full 1993-2010 period. Coefficient estimates for market frictions during the 2004-2010 period are all insignificant.

Table 8 results suggest that the most important factor influencing R^2 changes is *passive institutional ownership* changes. This is consistent with our main result which shows a positive relation between R^2 trend and *passive institutional ownership* growth.

6. Concluding comments

Comovement's trend is an actively researched topic in financial economics. It is extremely important to the discipline because of the intimate connection between correlations and systematic risk in classic asset pricing models. In our study, tests of comovement's trend for the period 1962-2011 show a sharp reversal that fits the statistical properties of a permanent break. Through the implementation of Bai and Perron (1998, 2003) on average R^2, we identify an approximate break date of September 1992. This suggests that systematic risk has been growing steadily over the past two decades and, because this increase is unrelated to cash flow correlations, it could have affected the real sector by reducing capital allocation efficiency (Wurgler, 2000).

What is the underlying cause of this reversal? A potential explanation could be the introduction of information technology to financial markets. However, the mechanism by which technological progress and comovement relate is not necessarily obvious. The emergence of online discount brokers and the immense resources deposited into mutual funds have increased market depth and program trading has reduced transaction costs (Hendershott, Jones, and Menkveld, 2011; Chordia, Roll, and Subrahmanyam, 2011). With larger and more liquid markets, one could reasonably assume that comovement rose in response to lower market frictions. However, this is just one side of the story.

At the same time that market frictions have been fading, there has been a shift in the predominance of passive investment strategies over active ones. This has happened because portfolio rebalancing costs have fallen faster than information acquisition costs. By their own nature, passive investors' trades are not informative. Passive investors typically follow indexes, and have no need to either perform fundamental research or monitor management (Porter, 1992; Bushee 1998, 2001; Wermers and Yao, 2010). The results from our analysis show that a declining number of investors trading on firm fundamentals are the primary reason for the increasing R^2 documented by Sullivan and Xiong (2012). This finding suggests that the US stock market has lost informativeness over the past two decades.

The results from our study provide empirical support to the notion that market model R^2 is an appropriate price informativeness proxy. Although in theory, price changes should summarize all information on a firm's future payoffs, how closely tied prices and information really are remains unknown. Therefore, whether R^2 relates to information is an empirical question. A large number of studies support the idea that high R^2 is indicative of low price informativeness. They show a negative relation between R^2 and firm-specific information proxies such as shareholder rights protection (Morck, Yeung, and Yu, 2000), financial reporting transparency (Jin and Myers, 2006), and the trades of informed investors (Piotroski and Roulstone, 2004). On the other hand, there is an equally large number of studies arguing that R^2 is unrelated to price informativeness, but the result of changes in securities regulation and product market competition, which influence cash flow correlations (Brown and Kapadia, 2007; Irvine and Pontiff, 2009), or by temporary spikes in idiosyncratic volatility during speculative periods (Brandt, Brav, Graham, and Kumar, 2010). The latest shift in comovement's trend gives us an opportunity to revisit this issue and provides evidence consistent with the times series of R^2 being negatively related to price informativeness.

Results from our tests suggest that average R^2's rise over the past two decades is primarily tied to the explosion of passive institutional investing. Interestingly, we find no evidence that correlated trading by open-ended index funds and ETFs are responsible for the increase.

An interesting result which deserves further exploration is the positive relation between *active* institutional ownership changes and R^2 changes in our first-difference regressions. This result seems to defy logic because, by definition, active managers should trade on firm-specific information as a way of making a living. This result elicits two questions: (1) if active managers are not trading on firm-specific information what are they exactly doing? And (2) if active managers are not trading on firm-specific information, who is? The answer to the first question might have to do with structural changes in the compensation scheme of financial managers, which have encouraged them to herd in an effort to avoid penalties related to underperformance (Rajan, 2005). This might be an interesting area for further study.

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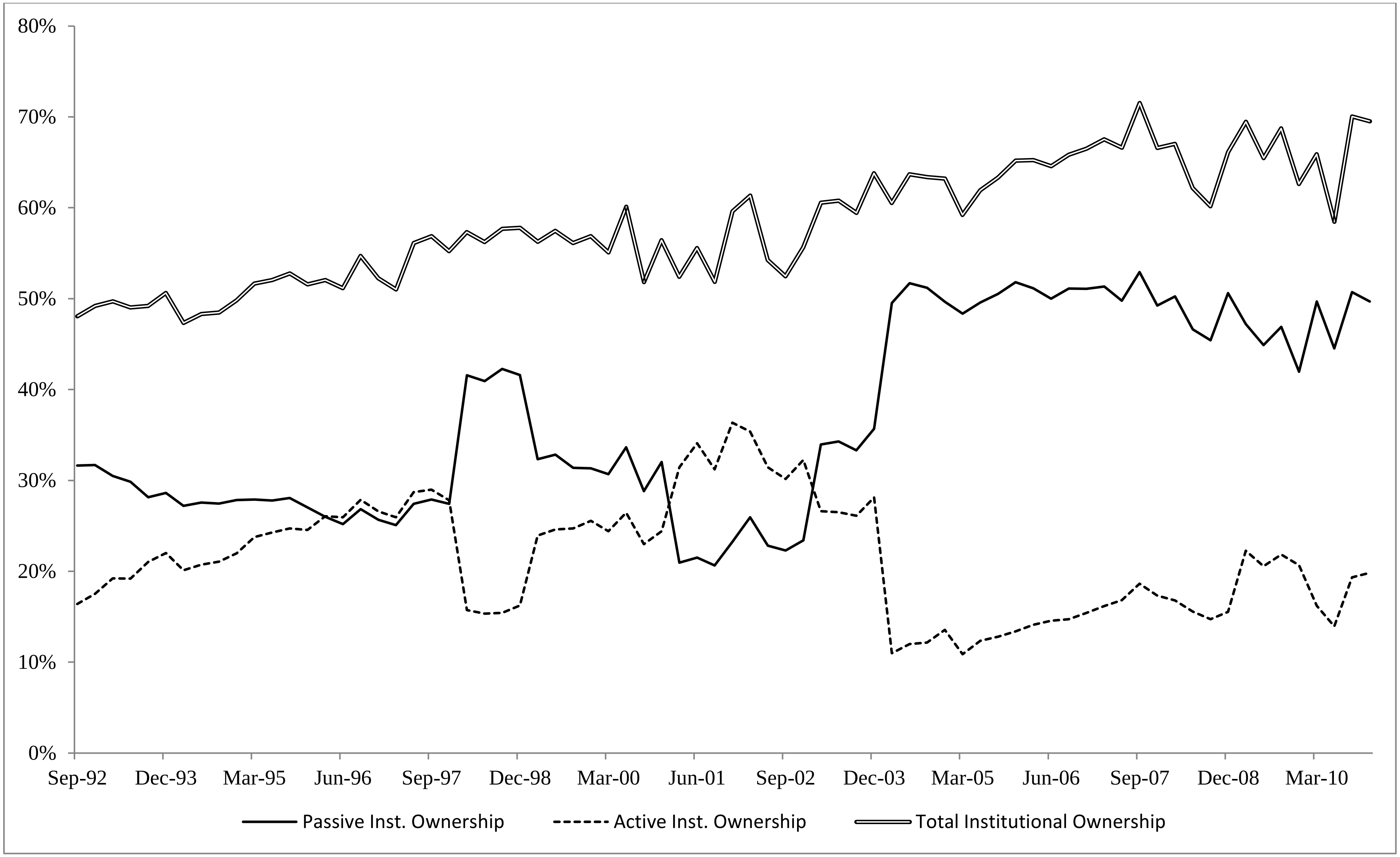
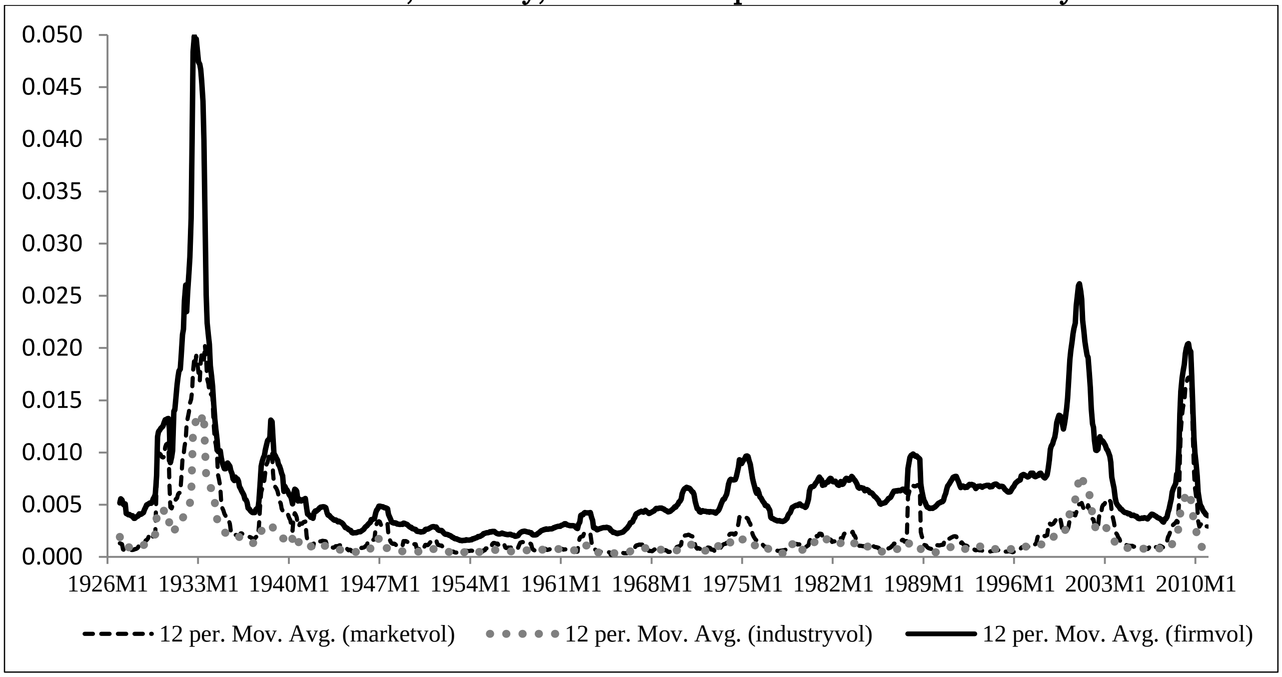


Figure 1. Stock ownership of all financial institutions, passive financial institutions (quasi-indexers), active financial institutions (transient and dedicated).

Panel A: Market, industry, and firm components of total volatility



Panel B: Ratio of Firm-Specific Volatility Relative to Market and Industry Volatilities

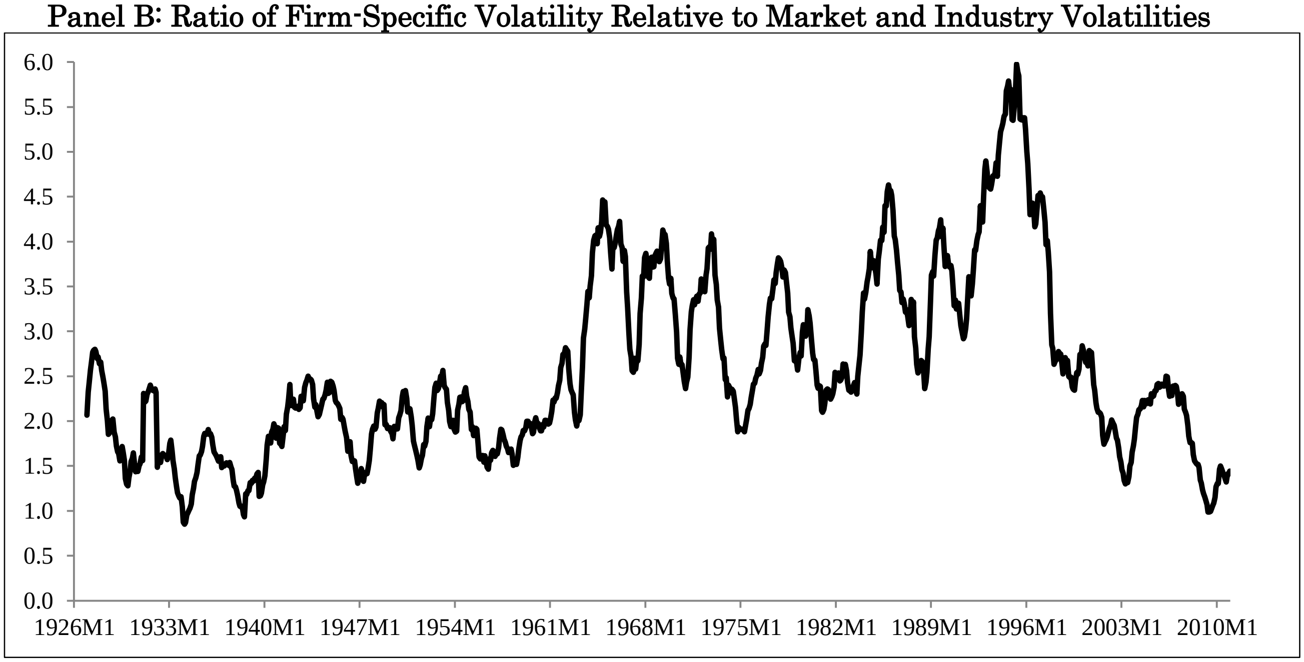
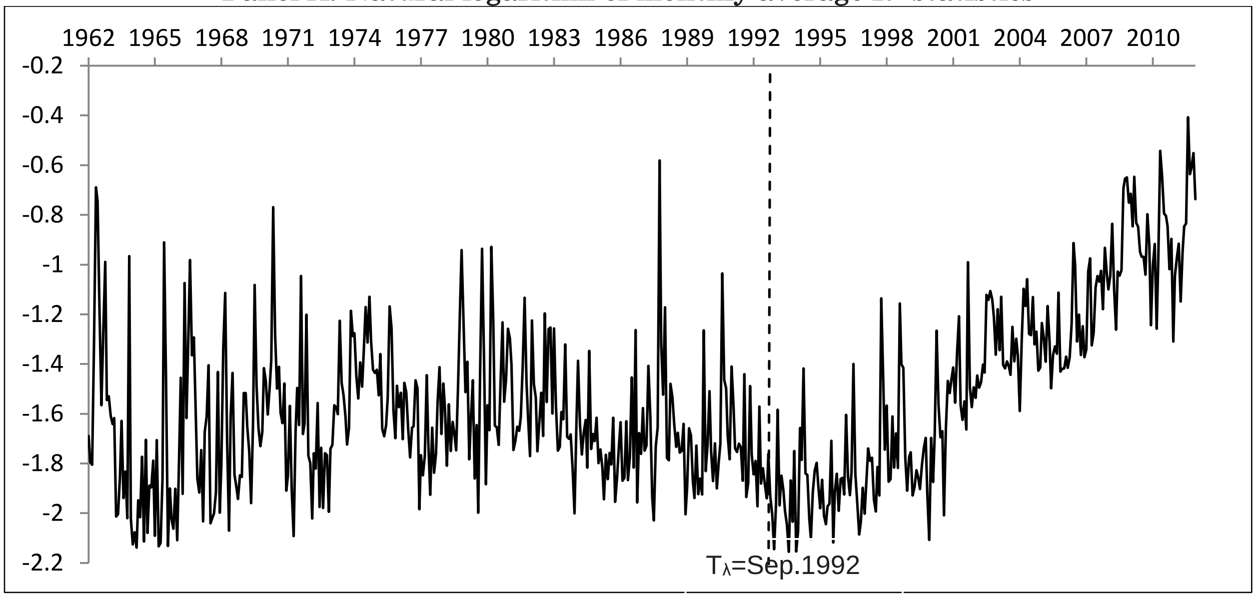


Figure 2: Panel A shows the three components of stock return volatility: market, industry, and firm-specific. The original series are smoothed using a 12-month moving average. Panel B shows the ratio of firm-specific volatility as a proportion of market and industry. This ratio can give an indication of the economic importance of firm-specific volatility with respect to the pervasive components of volatility (i.e. market and industry).

Panel A. Natural logarithm of monthly average R^2 statistics



Panel B. Natural logarithm of monthly proportion of market and industry volatility to total volatility

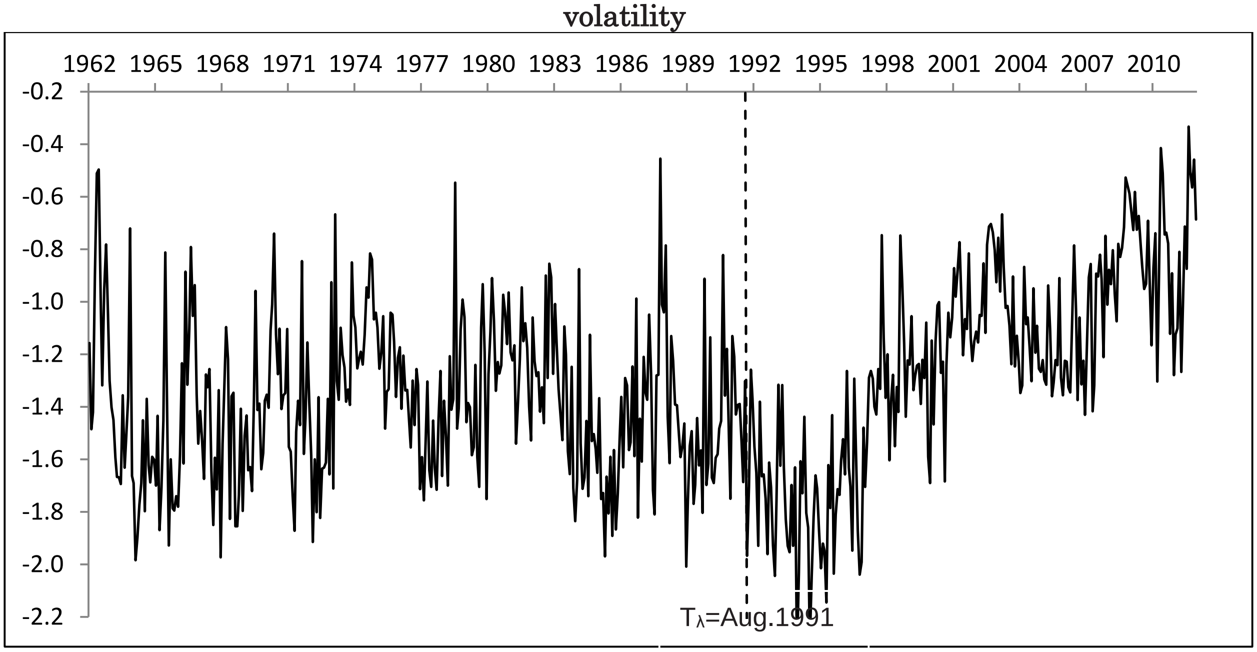


Figure 3. Comovement Measures Used in the Times Series Analysis, January 1962 – December 2011. Panel A shows monthly equally weighted average R^2 statistic from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns. To control for the mechanical relation between average R^2 statistic and number of stocks the stock in question is eliminated from its corresponding market and industry index on that particular day. Panel B shows the ratio of monthly market and industry volatility to total volatility, following Brockman, et al (2010). The market, industry, and firm specific volatilities used to form this ratio are obtained by implementing the beta free volatility decomposition in Campbell, Lettau, Malkiel, Xu (2001) to US daily returns. T_λ is the structural break date identified by the Bai and Perron (1998, 2003) dating algorithm.

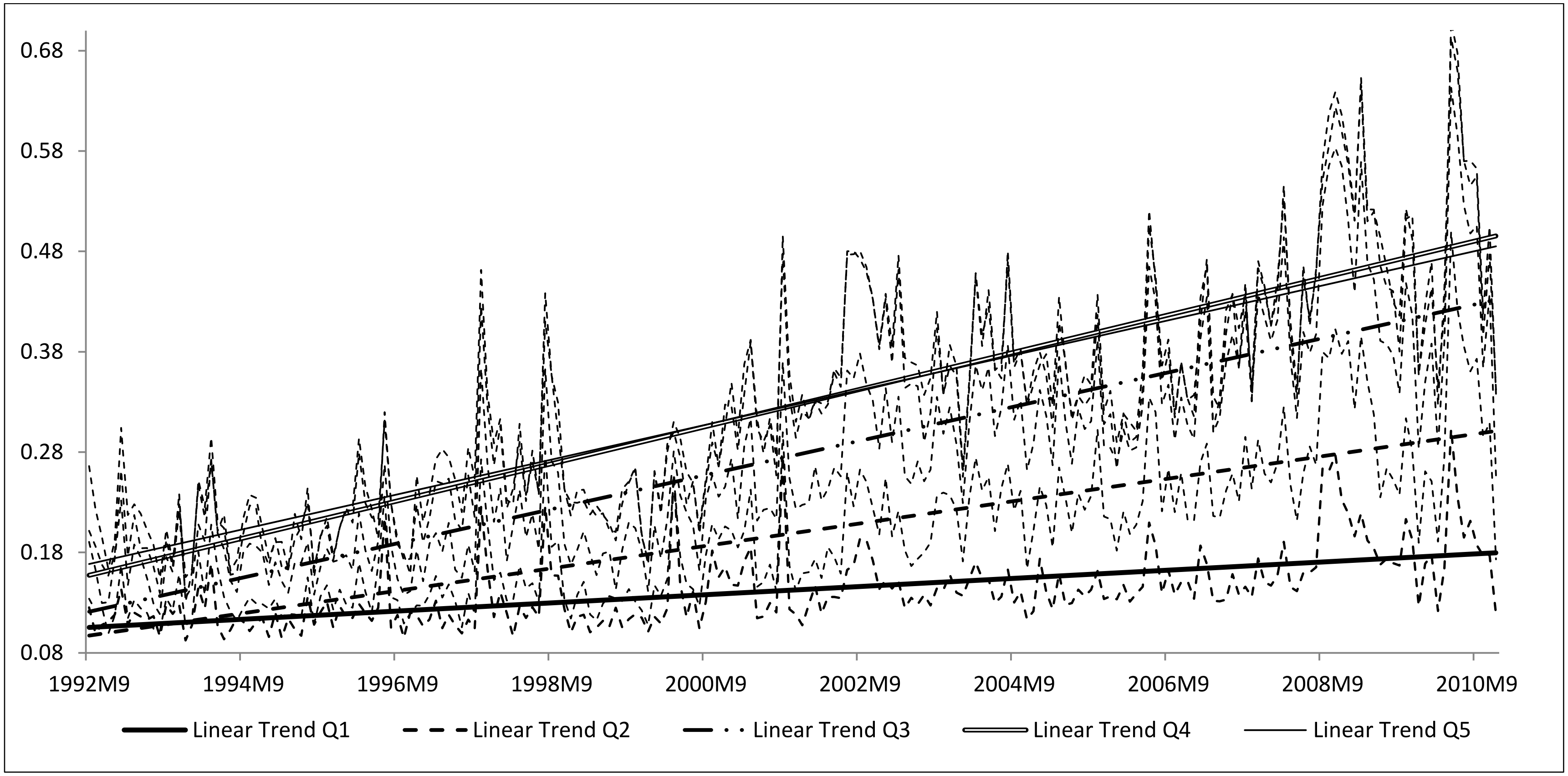


Figure 4. Equally weighted average market model R^2 for stocks sorted on passive institutional ownership. We compute monthly equally weighted average R^2 statistic from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns and then we group these individual R^2s by average ownership of quasi-indexers in the previous year. Quasi-indexers are identified using Brian Bushee's classification of financial institutions, available on his website, and institutional ownership is obtained from the SEC 13f reports. We smooth each series using a 12-month moving average.

Table 1
Summary statistics of stock return comovement: January 1962 - December 2011. This table shows summary statistics for the comovement measures used in the times series analysis, for the full sample period and the pre and post break periods. Monthly average R^2 statistic is the monthly equally weighted average R^2 from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns. To control for the mechanical relation between average R^2 statistic and number of stocks (i.e. correlation would be higher as the firm returns for individual stocks make up a larger proportion of the total market capitalization), the stock in question is eliminated from its corresponding market and industry index. The Bai and Perron (1998, 2003) algorithm identifies a structural break date for this series in September, 1992. The monthly proportion of market and industry volatility to total volatility is the ratio of market and industry volatility to total volatility in a given month, following Brockman, et al (2010). The market, industry, and firm specific volatilities used to form this ratio are obtained by implementing the beta free volatility decomposition in Campbell, Lettau, Malkiel, and Xu (2001) to US daily returns. The Bai and Perron algorithm identifies a structural break date for this series in August, 1991.

										Autocorrelation coefficients of the natural logarithm							
Series/Period	obs.	σ^2	mean	min	q1	median	q3	max	d.w.	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_{12}	ρ_{24}
Panel A. monthly average R^2 statistic																	
Jan 1962 – Dec 2011	600	0.09	0.22	0.12	0.16	0.20	0.26	0.67	0.68	0.66	0.55	0.52	0.48	0.50	0.47	0.41	0.32
Jan 1962 – Sep 1992	369	0.06	0.20	0.12	0.16	0.19	0.23	0.56	1.17	0.41	0.23	0.17	0.16	0.21	0.15	0.05	-0.02
Oct 1992 – Dec 2011	231	0.11	0.26	0.12	0.16	0.24	0.33	0.67	1.19	0.40	0.23	0.16	0.01	0.07	0.06	0.07	-0.17
Panel B. monthly proportion of market and industry volatility to total volatility																	
Jan 1962 – Dec 2011	600	0.10	0.28	0.10	0.20	0.26	0.33	0.72	0.77	0.61	0.54	0.49	0.47	0.46	0.41	0.34	0.19
Jan 1962 – Aug 1991	356	0.08	0.26	0.13	0.20	0.25	0.30	0.63	1.14	0.43	0.34	0.29	0.25	0.24	0.17	0.07	-0.06
Sep 1992 - Dec 2011	244	0.12	0.31	0.10	0.22	0.29	0.40	0.72	0.95	0.53	0.41	0.32	0.30	0.31	0.28	0.23	-0.06

Table 2
Statistical characteristics of comovement's trend: January 1962- December 2011. Monthly average R^2 statistic is the monthly equally weighted average R^2 statistic from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns. To control for the mechanical relation between average R^2 statistic and number of stocks, the stock in question is eliminated from its corresponding market and industry index. Monthly proportion of market and industry volatility to total volatility is the ratio of market and industry volatility to total volatility in a given month, following Brockman, et al (2010). The market, industry, and firm specific volatilities used to form this ratio are obtained by implementing the beta free volatility decomposition in Campbell, Lettau, Malkiel, and Xu (2001) to US daily returns. We estimate break dates and associated confidence intervals using the Bai and Perron (1998, 2003) dynamic programming algorithm, and the characteristics of the linear relation of comovement with a linear regressions of the natural logarithm of comovement on time and structural break indicators. We control for serial correlation by imposing an AR(5) structure on the error term. Regression parameters are estimated using the Yule-Walker algorithm. We estimate regression parameters for three models:

Model 1: $y_t = \mu + \theta DU_t(\lambda) + \beta t + \mu_t; \mu_t = \sum_{i=1}^{5} \phi_i \mu_{t-i} + e_t; DU_t(\lambda) = 1$ $\quad if t > T\lambda$

Model 2: $y_t = \mu + \beta t + \gamma DT_t^*(\lambda) + \mu_t; \mu_t = \sum_{i=1}^{5} \phi_i \mu_{t-i} + e_t; DT_t^*(\lambda) = t - T\lambda$ $\quad if t > T\lambda$

Model 3: $y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \mu_t; \mu_t = \sum_{i=1}^{5} \phi_i \mu_{t-i} + e_t;\ DU_t(\lambda) = 1\ and DT_t^*(\lambda) = t - T\lambda$ $\quad if t > T\lambda$

Model 1 allows for a change in the comovement function's intercept; *Model 2* allows for a change in the slope; and *Model 3* allows for a change in both, the intercept and slope. μ is the equation's intercept. $DU_t(\lambda)$ is an indicator that takes the value of one if $t>T\lambda$, the structural break point in the series identified by the Bai and Perron (1998, 2003) algorithm. t is a count variable for time. $DT_t^*(\lambda)$is a count variable for the post break period. ϕ_i are the autoregressive parameters of the error term.

Bai and Perron (1998,2003) Breakpoints and c.i.	model	Yule-Walker estimates of structural break parameters μ	θ	$\beta(x10^{-4})$	$\gamma(x10^{-4})$	AIC
		Panel A. natural logarithm of monthly average R^2 statistic				
	1	-2.33***	-0.13	11.74**		-82.01
		(-6.77)	(-0.92)	(2.33)		
$\widehat{T}_\lambda$ = Sep 1992	2	-2.28***		10.92**	-0.99	-81.63
95%c.i. Jul 1992<=T_λ<=Oct 1992		(-6.23)		(2.00)	(-0.56)	
	3	-1.57***	-4.75***	-1.02	54.36***	-105.57
		(-9.95)	(-9.80)	(-0.41)	(9.64)	
		Panel B. natural logarithm of monthly proportion of market and industry volatility to total volatility				
	1	-1.76***	0.03	6.09		28.13
		(-5.35)	(0.20)	(1.23)		
$\widehat{T}_\lambda$ = Aug 1991	2	-1.67***		4.55	1.04	27.81
95%c.i. Dec 1990<=T_λ<=Sep 1991		(-4.79)		(0.85)	(0.56)	
	3	-1.17***	-3.86***	-3.77	45.64***	15.96
		(-5.11)	(-5.49)	(-1.03)	(5.54)	

Table 3

Descriptive Statistics for the Pooled Samples: The samples consist on annual observations of stock return comovement and their determinants for the period 1993 to 2010. This table reports descriptive statistics for two samples, the *Full Sample* and the *Survivor Sample.* The *Full Sample* consists on all common and ordinary stocks in the CRSP database with available return comovement and control variables. The *Survivor Sample* consists only on the common and ordinary stocks in the CRSP database with return information available during the entire 1993-2010 period. *Stock return co-movement* is the R^2 statistic of the market model for each individual stock over the past 12 months, using daily data, as of December 31st of each year. Only stocks listed for a minimum of 250 trading days over the past 12 months are considered. The market model is estimated using the CRSP value weighted index as the market index. *Passive institutional ownership* is the percentage of common and ordinary shares held by quasi-indexers in the second quarter of each year, as defined by Bushee and Noe (2000) and Bushee (2001). *Non-passive institutional ownership* is the percentage of common and ordinary shares held by financial institutions other than quasi-indexers. *ETF Ownership* is the percentage of common and ordinary shares held by Exchange Traded Funds. ETF ownership data is available for the years 2004-2010 only. *Number of index memberships* is the number of Standard and Poor's indexes that a stock belongs to. *Sales per share co-movement* is the R^2 statistic of quarterly unanticipated shocks to sales per share of individual stocks on quarterly unanticipated shocks to sales per share of the market and industry over the past 5 years (or 20 quarters). Unanticipated shocks to sales per share are estimated on the fourth quarter of each year following Irvine and Pontiff (2009), using all quarterly sales per share information in Standard & Poor's Compustat with a minimum of twelve consecutive quarters of data. *Market capitalization.*is the market value of equity in millions of dollars at the end of the previous June. *Number of analysts* is the number of earnings per share forecasts from IBES. *Noise* is the absolute value of the autocorrelation coefficient of market model residuals. All variables are winsorized at the 0.5% and 99.5% levels.

	σ		mean		min		q1		median		q3		max
	full	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full & surv*
Stock return comovement	0.18	0.20	0.17	0.22	0.00		0.02	0.04	0.09	0.16	0.27	0.36	0.85
Passive inst. ownership	0.19	0.18	0.29	0.35	0.00		0.12	0.22	0.29	0.37	0.44	0.48	0.92
ETF ownership	0.02	0.02	0.01	0.02	0.00		0.00		0.00		0.02	0.03	0.13
Market capitalization ($mm)	11,618	17,691	3,068	6,279	2.19	2.54	62.36	160.0	293.29	865.2	1,420.95	3,692.8	162,714.4
Correlated trading proxy													
Num. of index memberships	6.01	5.94	5.04	7.40	0.00		0.00		0.00	11	12		17
Correlated cash flows proxies													
Sales/share co-movement	0.16	0.18	0.15	0.17	0.00		0.04		0.10	0.11	0.22	0.25	0.93
Information production proxy													
Number of analysts	7.60	8.74	5.96	7.89	0		0		3	5	9	13	40
Active inst. ownership	0.14	0.12	0.17	0.17	0.00		0.05	0.08	0.14	0.16	0.26	0.25	0.71
Market friction proxies													
Noise	0.11	0.10	0.12	0.11	0.00		0.04		0.09	0.08	0.17	0.14	0.54
Turnover	4.12	4.85	1.64	4.17	0.00		0.25	1.12	0.67	2.61	1.66	5.27	49.15
Volume ($mm)	1,979	2,606	626	1,020	0.00		8.52	17.7	65.35	154.2	379	792.3	3,600
Inv. amihud (x10^{-7})	500	742.8	121	231.6	0.00		0.16	0.80	3.31	16.94	44.3	129.5	9,096
Number of trading days	31.38	26.11	240.20	244.03	29		247	250	252		252		254

Table 4
Frequency counts for index and style investing indicators

year	Number of Additions								Number of Deletions							
	Large Cap		Mid Cap		Small Cap		Low-Priced		Large Cap		Mid Cap		Small Cap		Low-Priced	
	full	*surv*	*Full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*	*full*	*surv*
1993	2	1	7	3	0	0	44	6	0	0	2	1	0	0	82	23
1994	4	1	6	3	0	0	49	8	2	0	3	1	0	0	90	12
1995	14	7	8	4	295	75	88	10	5	3	5	1	0	0	68	13
1996	11	8	12	1	23	9	62	5	6	1	13	7	3	0	123	20
1997	8	2	12	3	26	10	70	8	5	2	12	6	8	2	58	14
1998	22	9	15	4	47	15	53	4	6	4	16	4	8	0	81	21
1999	17	7	21	3	25	6	165	27	7	1	24	9	17	4	33	4
2000	23	7	21	6	43	8	99	20	1	1	24	10	16	2	109	11
2001	22	6	38	15	58	13	167	20	6	5	27	7	25	4	55	9
2002	13	6	26	7	27	7	115	11	13	5	31	9	38	11	98	19
2003	6	1	18	6	24	5	166	16	4	2	20	7	24	4	39	5
2004	8	2	21	5	23	4	20	2	2	1	20	4	29	7	284	37
2005	31	4	13	6	21	6	91	6	2	1	15	4	22	4	72	8
2006	19	3	22	4	38	3	49	4	8	5	6	1	11	2	79	8
2007	13	5	22	8	43	3	59	4	6	0	14	4	13	4	66	12
2008	20	6	26	8	37	3	118	8	6	2	18	6	10	3	26	4
2009	28	5	41	9	50	13	363	60	8	2	14	7	16	5	6	0
2010	15	4	26	9	26	4	91	11	18	7	42	11	41	7	122	31
Total	276	84	355	104	806	184	1,869	230	105	42	306	99	281	59	1,491	251

Table 5

Pair Wise Pearson Correlations for the Pooled Samples: The samples consist on annual observations of stock return comovement and their determinants for the period 1993 to 2010. This table reports pairwise Pearson correlations for two samples, the *Full Sample* and the *Survivor Sample*. The *Full Sample* consists on all common and ordinary stocks in the CRSP database with available return comovement and control variables. The *Survivor Sample* consists only on the common and ordinary stocks in the CRSP database with return information available during the entire 1993-2010 period. Variable definitions are those in Table 3. All variables in the sample are Winsorized at the 0.5% and 99.5% levels.

	Ln(R^2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(2) Ln (Passive inst. ownership)	0.62											
	(0.60)											
(3) Ln (Active inst. own.)	0.50	0.58										
	(0.45)	*(0.49)*										
(4) Ln (ETF Ownership)	0.40	0.39	0.25									
	(0.31)	*(0.32)*	*(0.19)*									
(5) Ln(# of index memberships)	0.57	0.64	0.41	0.29								
	(0.64)	*(0.65)*	*(0.40)*	*(0.20)*								
(6) Ln (Sales per share comov.)	0.09	0.07	0.03	0.08	0.07							
	(0.12)	*(0.08)*	*(0.01)*	*(0.10)*	*(0.09)*							
(7) Ln(Market Capitalization)	0.74	0.67	0.51	0.21	0.70	0.10						
	(0.73)	*(0.61)*	*(0.42)*	*(0.08)*	*(0.74)*	*(0.13)*						
(8) Ln (Number of Analysts)	0.59	0.61	0.50	0.30	0.59	0.08	0.72					
	(0.55)	*(0.55)*	*(0.42)*	*(0.18)*	*(0.61)*	*(0.09)*	*(0.70)*					
(9) Ln(Noise)	-0.49	-0.38	-0.37	-0.17	-0.33	-0.05	-0.46	-0.37				
	(-0.46)	*(-0.34)*	*(-0.31)*	*(-0.14)*	*(-0.35)*	*(-0.06)*	*(-0.41)*	*(-0.31)*				
(10) Ln (Share Volume)	0.71	0.62	0.56	0.31	0.60	0.09	0.79	0.68	-0.54			
	(0.71)	*(0.61)*	*(0.51)*	*(0.20)*	*(0.68)*	*(0.12)*	*(0.81)*	*(0.70)*	*(-0.45)*			
(11) Ln (Turnover)	0.62	0.56	0.62	0.42	0.46	0.06	0.53	0.55	-0.58	0.78		
	(0.63)	*(0.56)*	*(0.49)*	*(0.42)*	*(0.51)*	*(0.10)*	*(0.49)*	*(0.51)*	*(-0.39)*	*(0.73)*		
(12) Ln (Inverse Amihud)	0.79	0.73	0.60	0.28	0.71	0.09	0.95	0.74	-0.56	0.85	0.39	
	(0.79)	*(0.68)*	*(0.51)*	*(0.17)*	*(0.77)*	*(0.13)*	*(0.95)*	*(0.72)*	*(-0.50)*	*(0.87)*	*(0.67)*	
(13) Ln (Number of Trading Days)	0.41	0.34	0.30	0.18	0.27	0.04	0.41	0.34	-0.44	0.72	0.27	0.48
	(0.41)	*(0.35)*	*(0.29)*	*(0.14)*	*(0.33)*	*(0.06)*	*(0.37)*	*(0.31)*	*(-0.35)*	*(0.66)*	*(0.40)*	*(0.45)*

Table 6
Linear trend of R^2 of individual stocks grouped by increases of passive institutional ownership: 1993-2010. This table shows regression coefficients of individual stock comovement on time and control variables. We impose an AR(1) structure on the error term to account for serial correlation in the residuals.

	All Stocks	Ownership of quasi-indexers quintile				
		Q_1	Q_2	Q_3	Q_4	Q_5
Average change in passive institutional ownership	0.144	-0.057	0.055	0.135	0.219	0.369
Model 1: $R^2_{it} = b_0 + b_1 {*} t + b_2 {*} \text{firm dummy}_i + \varepsilon_{it}$						
b_0	-245.51***	-179.02	-189.60***	-237.66***	-264.90***	-356.48***
	(-47.68)	(-13.02)	(-15.65)	(-24.02)	(-26.42)	(-38.56)
b_1	0.122***	0.088***	0.094***	0.118***	0.131***	0.177***
	(47.27)	(12.81)	(15.49)	(23.88)	(26.21)	(38.31)
R^2	0.149	0.058	0.094	0.210	0.209	0.361
Model 2: $R^2_{it} = b_0 + b_1 {*} t + b_2 {*} \text{firm dummy}_i + \delta_{it}$; $\delta_{it} = AR(1)_i {*} \delta_{it-1} + \varepsilon_{it}$						
b_0	-360.53***	-282.84***	-309.64***	-292.43***	-297.04***	-402.59***
	(-5.45)	(-3.11)	(-5.07)	(-7.17)	(-5.66)	(-10.96)
b_1	0.179***	0.139***	0.154***	0.145***	0.147***	0.200***
	(5.42)	(3.07)	(5.03)	(7.13)	(5.62)	(10.89)
Average AR(1)	0.694***	0.747***	0.747***	0.678***	0.655***	0.542***
	(79.91)	(45.43)	(48.06)	(31.88)	(33.04)	(24.34)
R^2	0.093	0.032	0.081	0.151	0.099	0.292
Model 3: $R^2_{it} = b_0 + b_1 {*} t + b_2 {*} \text{firm dummy}_i + b_3 \ln(\text{active institutional ownership})_{it} + b_4 {*} \ln(\text{num.S\&P index memberships})_{it} + b_5 {*} \ln(\text{salescomov.})_{it} + b_6 {*} \ln(\text{market cap.})_{it} + b_7 {*} \ln(\text{num.analysts})_{it} + b_8 {*} \ln(\text{noise})_{it} + b_9 {*} \ln(\text{share volume})_{it} + b_{10} {*} \ln(\text{turnover})_{it} + b_{11} {*} \ln(\text{inv. Amihud measure})_{it} + b_{12} {*} \ln(\text{num. trading days})_{it} + \delta_{it}$; $\delta_{it} = AR(1)_i {*} \delta_{it-1} + \varepsilon_{it}$						
b_0	-185.60*	-117.02	-84.18	-159.28**	-172.44**	-261.14***
	(-1.88)	(-1.24)	(-1.21)	(-2.02)	(-2.25)	(-3.81)
b_1	0.088*	0.052	0.038	0.073*	0.076**	0.120***
	(1.72)	(1.09)	(1.06)	(1.82)	(1.96)	(3.55)
Average AR(1)	0.429***	0.385***	0.382***	0.472***	0.476***	0.351***
	(38.29)	(14.09)	(15.02)	(20.85)	(21.16)	(14.91)
R^2	0.284	0.184	0.426	0.375	0.407	0.473
Number of securities (i)	720	144	144	144	144	144
Number of years (t)	18	18	18	18	18	18

Table 7

Linear trend of R^2 of individual stocks sorted on changes in market capitalization and noise: 1993-2010. This table shows Regression Coefficients of Individual Stock Comovement on Trend, controls, and AR(1) Structure on the error term.

Panel A: Linear trend of R2 of Individual Stocks Sorted on Changes in Market Cap.

	All Stocks	Market capitalization quintile Q_1	Q_2	Q_3	Q_4	Q_5
Avg.Chg. in Market Cap. ($MM)	5,833.4	-579.8	114.3	688.9	2,309.6	26,634.2

$$R^2_{it} = b_0 + b_1{*}t + b_2{*}\text{firm dummy}_i + b_3{*}\ln(\text{passive institutional ownership}) + b_4{*}\ln(\text{active institutional ownership})_{it} + b_5{*}\ln(\text{num.S\&P index memberships})_{it} + b_6{*}\ln(\text{salescomov.})_{it} + b_7{*}\ln(\text{num.analysts})_{it} + b_8{*}\ln(\text{noise})_{it} + b_9{*}\ln(\text{share volume})_{it} + b_{10}{*}\ln(\text{turnover})_{it} + b_{11}{*}\ln(\text{inv. Amihud measure})_{it} + b_{12}{*}\ln(\text{num. trading days})_{it} + \delta_{it}$$

$$\delta_{it} = AR(1)_i{*}\delta_{it-1} + \varepsilon_{it}$$

	All Stocks	Q_1	Q_2	Q_3	Q_4	Q_5
b0	-160.72	-112.89	-159.55	-283.28	-222.21	-184.90
	(-1.59)	(-1.28)	(-1.83)	(-4.00)	(-3.09)	(-2.09)
b1	0.072	0.051	0.075*	0.136***	0.107***	0.077**
	(1.41)	(1.15)	(1.69)	(3.86)	(2.84)	(1.99)
Average AR(1)	0.420	0.276	0.274	0.356	0.455	0.539
	(37.86)	(10.67)	(12.26)	(16.67)	(20.41)	(24.56)
Number of securities (*i*)	720	144	144	144	144	144
Number of years (*t*)	18	18	18	18	18	18
R^2	0.298	0.127	0.274	0.518	0.356	0.165

Panel B: Linear trend of R2 of Individual Stocks Sorted on Changes in Noise

	All Stocks	Noise quintile Q_1	Q_2	Q_3	Q_4	Q_5
Avg. Chg in Noise	-0.054	-0.272	-0.094	-0.028	0.017	0.102

$$R^2_{it} = b_0 + b_1{*}t + b_2{*}\text{firm dummy}_i + b_3{*}\ln(\text{passive institutional ownership}) + b_4{*}\ln(\text{active institutional ownership})_{it} + b_5{*}\ln(\text{num.S\&P index memberships})_{it} + b_6{*}\ln(\text{salescomov.})_{it} + b_7{*}\ln(\text{num.analysts})_{it} + b_8{*}\ln(\text{market cap.})_{it} + \delta_{it}$$

$$\delta_{it} = AR(1)_i{*}\delta_{it-1} + \varepsilon_{it}$$

	All Stocks	Q_1	Q_2	Q_3	Q_4	Q_5
b0	-191.06	-282.65	-116.87	-172.29	-189.05	-104.49
	(-2.62)	(-4.67)	(-2.11)	(-3.47)	(-3.42)	(-1.71)
b1	0.090**	0.136***	0.053*	0.082***	0.090***	0.047
	(2.42)	(4.44)	(1.91)	(3.24)	(3.22)	(1.55)
Average AR(1)	0.485	0.340	0.517	0.508	0.501	0.486
	(44.30)	(13.93)	(20.05)	(21.61)	(22.36)	(21.42)
Number of securities (*i*)	720	144	144	144	144	144
Number of years (*t*)	18	18	18	18	18	18
R^2	0.285	0.330	0.333	0.377	0.321	0.324

Table 8

Cross-Sectional Determinants of Changes in Stock Return Comovement: 1993-2010 full sample.

		1993-2010 Period			2004-2010 Period		
		(1)	(2)	(3)	(4)	(5)	(6)
ΔLn(Passive institutional ownership)		1.19***	1.12***	1.10***	1.85***	1.67***	1.66***
		(3.83)	(3.82)	(3.77)	(7.52)	(5.24)	(5.33)
ΔLn(ETF ownership)					0.02	0.02	0.02
					(0.75)	(0.83)	(0.83)
ΔLn(Num. of index memberships)				-0.05***			-0.07***
				(-4.86)			(-4.25)
Deletions from	large-cap indexes	0.17**	0.18**		0.05	0.06	
		(2.03)	(2.23)		(0.69)	(0.88)	
	mid-cap. Indexes	0.08**	0.09**		0.13**	0.14**	
		(2.08)	(2.16)		(2.07)	(2.20)	
	small-cap indexes	0.01	0.02		-0.03	-0.02	
		(0.13)	(0.30)		(-0.27)	(-0.18)	
	low-priced stocks	0.18***	0.11***		0.15**	0.09	
		(4.13)	(2.79)		(2.49)	(1.63)	
Additions to	large-cap indexes	-0.15***	-0.15***		-0.14***	-0.14***	
		(-4.34)	(-4.21)		(-3.09)	(-3.14)	
	mid-cap. Indexes	-0.06	-0.06		-0.07	-0.07	
		(-1.34)	(-1.27)		(-1.62)	(-1.52)	
	small-cap indexes	-0.13***	-0.14***		-0.24***	-0.25***	
		(-4.56)	(-4.64)		(5.78)	(-6.19)	
	low-priced stocks	0.01	0.03		-0.01	0.01	
		(0.31)	(0.69)		(-0.08)	(0.11)	
ΔLn(Market capitalization)		0.68***	0.49***	0.50***	0.66***	0.47***	0.48***
		(17.52)	(11.52)	(11.28)	(7.87)	(5.86)	(5.77)
ΔLn (Sales per share comovement)		-0.004	-0.004	-0.004	0.01	0.01	0.01
		(-0.83)	(-0.84)	(-0.80)	(0.70)	(0.65)	(0.67)
ΔLn(Active institutional ownership)		0.49***	0.34*	0.34*	0.20	0.01	0.02
		(2.79)	(1.76)	(1.78)	(0.59)	(0.02)	(0.05)
ΔLn(Number of analysts)		-0.01	-0.03	-0.03	-0.002	-0.01	-0.01
		(-0.49)	(-0.99)	(-1.00)	(-0.08)	(-0.62)	(-0.61)
ΔLn (Noise)			-0.55***	-0.56***		-0.30	-0.30
			(-3.55)	(-3.57)		(-1.42)	(-1.44)
ΔLn(Share volume)			0.01	0.01		0.09	0.09
			(0.49)	(0.47)		(0.84)	(0.84)
ΔLn(Turnover)			0.09*	0.10*		-0.04	-0.04
			(1.78)	(1.84)		(-0.27)	(-0.25)
ΔLn(Inverse Amihud measure)			0.08***	0.08***		0.09*	0.09*
			(3.04)	(3.01)		(1.93)	(1.89)
ΔLn(Number of trading days)			0.18	0.20		0.47	0.47
			(0.77)	(0.82)		(0.71)	(0.71)
Intercept		-0.35	-0.35	-0.34	0.14	0.10	0.09
		(-1.30)	(-1.28)	(-1.30)	(0.39)	(0.26)	(0.24)
Number of observations		46,318	46,318	46,319	19,523	19,523	19,523
		0.143	0.149	0.149	0.195	0.203	0.203
R^2 (w/o fixed effects)		0.031	0.043	0.042	0.022	0.046	0.046

Appendix A

Alternative Explanations for the Increase in Stock Return Comovement

Here we take a look at two alternative explanations for comovement's increase that because of their nature cannot be tested thoroughly in the cross sectional and trend analyses. First, cross-sectional changes in the characteristics of publicly traded stocks might have caused comovement to dip during the 1990s and early 2000s because of the entry and later exit from equity markets of low comovement stocks (typically small, young, and unprofitable firms). Second, comovement spikes during speculative periods, particularly those leading to the March 2000 and October 2008 crashes could have produced the statistical and graphical illusion of a positive trend in the comovement series. Results from our tests are inconsistent with either explanation.

A.1 Composition Effects in Comovement's Trends

Some researchers attribute the declining comovement documented by Campbell, Lettau, Malkiel and Xu (2001) for the second half of the 20th century to changes in the composition of publicly traded stocks in the 1980s and 1990s (Pastor and Veronesi, 2003; Bennett and Sias, 2006; Brown and Kapadia, 2007; Cao, Simin, and Zhao, 2008; Fink, Fink, Grullon, and Weston, 2010). During this time, low costs of capital enticed many firms to seek equity financing for the first time. These firms had higher idiosyncratic risks and low commonality in fundamentals with already listed stocks (Fama and French, 2004). The trend towards the inclusion of riskier stocks started to shift in the late 1990s, gaining momentum with the Internet market crash and the implementation of the Sarbanes-Oxley Act in 2002, which significantly raised the cost of becoming and remaining publicly traded. From its highest level, in May 1997, to one year after the passage of Sarbanes-Oxley, in December 2003, the number of common and ordinary stocks in CRSP dropped by about one third, from 9,013 to 6,641. This massive firm exit could have caused average comovement among surviving firms to increase as fundamentals became more homogeneous. To test this conjecture, we estimate the trend of average R^2s grouped by stock characteristics up to and after September 1992. If the shift in comovement's trend were driven by a particular type of stock, trend changes should disappear after eliminating stocks of this type from the sample. Table A.1 reports trend changes for equally weighted average R^2s of stocks sorted on firm characteristics.

We sort stocks on the characteristics used by prior studies to explain comovement's decline during the 1970s and 1980s: firm size, book-to-market ratio to proxy for growth options of the firm (Cao, Simin, and Zhao, 2008), vintage firm age to proxy for the stage of the firm's life cycle (Fink, Fink, Grullon, and Weston, 2010), and industry affiliation to differentiate between "new economy" stocks, and stocks in traditional industries (Brown and Kapadia, 2007). Firm size is market capitalization at the end of the previous month. Book to market ratio is book value of equity divided by market capitalization at the end of the previous June, following Daniel and Titman (2006). The firm size and book to market breakpoints are the NYSE quintiles in Kenneth French's data library.[11] Vintage firm age is the difference between the current year and the year of incorporation of the firm following Fink, Fink, Grullon, and Weston (2010), and industry affiliation corresponds to the 48 industry groups in Fama and French (1997).[12] We rebalance stock portfolios every month based on these categories, calculate average market model R^2 for each group, and fit Equation

[11]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[12]Many thanks to Jason Fink for providing vintage incorporation date data. Incorporation dates are current to 2010.

(3) on each series assuming a break in September 1992. The coefficient γ captures the effect of the break and is significantly positive in *all* groups. This indicates that the shift in comovement's trend is not driven by a particular type of firm but exists in stocks from firms with different characteristics and across virtually all industries.[13] When we sort individual R^2s in terms of size, the "changing growth" coefficient, γ, declines as we move from smallest (γ=64.15, t=11.83) to largest firms (γ=16.70, t=2.97). Similarly, γ also declines as we move from value (γ=51.14, t=9.74) to growth stocks (γ=45.77, t=6.51), and from young (γ=56.06, t=7.01) to mature firms (γ=38.92, t=7.53). At the industry level, stocks in new economy industries such as computers (γ=48.04, t=4.59) and communications (γ=36.06, t=6.22) experience strong changes in their trends, but so do old economy stocks such as coal (γ=81.48, t=7.11) and agriculture (γ=52.83, t=5.48). Results in Table A.1 suggest that comovement's rise since 1992 is unrelated to sustained changes in fundamentals of publicly traded stocks.

A.2. Effect of Speculative Episodes on Comovement's Trends

In addition to examining cross sectional composition effects, we look at the effect that spikes around speculative periods could have had on comovement's trend coefficients. Brandt, Brav, Graham and Kumar (2010) show a surge in idiosyncratic volatility during periods of high investor speculation and low transaction costs. These spikes are many times over the regular level of the series. After removing these spikes, the trend of idiosyncratic volatility disappears. The authors conclude that the positive trend of idiosyncratic volatility for the second half of the 20th century documented by Campbell, Lettau, Malkiel, and Xu (2001) and other studies is not really a trend but simply a temporary deviation of an otherwise flat series. Given that idiosyncratic volatility forms part of comovement, we investigate whether systematic risk spikes during asset pricing bubbles and market crashes could be driving comovement's trends.

To examine how temporary spikes could influence comovement trends, we rank monthly average R^2s from largest to smallest. If spikes were pulling correlations up, R^2 levels and rallies during speculative periods should be very large relative to the rest of the series. There have been two large speculative episodes between 1992 and 2011 that have ended in market crashes: the Internet bubble, which led to the March 2000 crash, and the housing bubble, which led to the October 2008 crash. Table A.2 shows that average R^2s before and during the March 2000 and October 2008 crashes are not extraordinary. While October 2008 has the 9th largest average R^2 in the series, March 2000 is not even in the top 50. Similarly, the three, six, and nine month R^2 increases leading to October 2008 rank respectively 35th, 22nd, and 28th in the series. The R^2 rallies leading to the March 2000 crash are even smaller. Hence, it is unlikely that these relatively modest increases could account for the shift in trend coefficients in Table 2.

Also contrary to the idea that temporary spikes could be driving comovement trends since the 1990s, we find that average R^2 continued to rise after the 2008 crash. Six of the eight months with comovements higher than that registered in October 2008 took place in 2010 and 2011; the first and second largest R^2s in the series are August 2011 and May 2010.

[13] With the exception of "Candy & soda", that has a positive but statistically insignificant change in its trend of γ=4.67 (t=1.27).

Table A.1. Composition Effects of the Shift in Comovement's Trend. Structural break coefficients for average market model R^2 of individual stocks sorted by stock characteristics, in Panel A, and industry affiliation, in Panel B. The functional form of this models is: $y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \mu_t; \mu_t = \sum_{i=1}^{5} \phi_i \mu_{t-i} + e_t;\ DU_t(\lambda) = 1\ and DT_t^*(\lambda) = t - T\lambda\ \ if\ t > T\lambda$. μ is the equation's intercept. $DU_t(\lambda)$ is an indicator that takes the value of one if $t > T\lambda$, the structural break point of September 1992 identified in Table II. t is a count variable for time. $DT_t^*(\lambda)$ is a count variable for the post break period. ϕ_i are the autoregressive parameters of the error term. We compute R^2 statistics of the market model for each individual stock during the month, using daily data during the period January 1962 to December 2011. Only stocks that traded every day during that month are included in the estimation. The market model is estimated using the CRSP value weighted index as the market index. From these individual measures we calculate the equally weighted average R^2s of individual stocks sorted on stock characteristics. Firm size and book-to-market ratio breakpoints are the NYSE quintiles available in Kenneth French's data library website. Book to market ratios of individual stocks are calculated following Daniel and Titman (2006). Vintage firm age is the difference (in years) between the current date and the year of incorporation of the firm from Fink, Fink, Grullon, and Weston (2010), firms that became publicly traded during 2011 are not included. Industry affiliation of each stock corresponds to the 48 industry groups in Fama and French (1997).

	μ	t_μ	θ	t_θ	$\beta(x10^{-4})$	t_β	$\gamma(x10^{-4})$	t_γ
				Portfolios Sorted on Firm Size				
Q1 (small)	-1.80***	-34.85	-0.35***	-4.44	-6.39***	-2.66	64.15***	11.83
Q2	-1.62***	-30.94	-0.34***	-4.16	-5.62***	-2.31	72.44***	13.18
Q3	-1.63***	-33.88	-0.31***	-4.11	-0.26	-0.12	62.25***	12.33
Q4	-1.63***	-32.60	-0.31***	-3.96	7.65***	3.29	41.72***	7.94
Q5 (big)	-1.54***	-28.74	-0.33***	-4.02	16.55***	6.67	16.70***	2.97
				Portfolios Sorted on Book-to-Market Ratio				
Q5 (value)	-1.65***	-33.09	-0.30***	-3.95	-4.10*	-1.76	51.14***	9.74
Q4	-1.67***	-33.17	-0.41***	-5.30	1.16	0.50	51.98***	9.83
Q3	-1.65***	-34.28	-0.40***	-5.35	1.06	0.47	52.95***	10.48
Q2	-1.60***	-29.65	-0.41***	-4.96	1.11	0.44	51.08***	9.01
Q1(growth)	-1.49***	-22.28	-0.42***	-4.17	-0.78	-0.25	45.77***	6.51
				Portfolios Sorted on Vintage Firm Age				
< 5 years	-1.61***	-25.81	-0.09	-0.91	-10.23***	-3.51	56.06***	7.01
5-25 years	-1.59***	-26.29	-0.36***	-3.86	-4.26	-1.51	51.05***	8.01
26-50 years	-1.56***	-28.82	-0.34***	-4.07	-2.86	-1.13	56.20***	9.86
51-75 years	-1.67***	-34.25	-0.35***	-4.68	4.13	1.82	46.78***	9.13
>75 years	-1.63***	-33.08	-0.33***	-4.32	7.71***	3.37	38.92***	7.53
				Portfolio Sorted on Affiliation to the S&P500 Index				
Not in S&P500	-1.66***	-31.86	-0.34***	-4.28	-4.37	-1.80	61.80***	11.28
In S&P500	-0.63***	-30.28	-0.27***	-3.33	15.21***	6.08	22.23***	3.93
				Portfolios Sorted on Industry Affiliation				
Coal	-1.67***	-15.14	-0.54***	-3.40	-1.71	-0.31	81.48***	7.11
Fabricated Products	-1.58***	-26.33	-0.35***	-3.71	-12.41***	-4.44	77.56***	12.30

Trading	-1.72***	-32.23	-0.40***	-4.86	-1.84	-0.74	72.24***	12.90
Steel Works Etc	-1.42***	-23.98	-33.68***	-3.71	-8.21***	-2.98	71.68***	11.49
Shipbuilding, Railroad	-1.56***	-21.77	-0.31***	-2.78	-9.09***	-2.72	69.21***	9.16
Construction	-1.85***	-24.30	-0.36***	-3.18	3.57	1.01	67.56***	8.45
Construction Materials	-1.70***	-29.61	-0.45***	-5.07	-1.20	-0.45	64.70***	10.70
Machinery	-1.59***	-24.71	-0.43***	-4.38	-3.45	-1.15	64.57***	9.54
Real Estate	-1.82***	-28.71	-0.41***	-4.14	-3.73	-1.27	64.41***	9.67
Aircraft	-1.62***	-24.41	-0.59***	-5.69	1.98	0.64	62.61***	8.95
Shipping Containers	-1.75***	-29.77	-0.55***	-6.03	2.35	0.86	60.57***	9.80
Apparel	-1.77***	-30.81	-0.41***	-4.53	-0.99	-0.37	60.21***	9.93
Restaurants, Hotels, Motels	-1.62***	-15.72	-0.40***	-2.79	-3.16	-0.67	59.41***	5.54
Measuring and Control Eq.	-1.46***	-20.42	-0.39***	-3.62	-7.96**	-2.40	59.28***	7.89
Healthcare	-1.38***	-18.99	-0.33***	-3.22	-15.21***	-3.45	58.11***	7.71
Personal Services	-1.67***	-24.97	-0.47***	-4.52	-2.51	-0.81	58.06***	8.24
Chemicals	-1.58***	-22.05	-0.56***	-5.18	-0.28	-0.08	57.83***	7.69
Rubber and Plastics	-1.74***	-34.19	-0.51***	-6.28	-1.57	-0.66	57.44***	10.71
Wholesale	-1.70***	-31.27	-0.48***	-5.61	-2.00	-0.79	57.44***	10.04
Recreation	-1.53***	-29.41	-0.34***	-4.12	-9.67***	-3.98	56.56***	10.32
Automobiles & Trucks	-1.58***	-26.81	-0.45***	-4.94	-0.53	-0.19	56.45***	9.09
Transportation	-1.31***	-25.33	-0.35***	-4.41	-6.80***	-2.83	55.79***	10.26
Medical Equipment	-1.41***	-19.65	-0.49***	-4.53	-9.11***	-2.74	55.33***	7.36
Electrical Equipment	-1.66***	-30.42	-0.39***	-4.55	-4.25*	-1.67	55.09***	9.57
Insurance	-1.61***	-23.98	-0.43***	-4.19	1.89	0.61	53.09***	7.54
Agriculture	-1.92***	-20.79	-0.38***	-2.60	-3.36	-0.75	52.83***	5.48
Textiles	-1.74***	-31.92	-0.40***	-4.64	-3.44	-1.36	52.74***	9.19
Petroleum and Nat. Gas	-1.55***	-16.24	-0.24*	-1.85	0.85	0.19	51.30***	5.15
Entertainment	-1.60***	-23.81	-0.43***	-4.17	-4.85	-1.55	50.28***	7.11
Retail	-1.78***	-37.09	-0.43***	-5.66	3.87*	1.73	49.70***	9.81
Non-Metallic & Metal Mining	-1.74***	-25.87	-0.47***	-4.56	4.14	1.32	48.72***	6.88
Consumer goods	-1.62***	-27.87	-0.43***	-4.80	-1.46	-0.54	48.15***	7.87
Computers	-1.29***	-12.83	-0.45***	-3.17	-7.86*	-1.71	48.04***	4.59
Banking	-1.67***	-30.82	-0.23***	-2.68	0.32	0.13	47.45***	8.31
Electronic Equipment	-1.49***	-21.05	-0.20*	-1.84	-4.76	-1.45	46.05***	6.19
Business Services	-1.75***	-32.52	-0.40***	-4.75	0.51	0.20	45.47***	8.03
Business Supplies	-1.73***	-30.28	-0.36***	-4.10	6.26**	2.35	45.14***	7.49
Defense	-1.54***	-18.28	-0.60***	-4.66	1.05	0.27	43.47***	4.90
Communication	-1.65***	-29.99	-0.49***	-5.66	4.57*	1.78	36.06***	6.22
Food products	-0.86***	-33.61	-0.52***	-6.04	7.76***	3.01	34.74***	5.96
Printing and publishing	-1.89***	-34.63	-0.49***	-5.73	11.56***	4.55	33.68***	5.88
Utilities	-1.96***	-36.11	-0.10	-1.24	10.99***	4.36	31.49***	5.53
Tobacco products	-1.85***	-24.37	-0.55***	-4.66	13.83***	3.90	30.61***	3.83
Pharmaceutical Products	-1.48***	-16.70	-0.46***	-3.65	-0.94	-0.23	27.27***	2.95
Beer and liquor	-1.79***	-26.56	-0.76***	-7.20	11.82***	3.77	26.89***	3.80
Precious Metals	-2.11***	-18.45	-0.44***	-2.73	29.90***	5.72	6.31	0.53
Candy & soda	-1.85***	-23.39	-0.45***	-3.81	17.09***	4.67	1.27	0.15

Table A.2. Top 50 monthly comovement levels and changes between January 1962 and December 2011.Comovement is the monthly equally weighted average R^2 statistic from the market model regression of individual daily returns on contemporaneous market excess returns and industry returns. To control for the mechanical relation between average R^2 statistic and number of stocks, the stock in question is eliminated from its corresponding market and industry index. * denotes observation since last market crash of October 2008.

	Monthly average R^2		Top three month changes		Top six month changes		Top nine month changes	
1	Aug '11	0.717*	Jul-Oct '87	0.470	Feb-Aug '11	0.384*	Oct'77-Jul '78	0.343
2	May '10	0.661*	Feb-May '62	0.374	Jan-Jul '78	0.327	Jan-Oct '87	0.336
3	Oct '87	0.634	Mar-Jun '62	0.368	Aug '72-Feb '73	0.318	Dec'10-Sep '11	0.325*
4	Nov '11	0.632*	May-Aug '11	0.355*	May-Nov '63	0.298	Nov'10-Aug '11	0.307*
5	Jun '62	0.609	Mar-Jun '10	0.328*	Jun '87-Jan '88	0.292	Feb-Nov'11	0.299*
6	Sep '11	0.603*	Nov '72–Feb '73	0.322	Dec '09-Jun'10	0.288*	Jan-Oct '97	0.292
7	May '62	0.600	Aug-Nov '63	0.291	Apr-Oct '11	0.287*	Nov'65-Aug'66	0.287
8	Jun '10	0.600*	Mar-Jun '65	0.290	Apr-Oct '87	0.284	Aug'09-May'10	0.275*
9	Oct '08	0.591	Apr-Jul '78	0.280	Feb-Aug '98	0.272	Aug'65-May'66	0.267
10	Jul '78	0.579	May-Aug '98	0.261	Nov '69-May '70	0.270	May'72-Feb'73	0.257
11	Nov '08	0.573*	Nov-Feb '84	0.235	May-Nov '11	0.270*	Nov'89-Aug'90	0.256
12	Oct '11	0.569*	Jul-Oct '97	0.235	Nov '09-May '10	0.260*	Feb-Nov'63	0.252
13	Mar '09	0.559*	May-Aug '90	0.234	Feb-Aug '90	0.251	Sep'64-Jun'65	0.247
14	Dec '08	0.556*	Feb-May '70	0.231	Feb-Aug '66	0.247	Jan-Oct'11	0.244*
15	Jan '09	0.518*	Dec '79-Mar '80	0.229	Nov '65-May '66	0.246	Aug'69-May'70	0.234
16	Feb '73	0.513	Feb-May '66	0.207	Dec '64-Jun '65	0.242	Jan-Oct'89	0.229
17	Mar '03	0.513	May-Aug '71	0.205	Jun-Dec '72	0.235	Jan-Oct'66	0.223
18	May '09	0.510*	Jul-Oct '89	0.204	May-Nov '08	0.231*	Oct'68-Jul'69	0.207
19	Dec '11	0.503*	Sep-Dec '72	0.197	Apr-Oct '89	0.231	Sep'09-Jun'10	0.206*
20	Oct '09	0.501*	Dec '67-Mar '68	0.195	Feb-Aug '71	0.222	Dec'79-Sep'80	0.204
21	Sep '02	0.494	Jul-Oct '82	0.194	Dec '10-Jun '11	0.212*	May'83-Feb'84	0.199
22	Aug '02	0.490	Mar-Jun '06	0.190	Apr-Oct '08	0.211	Nov'01-Aug '02	0.197
23	Jun '11	0.490*	Jul-Oct '79	0.190	Aug '83-Feb '84	0.208	Mar-Dec '72	0.194
24	Sep '08	0.489*	Apr-Jul '69	0.187	May-Nov '07	0.205	Jun '02-Mar '03	0.186
25	Nov '63	0.486	Dec '06-Mar '07	0.185	Dec '05-Jun '06	0.198	Aug'00-May '01	0.182

26	Apr '09	0.484*	Feb-May '10	0.183*	Apr-Oct '66	0.193	Feb-Nov '08	0.179*
27	Feb '09	0.483*	Aug-Nov '73	0.176	Apr-Oct '97	0.191	Dec'01-Sep '02	0.178
28	Oct '02	0.479	Apr-Jul '81	0.174	Aug '00-Feb '01	0.189	Jan-Oct '08	0.175
29	Aug '10	0.479*	May-Aug '07	0.172	Oct '86-Apr '87	0.189	Apr'07 - Jan '08	0.173
30	Feb '10	0.477*	Jun-Sep '02	0.168	Apr-Oct '79	0.188	Dec'65-Sep '66	0.173
31	May '70	0.477	Dec '10-Mar '11	0.167*	Mar-Sep '10	0.188*	Nov'70-Aug '71	0.170
32	Jul '10	0.475*	May-Aug '82	0.164	Feb-Aug '02	0.175	Jul '00-Apr '01	0.169
33	Oct '97	0.474	Apr-Jul '07	0.162	Jun-Dec '87	0.174	Sep'05-Jun '06	0.167
34	Aug '98	0.474	Jun-Sep '86	0.157	Dec '06-Jun '07	0.170	Mar-Dec '78	0.164
35	Nov '07	0.473	Jul-Oct '08	0.154	Oct '69-Apr '70	0.170	Oct'65-Jul '66	0.164
36	Jan '03	0.469	Jul-Oct '11	0.152*	Nov '99-May '00	0.164	Dec'06-Sep '07	0.162
37	Apr '01	0.462	Aug-Nov '78	0.144	Jan-Jul '66	0.163	Jan-Oct '79	0.161
38	Sep '10	0.459*	Jun-Sep '01	0.142	Jan-Jul '69	0.162	Nov'81-Aug '82	0.160
39	Jun '08	0.459	Feb-May '00	0.137	May-Nov '82	0.162	Jul '87-Apr '88	0.159
40	Oct '62	0.457	Oct '86–Jan '87	0.137	Mar-Sep '11	0.158*	Dec'85-Sep '86	0.153
41	Jun '09	0.457*	May-Aug '84	0.136	Oct '96-Apr '97	0.152	Nov'97-Aug '98	0.153
42	Jul '02	0.457	Aug-Nov '00	0.136	Aug '06-Feb '07	0.150	Apr'89 - Jan '90	0.151
43	Jun '06	0.456	Apr-Jul '11	0.136*	Aug '79-Feb '80	0.146	Jan-Oct '02	0.151
44	Jan '88	0.456	Apr-Jul '66	0.133	Mar-Sep '74	0.145	Feb-Nov '78	0.150
45	Aug '66	0.453	Jul-Oct '05	0.133	Mar-Sep '02	0.144	Nov'96-Aug '97	0.148
46	Aug '08	0.452	Dec '99-Mar '00	0.131	Apr-Oct '82	0.144	Dec'09-Sep '10	0.148*
47	Nov '02	0.448	Jun-Sep '98	0.128	Mar-Sep '62	0.143	Nov'06-Aug '07	0.146
48	Mar '08	0.447	Dec '03-Mar '04	0.128	Nov '72-May '73	0.143	Nov'83-Aug '84	0.143
49	Mar '11	0.445*	May-Aug '75	0.126	Mar-Sep '98	0.142	Jan-Oct '62	0.143
50	Jun '65	0.444	Nov '92–Feb '93	0.123	Nov '96-May '97	0.138	May'08-Feb '09	0.142*