Stock Return Comovement in the New Millennium

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Abstract

Long run dynamics in stock return comovement, its causes and consequences, is a hotly debated topic in Financial Economics. Average return correlation, or comovement, is an important indicator of the benefits from diversification. I study the long-run trend of US comovement during the period 1926-2009 and find a clear break in the series around 1997. After this date, the negative trend previously documented for most of the 20th century reverts to strongly positive. I also find that (1) market and industry volatilities have gained importance since the break, (2) evidence of similar breaks in international markets, (3) fundamentals-driven explanations cannot explain the break. I hypothesize that increasing comovement in the new millennium is the result of correlated trading, caused by technical change in the financial sector.

In a very influential study, Campbell, Lettau, Malkiel, and Xu (2001) (CLMX thereafter) documented that the average return correlation, or comovement, of stocks declined steadily during the second half of the twentieth century. This finding has had a profound effect on contemporary Financial Economics. Many scholars have tried to explain the significance of this decline for firm managers, individual investors, capital markets, and the economy at large. Most of them have interpreted the declining comovement as evidence of creative destruction and efficient markets at work. For investors, this means increased benefits from diversification and less uncertainty. For corporate managers, it means lower costs of equity capital and an increasing set of feasible projects. For the general economy, it means more informative prices and capital being allocated to value-enhancing activities (Morck, Yeung, and Yu, 2000; Wurgler, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; Durnev, Morck, and Yeung, 2004). Lower comovement has been linked to improvements in corporate governance mechanisms (Morck, Yeung, and Yu, 2000), more transparent accounting practices (Jin and Myers, 2006), more intense product market competition (Irvine and Pontiff, 2009; Fink, Fink, Grullon, and Weston, 2010), a greater number of informed market participants (Piotroski and Roulstone, 2004; and Chan and Hameed, 2006), more abundant financial information (Veldkamp, 2006; Brockman, Liebenberg, and Schutte, 2010, Hameed, Morck, Shen, and Yeung, 2010), and a healthier institutional environment (Brown and Kapadia, 2007). However, some scholars have also been skeptic of the existence of this decline. Specifically, Brandt, Brav, Graham, and Kumar (2010) argue that firm-specific volatility, and implicitly comovement, does not have a defined trend but simply rises and falls wildly around speculative bubbles and that the declining comovement in CLMX is simply an illusion caused by performing a long-run analysis on a relatively short series, and would indicate the existence of an important mispricing component in stock returns (Barberis, Shleifer, and Wurgler, 2005; Schutte and Unlu, 2009).

In this study, I examine what has happened to stock return comovement since CLMX disseminated their seminal findings. I am motivated by the mounting empirical evidence that contemporary asset prices might not be as informative as once thought. Since 1997, the last year in the CLMX sample, capital markets have witnessed two very large speculative bubbles and market crashes, two recessions, a major

overhaul in financial reporting standards, the rise of hedge funds, new financial products, and trading venues that, before the advent of information technology did not even exist. If, by the late 1990s, stock price informativeness and market efficiency were better than ever, it is hard to understand how investors as a group would have allowed stock prices to depart so far away from fundamentals in more than one occasion.

[Figure 1 around here]

I re-examine comovement's long-run trend after extending the sample period in CLMX by 49 years, to cover the period 1926 to 2009[1]. I compute comovement in two ways: as the average of market model R^2 measures of US traded stocks as in Panel B of Figure 5 in CLMX, and as the ratio of pervasive (i.e. market and industry) volatility to total volatility as in Brockman, Liebenberg, and Schutte (2010). This second measure is built from the CLMX beta-free decomposition of total volatility into market, industry, and firm-specific[2]. Figure 1 shows plots of these measures. Consistent with prior literature, I find that comovement declined steadily during most of the 20th century. The use of the long series lets me conclude that the negative trend in CLMX is real, and not just an illusion from looking at too short a series. Comovement declined steadily from the late 1920s until the mid 1990s, but after that, the series' trend experienced a drastic change in its slope, switching from strongly negative to strongly positive. Using Unit-root (Perron, 1989; Zivot and Andrews, 1992) and F (Chow, 1960) structural break tests, I find that this trend experienced an important structural break around 1997, characterized by a gradual decline in

[1] My sample period matches that in Brandt, Brav, Graham, and Kumar (2010) but in that article the authors only look at the idiosyncratic volatility component and implicitly assume that, because market, industry and firm volatilities do not have defined trends in the 1926-2009 periods, comovement does not have a defined trend either. This study, in contrast, centers on comovement as a stand-alone variable and does not infer its properties from those of its components.

[2] This volatility decomposition does not require the estimation of industry or firm betas and for this reason, the high-frequency variations of the two measures used in my analysis might differ. In the CLMX 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 long-run trend.

the series intercept and a change in its slope. Based on the Unit-root test results, I also rule-out the possibility that the break would have been caused by an exogenous crash; a gradual, endogenous change in the comovement function is a more likely scenario. Hence, the possible causes for the break are most likely intrinsic to the way stock returns relate to one another either through structural changes in the correlation structure of firm cash flows or the correlation structure of investor trading patterns.

I find two additional interesting pieces of information regarding the break. First, while market, industry, and firm-specific volatilities rise and fall together during speculative periods, the economic importance of these components does not. Between 1926 and 1997, firm-specific volatility grew with respect to that of common factors. At its highest, in August 1996[3], firm-specific volatility was about 7 times bigger than market and industry volatilities combined. This relation switched directions after that point and by the end of the series in 2009, the relation between firm-specific volatility to market and industry had shrunk to virtually one-to-one. Second, I find that trend changes similar to those observed in the US also occurred in other countries. Although the 1980-2010 period of the international sample is shorter and, perhaps for this reason, less reliable than the one I use for the US, I find consistent patterns (i.e. declines followed by sharp increases) in 12 of the 14 countries surveyed. The low points of these series occur between November 1996 and April of 2000. The Chow and Unit-root tests identify statistically significant breaks in Germany (2001), Italy (2001), Japan (1995), South Africa (1997), Switzerland (2001), and the United Kingdom (1998). These break points suggest that international comovement patterns tend to follow those in the US and that the structural break was most likely caused by structural changes in the global financial sector.

What could have caused comovement's trend to change so drastically in the late 1990s? Prior literature points to one or a combination of two explanations: (1) a structural break in cash flow comovement and/or (2) a structural change in correlated trading due to investor irrationality and market frictions. I first look for evidence of a structural break in cash flow comovement, which would provide a

[3] The maximum is identified after smoothing the series with a 12-month moving-average. The maximum unfiltered ration occurs in February 1931 and is identified as an outlier.

rational explanation for the break. I follow Irvine and Pontiff's (2009) decomposition of unanticipated cash flow volatility into market, industry, and firm-specific, and measure cash flow comovement in identical fashion to the measurement of return comovement in Brockman, Liebenberg, and Schutte (2010). I find that cash flow comovement declined steadily since 1964, and that while the series has flattened-out since the mid-1990, it has not increased. Hence, I rule-out the possibility that the break could be explained by changes in product market competition (Irvine and Pontiff, 2009) or the distribution of firm characteristics such as size, age (Fink, Fink, Grullon, and Weston, 2010), or growth opportunities (Cao, Simin, and Zhao, 2008)[4].

Given that cash flow comovement and stock return comovement do not share a common break, I propose that the break must be the result of changes in investor behavior and market frictions. Along these lines, I propose the existence of a possible link between higher comovement in the new millennium and the implementation of new information technologies on capital markets. My conjecture is that technical change has increased comovement due to (1) more intense institutional herding, (2) program trading used to rebalance index funds and ETFs, (3) homogenization in the speed of adjustment of stock prices to firm-specific news, and (4) information complementarity, caused by changes in the quantity and quality of financial information with the advent of the internet.

Technical change, paired with deregulation and institutional change, has allowed the general public to enjoy unprecedented access to low interest credit, a vast array of financial instruments, and the opportunity to share risks with investors from around the globe (Rajan and Zingales, 2003; Shiller, 2003; Rajan, 2005). The emergence of online discount brokers and the vast resources deposited into mutual funds increased market participation and depths. In addition, automated trading has had a positive effect on liquidity by narrowing spreads, and reducing adverse selection costs (Hendershott, Jones, and Menkveld, 2011). This has caused financial transactions to become more arms-length and their risks to be spread over a much larger pool of investors. The results from my research suggest that an additional

[4] According to the explanations presented in these articles, an increase in cash flow comovement would be consistent with less intense product market competition, or the entry (exit) of large (small), old (young), or stagnant (growing) firms to the market.

consequence of financial development might have been an increase in stock cross-correlations with its corresponding decline in the benefits from diversification. While technical change might have enhanced stock price informativeness due to reduced transaction costs and improved liquidity, particularly among large stocks (Hendershott, Jones, and Menkveld, 2011), the higher excess comovement, could have offset any price informativeness gains obtained through increased market participation and depths. The results from this study open the door to future investigations on the underlying causes for the rise of excess comovement in the new millennium and its implications for investors, corporate managers, capital markets, and the overall economy.

The remainder of this study is organized as follows: Section I reviews the theories set forth to explain why stock returns commove; Section II provides and empirical characterization of comovement's trend in the US and international markets; Section III discusses what might or might not explain the structural break in comovement; and Section IV concludes.

I. Related Research

Barberis, Shleifer, and Wurgler (2005) consider that there are two broad sets of theories for why stock returns commove. In the first, more traditional set, under the assumption of frictionless markets and rational investors, comovement in prices directly reflects comovement in fundamental values. This happens because under such conditions prices and fundamental values are one and the same. The second, newer set of theories, proposes that comovement could arise from correlated trading unrelated to fundamentals. In these theories comovement may arise due to investor sentiment[5] and market frictions such as conflicts of interests between financial institutions and their clients, and the quantity and quality of information production[6].

[5] Sentiment can be defined as the general feeling or tone of a market. A bearish market would indicate that investors in general believe the general level of stock prices will decline in the future. A bullish market, on the contrary, would be a general feeling of optimism on the prospects of all stocks in the market.

[6] There is also a substantial number of articles that examine the consequences of comovement for market efficiency (see for example, Morck, Yeung, and Yu, 2000; Wurgler, 2000; Durnev, Morck, Yeung, and Zarowin, 2003; Durnev, Morck, and Yeung, 2004), and the articles that document patterns of comovement in asset returns.

A. Correlated Firm Fundamentals

The first set of studies on comovement contends that stock returns correlate because firm cash flows correlate. This notion originates on the classic assumptions of markets with no frictions, perfect competition, product homogeneity, and rational economic agents. Under these conditions returns are a measure of change in fundamental values and as such, common patterns in returns and fundamental values should go hand in hand. A number of articles propose that the negative trend in comovement during the twentieth century is related to the implementation of new technologies in different industrial processes and is inherent to technological progress. CLMX hypothesizes that firm fundamentals could have become less correlated during this period due to the break-up of conglomerates into smaller, more focused firms. The cash flows from these firms would be more idiosyncratic in nature and would tend to commove less with the cash flows from other firms in the market and industry. Alternatively, Irvine and Pontiff (2009) holds that comovement's trend is driven by product market competition, fueled by better information and transportation technologies. Although not all forms of competition increase idiosyncratic volatility (i.e. reduce comovement), some do. For example, competition related to consumers' search for the product that best fits their needs. Comovement fell during the second half of the twentieth century as search costs became lower due to the introduction of new technologies that would make it easier for the consumer to compare products and take their business to different firms. The competition in Irvine and Pontiff is both, domestic, as financial innovation has allowed small, risky firms to raise capital, thus inducing greater economy-wide competition, and foreign, as technological progress has facilitated

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Examples of the latter are the articles on the small-firm effect (Banz, 1981), the value effect (Fama and French, 1993), the momentum effect (Jegadeesh and Titman, 1993), country and industry effects (Heston and Rouwenhorst, 1994), commonality in liquidity (Chordia, Roll, and Subhramanyam, 2000), and comovement in yields of bonds of similar ratings and maturity (Fama and French, 1992). In addition, comovement in asset returns is also the core concept of the multifactor asset pricing models, and the literature on bubbles and market crashes. Schwert (2003) provides an excellent survey of the literature on anomalies, or common returns across asset classes not explained by standard asset pricing theories. Finally, the recent and burgeoning literature on idiosyncratic risk pricing is also related, given that idiosyncratic volatility, the proxy for idiosyncratic risk, as a proportion of total volatility is the complement to comovement (i.e. price fluctuations not common to all firms). Smith and Calvert (2011) have written a very comprehensive and up-to-date survey of this literature, including working papers. These substantial streams of literature lie outside of the scope of this study.

commerce around the globe. Finally, Chun, et al (2008) contends that comovement declined due to the implementation of information technology with different levels of intensity in businesses across the US, thus increasing the intensity of the creative destruction process, and making cash flow shocks less common and more idiosyncratic.

CLMX, Irvine and Pontiff (2009), and Chun et al (2008) assume that divestitures, competition, and information technology have changed the average cash flow correlation of the average stock in the economy. This view is contested by several studies that argue that not all cash flow patterns have changed, just those from certain firms. These articles argue that comovement in firm cash flows responds to firm composition: as firms in the market are more dissimilar, their cash flows become more heterogeneous and commove less with one another. In Fink, Fink, Grullon and Weston (2010), comovement relates to the relative importance of young firms in the market; in Cao, Simin and Zhao (2008) comovement relates to the relative importance of firms with high growth options. As growth options are hard to value, the return volatility of these firms will be naturally higher and more idiosyncratic than those of other firms. Finally Brown and Kapadia (2007) posit that entry of more volatile firms into the market can explain comovement's decline during the period 1963-1997.

B. Correlated Trading

The second set of theories addresses the fact that comovement often exceeds what is predicted by fundamentals alone (Pindyck and Rotemberg, 1990; Barberis, Shleifer and Wurgler, 2005). Besides fundamentals, correlated trading may arise due to sentiment and market frictions, including the incentive set of investment managers and the quantity and quality of financial information available.

B.1 Investor Sentiment and Market Frictions

Barberis, Shleifer, and Wurgler (2005) examine three specific scenarios in which excess comovement (from fundamentals) could arise due to sentiment and market frictions, they call them category view, habitat view, and information diffusion view. In the category view, proposed by Mullainathan (2002) and Barberis and Shleifer (2003), investors, for various reasons, group assets into categories and learn about asset categories as opposed to the individual securities inside of them. When investors make trading

decisions at the category level, rather than at the firm or security levels, security returns in the different categories tend to commove. For example, in response to a positive piece of news on Microsoft, investors might choose to buy not only Microsoft stock but also one or more other tech stocks. A similar argument is proposed by Morck, Yeung, and Yu (2000) and Jin and Myers (2006) at the international level. In this case, due to corruption and opacity, investors are unable to determine the fundamental values of firms in certain countries so they group, seek news, and make trading decisions at the country level, rather than at the individual firm level. This causes returns of stocks from countries with weak investor protection and opaque information environments to commove more strongly with each other than with stocks from other countries.

In the habitat view, investors fix their attention on a subset of all stocks available and seek information and make trading decisions only about them. Some of these habitats might be already built and widely covered by the media, for example indices like the Dow Jones, S&P 500, or Russell 2000. When an investor decides to trade on sentiment, or to fulfill a liquidity need, this decision would only be done on stocks in the habitat. The decision to buy or sell more than one stock in the habitat simultaneously would cause the returns of stocks within the habitat to commove. Barberis, Shleifer, and Wurgler (2005) argue that "When a stock is added to the S&P, it enters a category (habitat) used by many investors and is buffeted by fund flows in and out of that category (habitat). If arbitrage is limited, these fund flows raise the correlation of the included stock's return with the returns of other stocks in the S&P." (page 285). Vijh (1994) and Greenwood (2008) provide evidence consistent with this view; they observed significant increases in market betas of stocks after being added to the S&P 500 and Nikkei 225 indices, not explained by changes in fundamentals.

Finally, in the information diffusion view, stock market frictions cause information to be incorporated at different speeds in different assets. Stocks that incorporate information at similar speeds tend to move closer together as long as the sign of the information signal is the same (e.g. prices of stocks that receive positive news and also incorporate information at the same rate will increase simultaneously). According to the sentiment and market frictions explanation, comovement would be high during times of high

investor sentiment. Consistent with this argument Brandt, Brav, and Graham, and Kumar (2010) find that stock market volatility and implicitly, comovement, rises during periods of high investor speculation and low transaction costs.

B.2 Information Markets

Veldkamp (2005, 2006) and Van Nieuwerburgh and Veldkamp (2006) provide a theoretical framework to understand how excess comovement arises due to insufficient information. Velkamp (2006) illustrates how news generates comovement with the following example: "Suppose the payoff to asset A was equal to the sum of normally-distributed payoffs from two uncorrelated assets B and C. If investors purchase information about the current-period payoff to A, but not information about B and C, then when A's payoff rises, investors will attribute some of the increase to B and some to C. Because they infer that the valuations of both assets rose, both prices will rise. If A's payoffs fall, the prices of B and C will both fall. Prices of B and C will covary, even though investors know their payoffs are uncorrelated. The common source of information adds a new common shock to the prices of B and C, which causes apparent excess covariance in their prices." (page 1).

Information is a non-rival good with a high fixed cost of discovery and low marginal costs of replication. The maket equilibrium of information is a function of its strategic complementarity. Complementarity means that information on one firm can be used to understand another, because the prospects of one firm can often be inferred by knowing about the prospects of other, similar firms. Due to information's unique cost structure, when the equilibrium price of firm-specific information increases, the financial sector releases less information about fewer firms. This results in excess comovement as investors use information on fewer firms to draw conclusions on the future payoffs of all firms in the market. Consistent with information's strategic complementarity, Hameed, Morck, Shen, and Yeung (2010) find that analyst information on highly-followed stocks is often used to price other "neglected" stocks that share a common fundamental trait. They find that returns of stocks followed by few analysts tend to co-move significantly with the returns of highly followed stocks in the same industry.

Strategic complementarity causes information-induced-comovement to be countercyclical (Brockman, Liebenberg, and Schutte, 2010). Not only is more information produced during economic expansions, but more information is also bought and sold during these periods (Veldkamp, 2006). Information production increases endogenously during expansions because, as more investments are undertaken, the economy naturally generates more information signals. Consistently, as economic activity declines, information becomes more scarce and expensive, so market participants adjust by demanding less of it. With less firm-specific information to go around, stock return comovement rises during recessions. Comovement's countercyclicality is more noticeable in countries in which, due to a lack of institutionality, a constant flow of financial information throughout time is hard to guarantee. Consistent with this prediction, Schutte and Liebenberg (2010) find that the relation between comovement and the business cycle is stronger in emerging markets. These countries are generally poor, have less developed financial markets, and weaker accounting and transparency standards; as a result, these countries experience large inter-temporal swings in information production and comovement.

Veldkamp (2006) suggests that information-signal quality, and not just quantity, contributes to excess comovement. Not all information signals induce comovement; only those that contain information on the value of multiple assets and are observable by multiple people do. A private research report on a single firm that only one investor can read should not produce comovement, but a sector analysis widely available online should. Following Grossman and Stiglitz (1980) the latter should be less valuable, because the profit opportunities from news known by many are rare. Nevertheless, investors will still demand the less valuable comovement-inducing report because it is cheap and can serve as a strategic substitute of more expensive, yet more precise news. Hence, as the proportion of cheap news available to many increases, whether due to temporary changes in asset values, or in the information production function, comovement should rise.

II. Empirical Characterization of Comovement's Trend

I begin by estimating and plotting two measures of stock return comovement for the period January 1926 to December 2009, using returns from all publicly traded common and ordinary stocks in the NYSE, Amex, and Nasdaq available at the University of Chicago's Center for Research in Securities Prices (CRSP). Market returns are the returns from the CRSP Value-Weighted Index, the industry groups are those in Fama and French (1997). The results from the estimation are shown in Figure 1. Comovement in Panel A of Figure 1 is measured by the monthly equally-weighted average market model R^2 from 60-month rolling windows, as in Panel B in Figure V of CLMX[7]. The lowest point in the series corresponds to January 1997. The second measure in Panel B is the monthly ratio of market and industry volatilities in total volatility, estimated from daily returns as in Brockman, Liebenberg, and Schutte (2010). The lowest point in this series corresponds to May 1995[8]. I smooth both series using 12-month moving averages and break down each series into two: before and after their lowest points, and denote the linear trend and the trend's 90% confidence interval for each sub-period. Both panels in Figure 1 show that comovement declined steadily during most of the 20th century, but that this trend reversed in the mid 1990s. The change in trend and inflection point is captured by the two comovement measures. In addition, the data points from the CLMX comovement measure (Panel A) are more widely dispersed at the beginning of the series than at the end, suggesting that comovement has become less volatile since the mid-1990s.

[Table I around here]

To characterize comovement more formally, I estimate summary statistics for the comovement measures, the series' linear trend and autocorrelation structures. Results are summarized in Tables I and II. Panel A of Tables I and II shows descriptive statistics for the CLMX comovement measure, while Panel B repeats the analysis on the comovement measure from Brockman, Liebenberg, and Schutte

[7] I also estimated these measures in quarterly frequencies, using value-weighted averages, and changed the size of the rolling window to 30 and 120 months. The main takeaways from these figures remain the same.

[8] I also performed the volatility decomposition using quarterly frequencies and forming equally-weighted market and industry volatility averages (as opposed to the original value-weighted averages in CLMX) with very similar results.

(2010). Average comovement for the full sample period according to the CLMX and Brockman, Liebenberg, and Schutte (2010) methods is 0.32. Similarly, median comovement for the full sample is under both methods is 0.30. This means that in a typical month, about 30% or return variation in stocks comes from news related to pervasive factors, while the remaining 70% comes from news specific to the firm[9]. I also observe that these proportions vary greatly through time, the monthly standard deviation is 0.12 (0.11).

[Table II around here]

Table II shows linear trend estimates for the log of comovement for the full sample series and the sub-periods defined by the series' minima: January 1926 to January 1997 (May 1995), and February 1977 (June 1995) to December of 2009. I study the trend of the natural logarithm of comovement because with this transformation the regression slope coefficients on time can be directly interpreted as growth rates. I correct for the autocorrelation in the comovement measures using a Yule-Walker correction with eight monthly lagged autocorrelation parameters. In the comovement measure used in Brockman, Liebenberg, and Schutte (2010) the autocorrelation at lag 1 is the highest at 0.33 and dies out slowly, as is characteristic in a stationary process. On the other hand, in the comovement measure used in CLMX, the autocorrelation at lag 1 is virtually the unity and almost completely disappears in subsequent lags, as it is characteristic in a stationary process. Durbin Watson statistics indicate that the Yule-Walker method removes the autocorrelation in the case of the comovement measure from Brockman, Liebenberg, and Schutte (2010), but not in the case of the comovement measure from CLMX. This suggests that tests designed for stationary series might not be applicable to the CLMX series. Given the sample size, the Durbin Watson statistics of 1.86, 1.79, and 1.92 are not significant at traditional levels. The slope coefficients of comovement on time show that comovement declined during most of the twentieth century but that since after the series' inflection point, comovement has been rising. Comovement declined at an average monthly rate of 8.6 (13.38) basis points during most of the twentieth century but since about the

[9] These proportions are very much consistent with those reported in Roll (1988). For the period September 1982 to August 1987, he finds that an average market model R^2 for stocks in the NYSE of 35% when using monthly date and 20% when using daily data.

mid 1990s, it has been rising at a rate of 40.65 (44.99) basis points per month, when the measure of comovement is built following the method in Brockman, Liebenberg, and Schutte (2010) (CLMX). Comovement has not only been growing over the past 15 years, but this growth has been fast, about four times faster than the rate of decline of comovement during the 20th century. Figure 1 and Table II show what could be a structural break in the comovement series. The following step is to ascertain statistically that what I have observed is not a temporary deviation from a negative trend but an actual separation of the series into two processes.

I perform two types of structural break tests on comovement: the ADF-style unit-root tests with allowance for one structural break point (Perron, 1989, 1997; and Zivot and Andrews, 1992) and the F-tests for difference in regressions before and after the break (Chow, 1960). The ADF-style tests in Perron (1989, 1997), and Zivot and Andrews (1992) not only verify the existence of a structural break; they also provide information on the magnitude of the trend before and after the break, the break's speed, the magnitude of the change in the series' level, its slope, or both. In contrast, the Chow (1960) test only provides information on the break's presence and approximate date in which it occurred. Chow (1960) tests whether the coefficients of separate linear regressions from two subperiods fit the data better than the coefficients of a linear regression fitted on the full sample period. This test relies on the assumption that the series is covariance stationary so that the test statistic built from the coefficient would follow an F-distribution.

[Table III around here]

The autocorrelation coefficients in Table II suggest that the R^2 measure from CLMX is a unit-root process so the Chow test would not be applicable to this series. Hence, I test the null of a unit-root in the comovement measures, using the Augmented Dickey-Fuller (ADF thereafter) test with drift and a linear trend. Results are summarized in Table III. This test is based on the regression $y_t = \mu + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-1} + e_t$, where y_t is comovement at time *t*, *t* is the count dummy, and Δy_{t-i} is the first difference of comovement lagged *i* times. The presence of a unit-root in the series is tested on the null that

α=1[10]. I draw conclusions on this test based on the p-value of the t-statistic on the null, denoted by $p_{Ho:\alpha=1}$ in Table II. This test fails to reject the null in the comovement measure from CLMX, for the full series (p=0.13), and the December 1930 to January 1997 sub-period (p=0.20), while rejects the null in the February 1997 to December 2009 sub-period (p=0.002). Alternatively, the ADF rejects the null of a unit root in the comovement measure in Brockman, Liebenberg and Schutte (2010), for the full series (p<0.001), and the January 1926 to May 1995 (p<0.001), and June 1995 to December 2009 (p=0.06) sub-periods.

Given that results in Table III show that the CLMX comovement series is most likely a unit-root process, while the Brockman, Liebenberg, and Schutte (2010) series is not, I limit the break point determination to the latter since its stationarity allows me to assume that the asymptotic distributions of the coefficient statistics are standardized normal at the usual significance levels.

[Table IV around here]

Table IV summarizes the results of performing ADF-style structural break tests on comovement as measured by Brockman, Liebenberg, and Schutte (2010). The functional forms of the models are as follows:

Model 1: $y_t = \mu + \beta t + \gamma DT_t^* + \tilde{y}_t; \tilde{y}_t = \alpha\widetilde{y_{t-1}} + \sum_{i=1}^{k} c_i\, \Delta\widetilde{y_{t-i}} + e_t;\ DT_t^* = 1(t > T_b)(t - T_b)$ (1)

Model 2: $y_t = \mu + \theta DU_t + \beta t + \gamma DT_t^* + \tilde{y}_t; \tilde{y}_t = \alpha\widetilde{y_{t-1}} + \sum_{i=1}^{k} c_i\, \Delta\widetilde{y_{t-i}} + e_t;$

$DU_t = 1(t > T_b), DT_t^* = 1(t > T_b)(t - T_b)$ (2)

Model 3: $y_t = \mu + \beta t + \gamma DT_t^* + \alpha y_{t-1} + \sum_{i=1}^{k} c_i\, \Delta y_{t-i} + e_t;\ DT_t^* = 1(t > T_b)(t - T_b)$ (3)

Model 4: $y_t = \mu + \theta DU_t + \beta t + \gamma DT_t^* + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t;$

$DU_t = 1(t > T_b), DT_t^* = 1(t > T_b)(t - T_b)$ (4)

[10] The significance probabilities of this test are calculated using the PROBDF function in SAS. The PROBDF function derives its probabilities from approximating functions fit to empirical quantiles that are produced by a Monte Carlo simulation that employs 10^8 replications for each simulation. The number of lags is chosen based on the lowest AIC among models with lags ranging from 0 to 24 months.

y_t represents comovement. μ is the equation's intercept. θ is the regression coefficient for DU_t, which is an indicator that takes the value of one during the post-break period, and zero otherwise. t is a count variable for time. γ is the regression coefficient for DT_t^*, which is a count variable for the post-break period.α is the first-order autocorrelation coefficient, used to test for the presence of a unit-root. I test the null of a unit-root using the asymptotic distributions probabilities calculated by the PROBDF function in SAS[11]. Following traditional ADF testing procedures (Dickey and Fuller, 1979; and Said and Dickey, 1984), all models are fitted using Ordinary Least Squares[12].

Model (1) corresponds to Perron's (1989) exogenously-determined models. Alternatively, models (2), (3) and (4) are variations of Zivot and Andrews (1992) data-driven models. In model (1), the break is produced by an exogenous event, which I have set to match the visual break date of May 1995. A reader could argue that the economic and statistical significance in the regression coefficients in model (1) might be overstated because the break date, T_b, is fixed arbitrarily (Christiano, 1992; Banerjee et al, 1992; Zivot and Andrews, 1992). This is particularly true in this case because the visual identification of the break was done after studying the plots. As an alternative, models (2), (3) and (4) provide a more robust estimation. In these models, T_b is not fixed a priori but considered unknown, and its selection a part of the model's estimation[13]. The rejection of the unit-root hypothesis at the 1% level or better in all models suggests that comovement can be represented as a series of stationary fluctuations around a breaking trend. Given that the unit-root hypothesis is rejected, I assess the statistical significance of the other coefficients assuming a standard normal asymptotic distribution of their t-statistics. The positive and

[11] The p-values obtained using the PROBDF function in SAS and the asymptotic probabilities for the unit-root t-statistics in Zivot and Andrews (1992) yield the same conclusions.

[12] Models (1), and (2) are estimated in two steps. First, the series is de-trended and then the de-trended value is used to perform the Augmented Dickey-Fuller test.

[13] In models (3) and (4), T_b and k are determined endogenously. I fit the models on every potential structural break date and identify the date that produces the lowest (i.e. the most negative) Augmented Dickey-Fuller t-statistic ($t_{Ho:\alpha=1}$ in Table 2) as the data-driven break date. I choose the optimal number of lags by fitting 25 different models on each potential break date; these models include lags of the first-difference of the dependent variable of orders 0 to 24. These lags are added to control for serial correlation. The specification with an optimal number of lags, k, is the model that yields the lowest Akaike Information Criterion (AIC). Similar to Zivot and Andrews (1992), I trim the series at the end points so that the first and last 120 observations of the series are not potential break dates.

significant γ values of 15.4 (t=17.16), 14.5 (t=10.62), 6.6 (t=5.39), and 3.9 (t=2.53) basis points per month confirm a significant increase in the trend's slope after the break.

Table IV provides additional information on the nature of the break. Models (1) and (3) allows for a change in the trend's slope but not the intercept. These models assume that the trend's slope changed quickly while the segments remained joined and are "Additive Outlier" models in the terminology of Perron (1989). As an alternative, Models (2) and (4) allow for a change in the trend's intercept and slope. These models assume a gradual change in comovement's trend originated by an endogenous change in the correlation structure of the series' noise function (Zivot and Andrews, 1992; and Perron, 1997). These models are called "Innovation Outlier" models. Perron argues that if a structural break were caused by an external event, or crash, the regression coefficients should meet the joint condition $\propto = 1, \beta = 0.$ Given that neither condition holds in any of the models, I rule out the possibility that the break would have been caused by an exogenous crash. A gradual, endogenous change in the comovement function is a more likely scenario. Hence, the possible causes for the break are most likely intrinsic to the way stock returns relate to one another either through the structural changes in the correlation structure of the firm's cash flows or the correlation structure of investor trading patterns.

The estimated coefficient of the intercept in Model (4) of 0.16 (t=7.94) is statistically significant at the 1% level. The estimated coefficient of the post break dummy of -0.30 (t=-2.11) is statistically significant at the 5% level and suggests that average comovement after the break has been about 0.30 lower than before the break. This is an important drop, since average comovement for the full series is 0.31 and the highest comovement on record is 0.73. The series also shows a trend with a negative slope of $-1.1\text{x}10^{-4}$ (t=-6.23), significant at the 1% level, and a very strong increase after February 1997. The interaction term for the trend is $3.9\text{x}10^{-4}$ (t=2.53), significant at the 5% level, which suggests that comovement during the post-break period grew at an average rate of -1.1+3.9=2.8 basis points per month. The selected T_b of January 1997 happens almost two years after the visual inflection point of May 1995, in Figure 1, but is a perfect match for the visual inflection point in the CLMX series.

[Figure 2 around here]

Figure 2 shows graphically the procedure to select the approximate time of the break under the Zivot and Andrews (1992) and Chow (1960) methods. Panel A shows the unit-root t-statistics for Model (4) in Table III. This model consists on an Augmented Dickey-Fuller (ADF) test with allowance for a single structural break in the intercept and slope of the trend function. For each possible break point, I test 25 different ADF model specifications, including the first difference lags of order one through 24. For each tentative break point I select the ADF t-statistic of the model with the lowest Akaike Information Criterion (AIC). The ADF t-statistic is the t-value of the test $Ho: \propto = 1$, or that the series has a unit-root. The structural break point is identified as the point with the lowest ADF-t statistic. The strctural break point identified through this method corresponds to January 1997. Panel B shows the F-statistic for the Chow (1960) test over time for structural breaks in the linear trend. In this case, The F-statistic is calculated for each break point candidate as: $Chow_F = \frac{(RSS - RSS_1 - RSS_2)/k}{(RSS_1 + RSS_2)/(n_1 + n_2 - 2k)} \sim F_{k, n_1 + n_2 - 2k}$. Where RSS is the sum of square residuals for the full sample period, RSS_1 is the sum of square residuals for the sub-period before the break, and RSS_2 is the sum of square residuals for the sub-period after the break. The structural break point is the point with the highest F-statistic and corresponds to September 1996. The structural break dates identified under both methods are only four months apart.

Taken together, the graphical and statistical evidence presented so far suggest that stock return comovement in the US experienced an important structural break around 1997, characterized by a decline in the series' intercept and a change in its slope from significantly negative to significantly positive. This break is unlikely to have been cause by an external shock, but rather be the result of structural changes in firms and capital markets.

B. The Economic Importance of Market, Industry, and Firm Volatilities over Time

Brockman, Liebenberg, and Schutte (2010) define comovement as the proportion of price fluctuations common to all stocks in a particular market and industry. The previous section documents how comovement declined steadily during most of the 20th century but has increased since 1997.

Comovement's behavior is vastly different to that of its components and might come as a surprise, since it has been widely documented that market, industry, and firm-level volatilities have no defined trends (Schwert, 1989; CLMX; Brandt, Brav, Graham, and Kumar, 2010). Hence, it might be logical to assume that comovement should have no trend either. My findings suggest this is not the case: although rising and falling together, the relative importance of the different volatility components have shown clear patterns through time. Panels A and B in Figure 3 illustrate this point.

[Figure 3 around here]

Panel A in Figure 3 plots the market, industry, and firm-specific components of US total stock volatility during the period January 1926 to December 2009. This figure updates and combines Panel B in Figures 2, 3, and 4 in CLMX. While it is evident that firm-specific volatility is considerably larger than market and industry and that the three series rise and fall together during speculative periods, it is also evident that during periods in which the series rise, the pervasive components of volatility rise faster than that of the individual firms. In other words, even though firm-specific volatility increases dramatically during speculative periods, the rise is proportionally smaller than that of the market and industry, making the relative importance of price fluctuations from individual firms very low, and comovement very high. In October 1929, the month of the Stock Market Crash, the relative importance of firm-specific volatility declined to only 36% of the combined market and industry volatilities, while the typical ratio during the late 1920s and 30s was in the order of 2:1. Similar drops in the relative importance of firm-specific volatility can be observed in October 1987, when firm-specific return variations were 58% of the combined market and industry variations, March of 2003 (96%), and October of 2008 (69%). It is therefore evident, that the long run comovement dynamics I have described earlier, do not respond to absolute changes in market, industry, of firm-specific volatilities, but to their relative importance with respect to the other volatility components.

Panel B in Figure 3 shows that the underlying source for the declining comovement during most of the 20th century was a steady increase (decline) in the importance of individual firms (market and industries) as sources for price variation. Price variation from individual firms gained importance over

those from pervasive factors during most of the 20th century. This is consistent with the conclusion reached by many scholars that during those years stock prices became more informative, as the gains in firm-specific volatility would result from investors differentiating across individual firms instead of asset-classes or industry sectors. The relative importance of firm-specific volatility reaches its highest point in October 1996. In that month, firm-specific return variations were about seven times those from the market and industries. From that point onwards, the relative importance of firm-specific volatility has dropped dramatically and by 2009 the relation had shrunk to one-to-one, virtually cancelling-out the price informativeness gains achieved during the 20th century. The average ratio of firm-specific volatility to market and industry for the year 2009 is 1.09.

C. Comovement in International Markets

Finally, I ask whether a structural break in comovement's trend is also observable in international data. If the break only existed in the US, it could result from changes in macroeconomic policy, or changes in capital market regulation. Alternatively, if breaks were also found in markets outside of the US, other reasons such as a decline in global competition or technical change are more likely. In particular, given that financial deregulation since the enactment of the 1999 Gramm-Leach-Bliley Financial Services Modernization Act, has been considered the culprit of the past two asset pricing bubbles and crashes by the popular press, the existence of comovement breaks in other markets could rule out the possibility that the US break is solely the consequence of deregulation and could point out to other broader industry factors.

[Figure 4 around here]

Consistent with the analysis performed on US data, I measure comovement following Brockman, Liebenberg, and Schutte (2010) in 14 markets for the period March 1980 to May 2010 using all available daily returns in Thomson Financial Datastream. Although Datastream provides market coverage for stocks traded in 81 markets, only 14 of these go as far back as 1980[14]. Just like for the US comovement in

[14] Datastream's market information can be traced as far back as 1973. However, coverage during the early part of the sample is sparse, so I limit the analysis to return observations starting in 1980, consistent with prior studies.

Figure 1, I smooth each series using a 12-month moving average. Figure 4 shows the plots of these 14 series, their monthly averages, top, and lower quartiles. The general pattern in US comovement, a decline until the mid to late 1990s followed by a sharp increase, can also be observed in 12 of the 14 countries studied[15]. The inflection point of these series ranges between November 1996 (Canada and Switzerland) and July 2000 (United Kingdom). The low point of average comovement is April 2000. This suggests that international comovement patterns tend to follow those in the US.

[Table V around here]

Table V presents the result of running unit-root and F-style structural break tests on international data. I only run the models on six of the 14 series shown in Figure 4 because I am not able to reject the null of a unit-root in eight of the series. In all six countries, there is a structural break in the comovement series with similar characteristics to those observe in the US: a statistically significant negative trend before the structural break points followed by a change in direction from strongly negative to strongly positive. In all countries studied, the magnitude of the coefficient estimate for the break dummy (γ) is considerably larger than the coefficient estimate for the full sample period (β). According to the Zivot and Andrews (1992) structural break model, comovement in the post-break period rose at rates of 8.1 (Germany), 3.2 (Italy), 7.6 (Japan), 1.1 (South Africa), 1.7 (Switzerland), and 7.5 (United Kingdom) basis points per month. Given that the same model produced a post-break growth rate of 2.8 basis points per month for US comovement, the growth rates in Germany, Switzerland, and the United Kingdom are quite high. Given that the structural break date in the Perron's (1989) model is the visual low-point of the smoothed comovement series in Figure 4, I rely on the estimates from the other two models (Chow, 1960, and Zivot and Andrews, 1992) to draw conclusions on the timing of the international breaks. With the exception of Japan, whose break dates to 1995, all other break dates occur after the US break date of

These countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, South Africa, Switzerland, and the United Kingdom.

[15] In the comovement series of Australia and Hong Kong, there is a negative slope that persists throughout the period of study. A break in these series cannot be appreciated visually.

January 1997. This is consistent with the conjecture that the breaks are the result of technological innovation first implemented in the US and later adopted in other countries.

III. What Might Explain a Structural Break in Comovement?

The break could result from one or a combination of two possible explanations: changes in cash flow comovement and changes in correlated trading due to investor irrationality and market frictions, both depend on economic institutions. I will first look for evidence of a rational explanation for the break, linked to cash flow comovement.

A. Correlated Firm Fundamentals

If the break had a fundamental-based explanation the structural break in return comovement should be mirrored by a structural break in cash flow shock comovement. So to start, I measure cash flow shock comovement in the US using quarterly financial information from Standard & Poor's Compustat for the period between July of 1962 and December of 2010. For this effect, I decompose cash flow shock volatility into market, industry, and firm-specific, and build a measure of cash flow comovement with those components following Brockman, Liebenberg, and Schutte (2010). The proxies for free-cash-flow used in these measures are quarterly earnings per share, cash flow per share, and sales per share. I follow Irvine and Pontiff (2009) in measuring unexpected cash flow shocks from accounting cash flow measures, this is necessary to control for persistence in cash flow levels. Unanticipated cash flow shock is estimated as the residual from the following pooled cross-section times-series model:

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

Where E_{it} is a measure of cash flow per share at quarter *t.* The residual e_{it} represents unexpected innovations to cash flow per share. The dependant variable is the difference between cash flow per share in quarter *t* and cash flow per share on the same quarter a year before. Cash flow shocks are standardized by dividing them by price at the end of the last quarter. Next, I create quarterly market and industry indices of cash flow shock to price ratios and decompose cash flow shock volatility into market, industry and firm-specific following CLMX. Cash flow comovement is the ratio of market and industry cash flow

shock volatility to total volatility, following Brockman, Liebenberg and Schutte (2010). I do not perform the cash flow transformations into monthly frequencies in Irvine and Pontiff (2009). Since my end objective is to calculate a ratio of the volatility components, such transformations would only add noise to my comovement estimation. Panel A of Table VI presents descriptive statistics of US cash flow and cash flow shock comovement measures[16].

[Table VI around here]

Table VI shows that in general, the order of magnitude of cash flow shock comovement is much smaller than that of stock return comovement, reported in Table 1. On average, cash flow shock comovement is on the order of 7 to 12%, depending on the cash flow measure being used. The inter-quartile range is also narrower than for stock return comovement, but standard deviations are very similar so I expect a fair amount of variation in these series.

[Figure 5 around here]

I plot cash flow shock volatilities and comovement in order to identify patterns in the series. In particular, I am interested in knowing if a similar break to that observed in return comovement (Figure 1) can also be found with cash flow shocks. Panel A of Figure 5 shows quarterly market and firm-specific cash flow shock volatility from earnings per share[17]. This figure updates Figure 2 in Irvine and Pontiff (2009) and shows the same increasing pattern in the firm-specific volatility of shocks to earnings per share for the period 1964 to 2010. Panel A also shows that not only firm-specific cash flow volatility increased during that period, market volatility grew as well, but at a slower rate. The end result of these patterns is a negative trend in cash flow shock comovement, illustrated in Panel B of Figure 5. Cash flow comovement declines during the full sample period using all three cash flow measures and since mid-1990s, the behavior of the series is flat. I do not observe any increase in cash flow comovement similar to that of return comovement. Table VII confirms the negative trend in cash flow shock comovement under all three cash flow measures.

[16] Many thanks to Paul Irvine and Ivonne Liebenberg for clearing methodological issues on this decomposition.
[17] Plots of the different volatility components using cash flow and sales per share are very similar to the plot of earnings per share volatility.

Since I cannot identify a structural break point in cash flow comovement either visually or through the implementation of any of the models applied to return comovement, I conclude that there is no statistically significant break in the cash flow comovement series and that the structural break in return comovement described in Section II cannot be explained by a similar break in firm fundamentals.

B. Correlated Trading

Since my structural break tests on cash flow comovement rule out a fundamentals-driven explanation of the return comovement break, I conclude that the latter responds to a steady increase in correlated trading, which may have arisen due to several non-competing factors. In this sub-section, I identify three such factors and discuss how each might have contributed to the increase in excess comovement since 1997. Empirical testing of these hypotheses is an area for future investigation.

First, increasing correlated trading might result from intensification in style and habitat-investing, particularly among financial institutions (Barberis, Shleifer, and Wurgler, 2005). More intense style investing could be the result of institutional herding (Xu and Malkiel, 2003; Rajan, 2005) and trading by Exchange Traded Funds (ETFs), which allow investors to buy and sell shares that mimic stock portfolios in a single transaction (Bradley and Litan, 2011). Second, it could be the result of homogenization in the speed of adjustment of stock prices to market, industry, and asset-class news (Barberis, Shleifer, and Wurgler, 2005). Increased reliance of market participants on the same news sources, and the 1994 invention, and later widespread utilization, of the Financial Information eXchange (or FIX) Protocol[18], might have increased the proportion of traders submitting buy and sell orders simultaneously, particularly across previously neglected stocks. This could have caused more stocks to adjust in lockstep to news events. Third, it could be a rational response of investors to changes in the quantity and quality of financial information (Veldkamp, 2005, 2006). HTML file transmission and Internet web browsing, introduced in 1994, brought a deluge of information. This new information, however, due to its unique

[18] FIX is a standard protocol for transmitting messages from their buy-side managers to their traders, it is designed to match and execute institutional block orders through their own internal books. FIX is not dependent on a given computer architecture; this flexibility allows investment houses to gain access to each other's book, fill block orders, and trade entire baskets of stocks at one time (SEC, 1997).

cost structure, is of the type that induces information complementarity and comovement because of its low price and limited information content (Romer, 1990; Veldkamp, 2005). Correlated trading may arise as investors rely increasingly on virtually-free on-line information to make forecasts about the distribution of firms' future payoffs (Xu and Malkiel, 2003).

B.1 Institutional Herding and the Rise of ETFs

Xu and Malkiel (2003), and Rajan (2005)[19] posit that use of the same information sources and a disassociation between financial manager incentives and those of their clients could have intensified information cascades and reputational herding. There is a rich literature on institutional herding, some of which is linked to comovement. Institutional investors following each other in and out of asset classes (Bennett, Sias, and Starks; 2003; and Choi and Sias, 2009) could have caused synchronization in trading unrelated to fundamentals across groups of stocks[20].

According to Rajan (2005), the downside of more intense competition in capital markets has been an increased incentive by financial managers to herd, as more of their compensation is now tied to the risk-adjusted returns of their portfolios relative to those from other managers. In this environment, financial managers choose to herd rather than compete to avoid penalties from negative performance. In addition, herding might have intensified since the adoption of the FIX protocol. The increased communication speeds between investment managers since the introduction of FIX might have made it easier for financial managers to follow each other's trades while the multiplication in the number of transactions and stocks might have made it harder, thus promoting a step increase in herding at the index, industry, and asset-class levels, which might have caused comovement to rise.

Another factor contributing to higher comovement could be the increasing trading volume from Exchange Traded Funds, or ETFs. Just like their predecessors, the Toronto Stock Exchange Index

[19] Xu and Malkiel (2003) examine the conjecture that the increased importance of institutional investors could have influenced idiosyncratic volatility and hence, comovement. They argue that financial institutions generally get their news from the same sources and "are often likely to change their sentiment simultaneously about both individual stocks and the market as a whole" (page 635). This is an argument consistent with Veldkamp (2006).

[20] This literature is very closely related to Style Investing. See for example, Shleifer and Vishny (2003), Teo and Woo (2004), Barberis, Shleifer, and Wurgler (2005), and Froot and Teo (2008).

Participation shares (TIPs) and the Standard and Poor's Depository Receipts (SPDRS), ETFs provide retail investor a low-cost opportunity to buy and sell indexes as a share in an exchange, thus automatically increasing investor diversification and meeting specific investment objectives[21]. The increasing popularity of ETFs has been nothing but extraordinary. While these financial products have only existed for the past eight years or so, as of today they account for roughly half of all the trading in U.S. equities (Bradley and Litan, 2011). The result is a drastic increase in style trading, as constituents of the different funds are bought and sold together whenever ETFs rebalance their portfolios, which is in turn the result of changes in the supply and demand of bundles of stocks and not of individual stock future cash flows.[22]

ETFs have become popular with investors, among other reasons, because of their low transaction costs[23], which are possible thanks to program trading. Program trading, or the computerized trading in baskets of fifteen stocks or more, became viable after the widespread adoption of the FIX protocol and the introduction of three institutional changes: (1) new enactment of new SEC regulation, particularly the 1997 Order Handling Rules and the 1998 Regulation ATS. The latter permitted Electronic Communications Networks (or ECNs) the option of registering as stock exchanges or else being regulated under a separate set of standards[24] and promoted a resurgence of ECNs; (2) the switch from tick-by-tick to decimal pricing in 2001, which has made order splittling easier, and given algorithmic trading an advantage in doing so (Hvidkjaer, 2008; and Chordia, Roll, and Subrahmanyam, 2010); and (3) the proliferation of hedge funds with the necessary computing capabilities to drive trading volume.

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[21] The first SEC-regulated portfolio product that could be used by an individual investor was the Index Participation Shares, or IPSs. Trading of IPSs started in 1989 at the Philadelphia Stock Exchange. The shares were eventually liquidated after a federal court in Chicago ruled that IPSs were illegal futures contracts and had to be traded in a futures exchange and regulated by the Commodity Futures Trading Commission, CFTC (Gastineau, 2002).

[22] This argument was set forth by members of the Kauffman Foundation in an expert testimony to the Subcommittee on Securities, Insurance, and Investments of the US Senate Banking Committee on October 19th, 2011 (Bradley and Litan, 2011).

[23] Other reasons why ETFs are popular among investors are their tradeability and high liquidity; incurring capital gains taxes only when the entire ETF is sold, thus allowing investors to defer tax payments; the opportunity to leverage up returns by using options; no minimum investment amount; and the ability to buy and write options on the underlying ETFs (Gastineau, 2002).

[24] This regulation became effective on April 21st, 1999 (NASD, 1999).

B. 2 Homogenization in the Speed of Adjustment of Stock Prices to News

Amihud and Mendelson (1987) and Damodaran (1993) posit that prices adjust to news at different speeds across stock. Theoretically, this unevenness arises because investors receive information signals at different times, so late informed investors follow early informed investors (e.g., Froot, Scharfstein, and Stein, 1993; Hirshleifer, Subrahmanyam, and Titman, 1994). Furthermore, studies find price adjustments to be asymmetric, generally faster for positive than negative news (e.g. Koutomos, 1999; and Hong, Lim, and Stein, 2000), and to exhibit certain commonality across industries and asset classes (Moskowitz and Grinblatt, 1999; Mayhew and Mihov, 2004; and Hou, 2007).

Consistent with Damodaran and Lim (1991), the introduction of new IT to financial markets could have resulted in increased information collection, which paired with higher institutional activity, could have sped-up and homogenized price adjustment for all stocks.

The speed of adjustment of prices to news might also converge as more stocks are traded through Exchange Crossing Networks (ECNs) instead or regular exchanges. Given that ECNs allow for real-time communication between investors and higher order execution speeds, stocks traded through ECNs should have less of a lag between early and late investors responding to news stories, causing transaction to become more synchronized and prices to adjust faster to new information. If gains in the speed of adjustment are common across indices, industries, and asset classes, comovement should increase. As the proportion of trades performed by ECNs increases in a group, comovement in stocks within that group should rise.

B.3 Information Complementarity

Finally, the introduction of IT might have also contributed to higher comovement due to major changes in the quantity and quality of financial information (Veldkamp, 2005, 2006). HTML file transmission and Internet web browsing, introduced in 1994, brought a deluge of information. This new information, however, is of the type that induces comovement: it has fixed discovery costs, near-zero replication costs, and prices that decline as demand rises (Romer, 1990; Veldkamp, 2005). Since the introduction of the internet, investors have relied increasingly on information available online (i.e.

shareholder reports, investor newsletters, and advice from discussion forums and social networks) because of its low or negligible price, even though they know other investors are also using it. Correlated trading and comovement inevitably arises as institutional investors rely on the same news sources to make forecasts about the firms' future payoffs (Xu and Malkiel, 2003).

IV. Conclusion

Long run dynamics in average return correlation (or comovement), its causes and consequences, is a hotly debated topic in Financial Economics. While for many scholars, the negative trend in comovement during the period 1963-1997 in CLMX is evidence of creative destruction and market efficiency, for others it is merely an illusion from looking at local rather than global maxima and minima (Brandt, Brav, Graham, and Kumar, 2010). Tests of comovement's trend for the period 1926-2009 show a steady decline in the series from the late 1920s to the mid 1990s, followed by a drastic change in its slope around 1997. Statistical tests show that this change is not just a temporary deviation from the trend, but a structural break, most likely endogenous to the series. Additional tests reveal similar patterns in international data and rules out the possibility that the trend change mirrors a similar change in cash flow shock comovement.

What are the underlying causes of such a drastic break in the comovement series? A potential explanation for this phenomenon could be the adoption of new information technologies in financial markets. Technical change could have contributed to higher comovement due to more intense style-investing, institutional herding, and homogenization in the speed of adjustment of prices to new information. These behaviors could have resulted from a dramatic increase in arms-length financing, changes in financial manager incentives, program trading and high frequency trading, and the increased communication speeds between financial institutions (Rajan, 2005). In addition, the introduction of web browsing could have caused comovement to rise by increasing the reliance of market participants on cheap news with limited information content (Veldkamp, 2005, 2006).

This research contributes to the Financial Economics discipline in two ways: first, it helps settle the question of whether comovement has a defined trend and second, it compares the relative importance of cash-flow-based vs. transaction-based comovement theories. Learning about what makes asset prices commove, also sheds light on an even more fundamental question: what makes asset prices *move*? An increasing trend in comovement unrelated to fundamentals suggests that the mispricing component of returns might be growing, thus hampering price informativeness. Finally, this investigation also contributes to the Asset Pricing literature, as common factors are the building blocks of market models. Sustained increases in comovement are tantamount to sustained reductions in the benefits from diversification; this implies higher uncertainty, required returns on equity, and cost of capital. This research is particularly important for policymakers, since results from my tests suggest that the reversal in comovement's trend is permanent and endogenous. To the best of my knowledge, this is the first academic article to document such a reversal. If, as Rajan (2005) suggests, technical change and deregulation permanently changed the way stocks relate to one another, higher systematic risk could be a new reality, that could limit the market's ability to attract funds to be channeled into new investment and, ultimately, employment and growth.

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Panel A: Comovement as in Campbell, et al (2001)

Panel B: Comovement as in Brockman et al (2010)

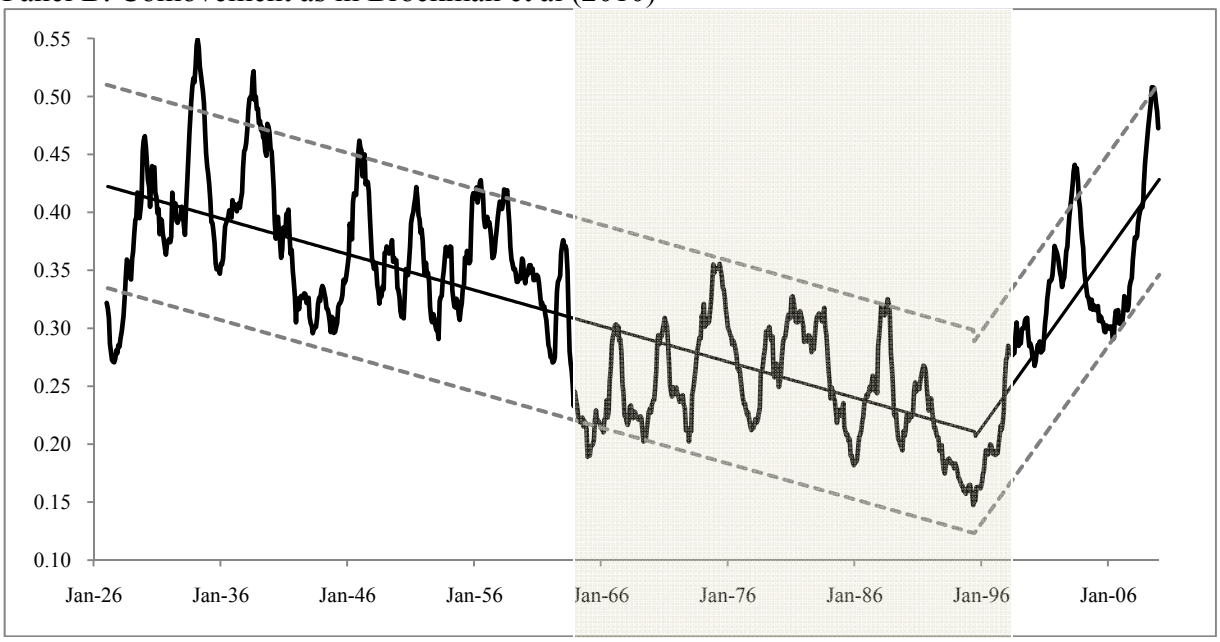
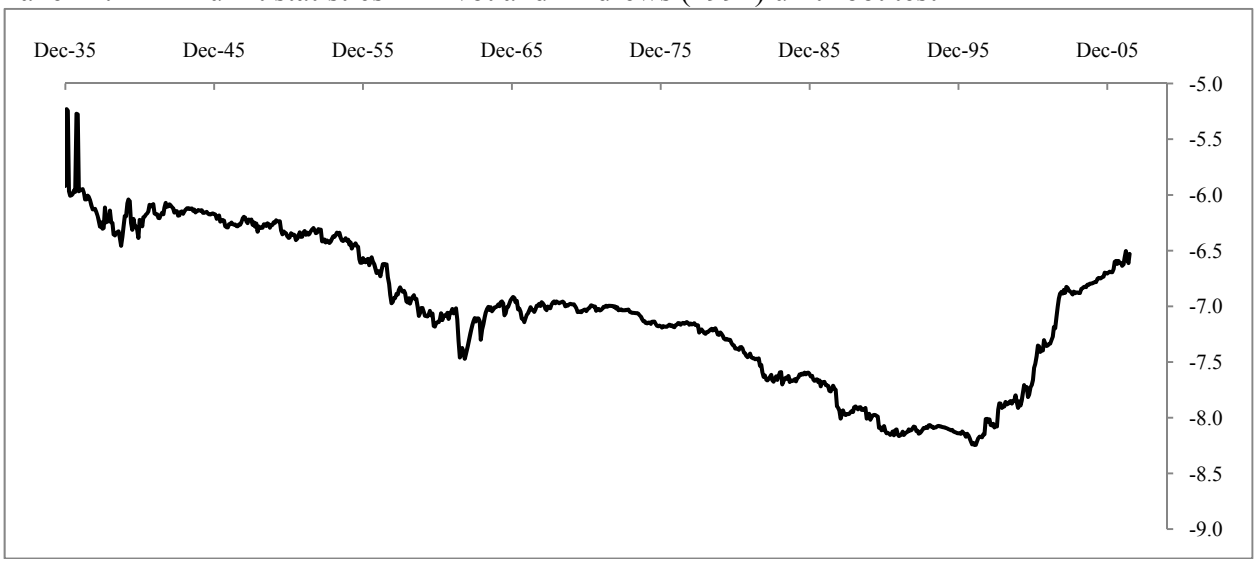


Figure 1: Panel A shows the equally-weighted average market model R2 using 60 month rolling windows, used in Figure 5 of Campbell, et al (2001). I only keep firms with 60 consecutive observations in the rolling window. The lowest point in the series corresponds to January 1997. Panel B shows Market and Industry volatility as a proportion of total volatility, which is the measure of comovement in Brockman, Liebenberg, and Schutte (2010). I smooth the series using a 12 month moving average. The lowest point in this series corresponds to May 1995. In both panels I break down the series into two, before and after the minimum observed comovement. I denote the linear trend and 90% confidence interval for each of the sub-periods. The area shaded in gray shows the sample period used in figure 5 of Campbell, et al (2001).

Panel A: Minimum t statistics in Zivot and Andrews (1992) unit-root test



Panel B: F-statistics in Chow (1960) test

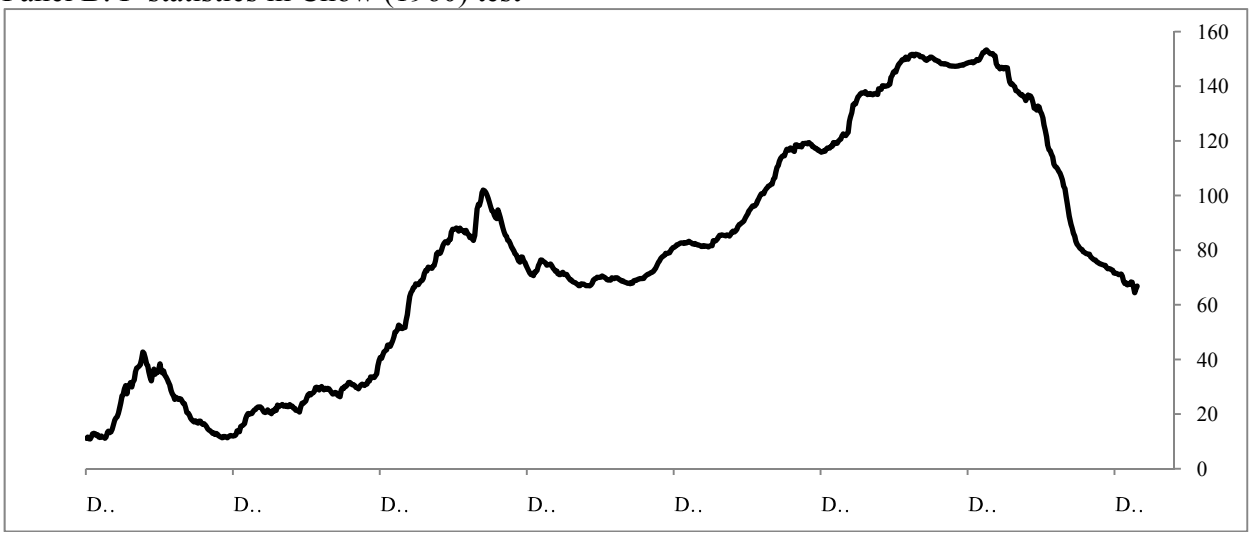
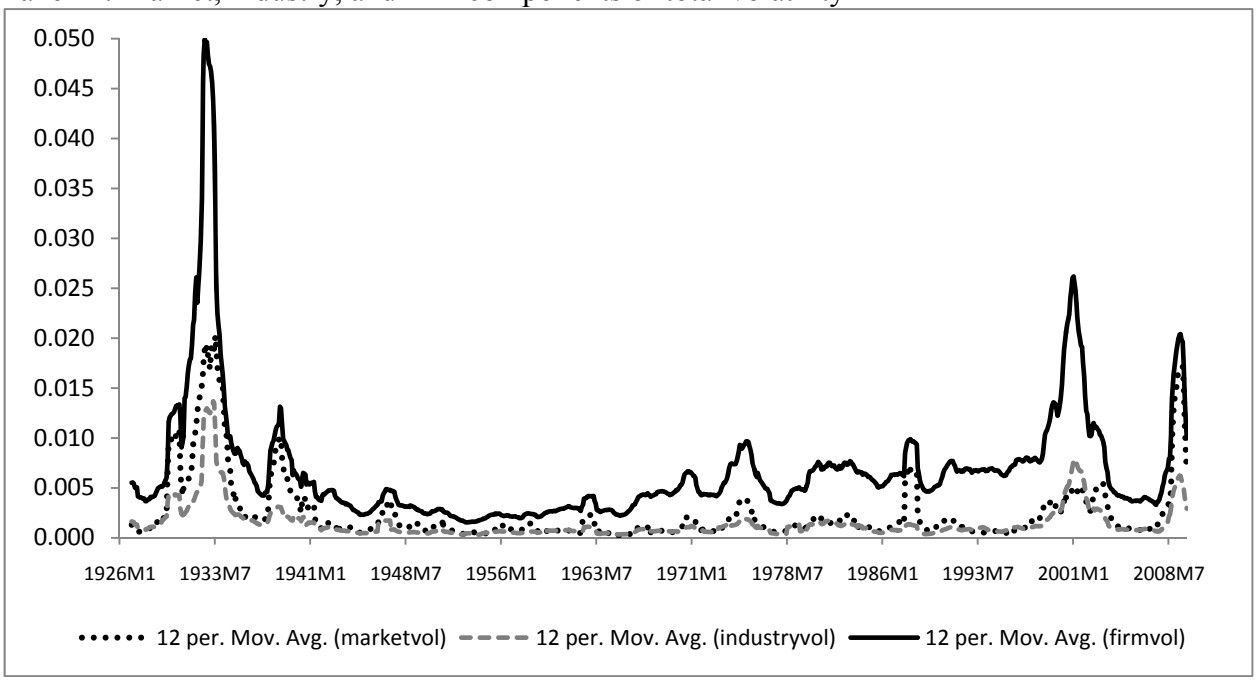


Figure 2: Test statistics to identify structural breaks in the comovement series. Comovement is constructed following Brockman, et al (2010). Panel A shows the t-statistics for Model (3') of Zivot and Andrews (1992) Augmented Dickey-Fuller (ADF) test with allowance for a single structural break in the intercept and slope of the trend function. The model specification is: $y_t = \mu + \theta DU_t + \beta t + \gamma DT_t^* + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t;\ DU_t = 1(t > T_b), DT_t^* = 1(t > T_b)(t - T_b)$. I test 25 different ADF model specifications, including the first difference lags of order one through 24 on each possible structural break point. For each tentative break point I select the ADF t-statistic of the model with the lowest Akaike Information Criterion (AIC). The ADF t-statistic is the t-value of the test $Ho: \propto = 1$, or that the series has a unit-root. The structural break point is identified as the point with the lowest ADF-t statistic. Panel B shows the F-statistic for the Chow (1960) test for structural breaks in the linear trend. The structural break point is identified as the point with the highest F-statistic. The F-statistic is calculated for each break point candidate as: $Chow_F = \frac{(RSS - RSS_1 - RSS_2)/k}{(RSS_1 + RSS_2)/(n_1 + n_2 - 2k)} \sim F_{k, n_1 + n_2 - 2k}$.

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



Panel B: Relative importance of firm-specific volatility relative to market and industry

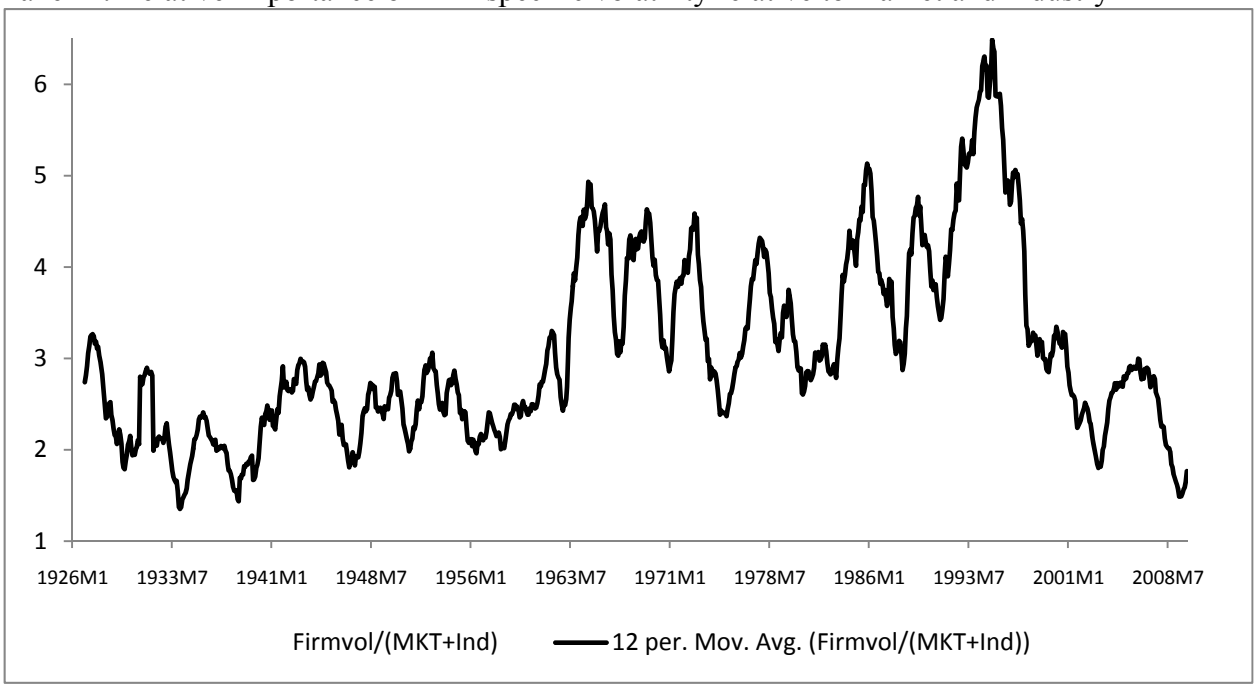


Figure 3: Panel A shows the three components of stock return volatility: market, industry, and firm-specific. The original series are smoothed using a 12-month moving average. Panel B shows the ratio of firm-specific volatility as a proportion of market and industry. This ratio can give an indication of the economic importance of firm-specific volatility with respect to the pervasive components of volatility (i.e. market and industry).

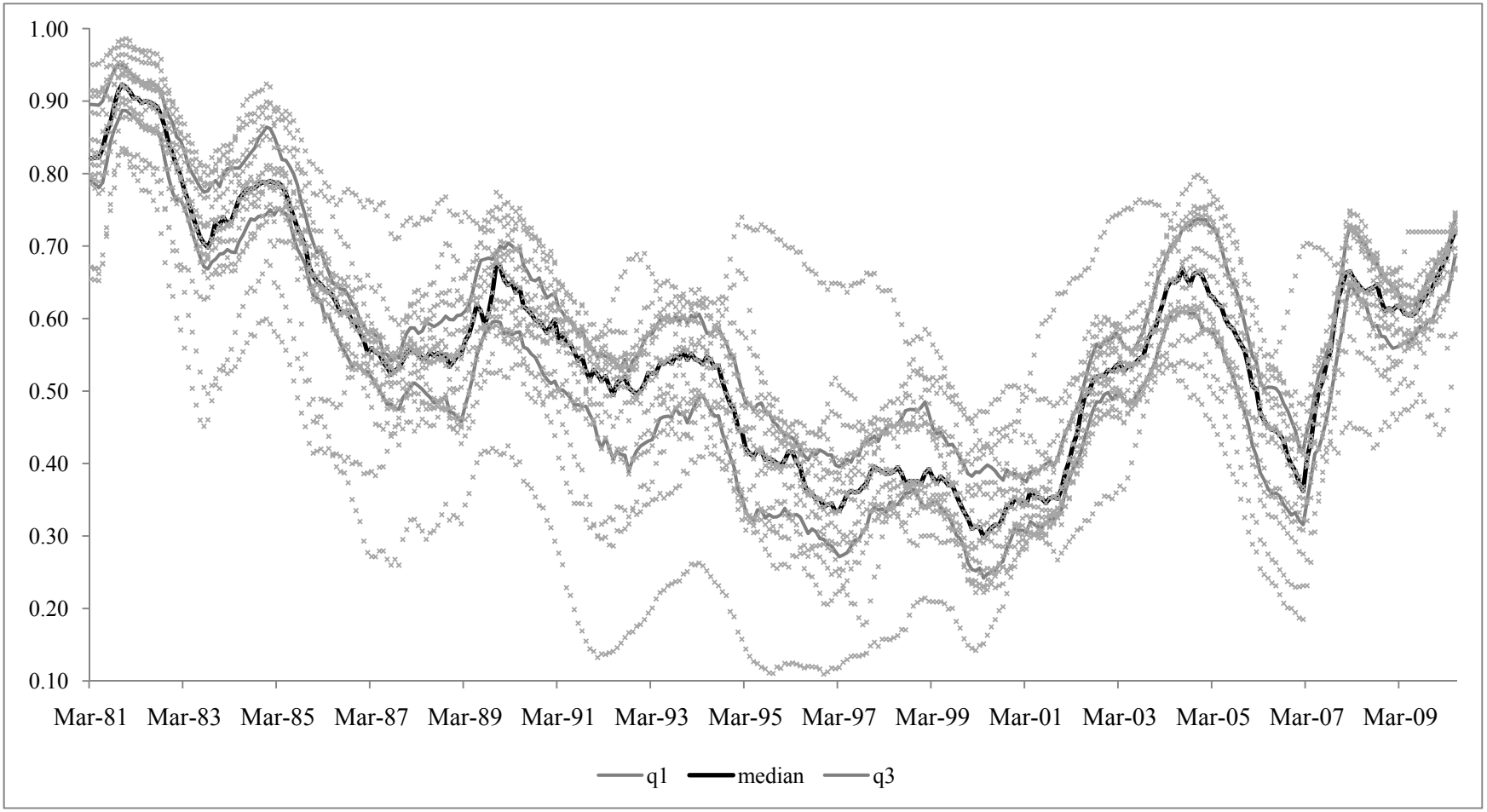
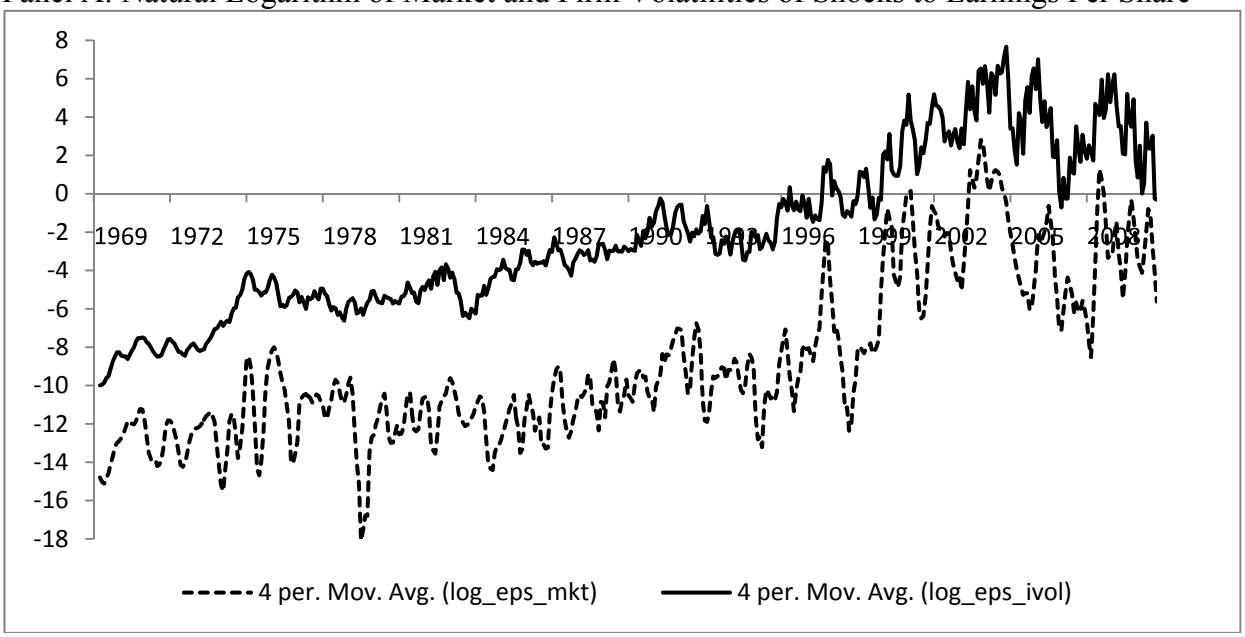


Figure 4: Stock return comovement in 14 international markets. I measure comovement as the proportion of market and industry volatility in total volatility, following Brockman, Liebenberg, and Schutte (2010). I construct this measure using all available daily returns in Thomson Financial Datastream for the period March 1980 to May of 2010. I only consider countries with return information available during the entire 1,008-month period. I construct market, industry, and firm-level volatilities from equations (17) – (22) in Campbell et al (2001). I smooth each series using an MA(12) transformation. I include in this figure the median, lower, and upper quartiles of the comovement distributions in each month.

Panel A: Natural Logarithm of Market and Firm Volatilities of Shocks to Earnings Per Share



Panel B: Cash Flow Shock Comovement Measures

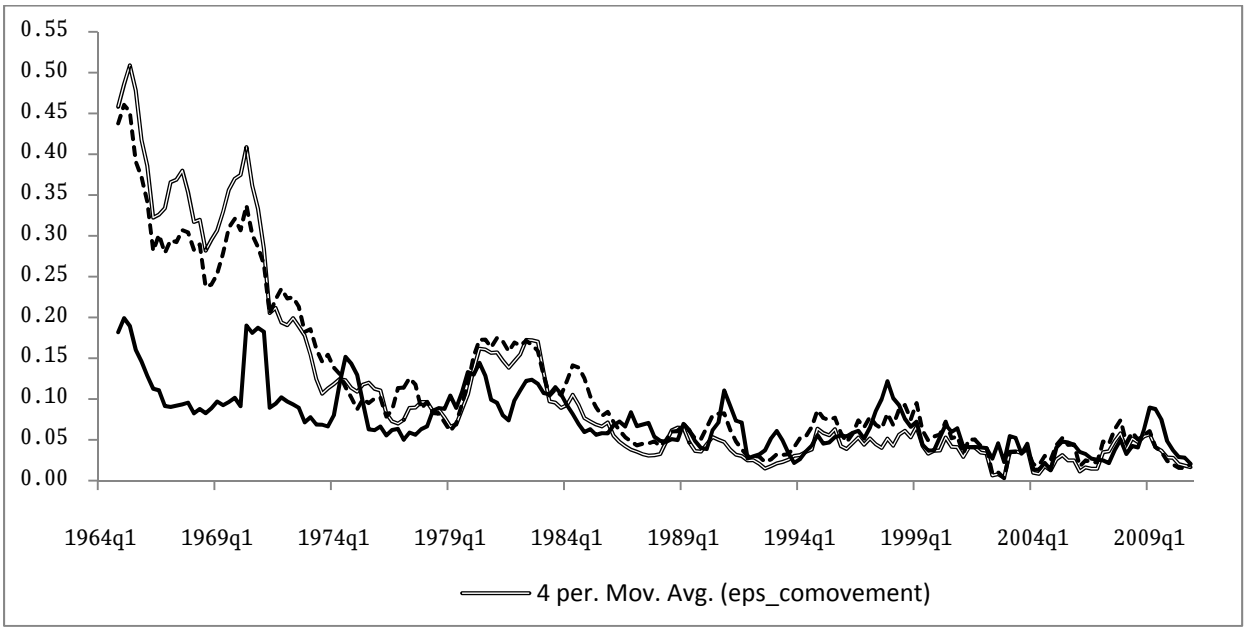


Figure 5: Panel A shows market and firm level volatilities of unanticipated shocks to earnings per share. Market and firm cash flow volatilities are built following the method in Irvine and Pontiff (2009). Panel B shows the natural logarithm of quarterly comovement of cash flow shocks to earnings, cash flows, and sales per share between the first quarter in 1964 and the fourth quarter in 2010. The series have been smoothed for this graphical representation using a 4-quarter moving average.

Table I
Summary Statistics of Stock Return Comovement

This table shows summary statistics for monthly stock return comovement in the US, measured using two alternative methods. I compute these measures using all available daily returns in CRSP for the period January 1926 to December of 2009. I identify a visual break point by smoothing each series using a 12 month moving average and identifying the lowest point. Comovement in (a) is the monthly equally-weighted average market model R^2 of individual stocks. The long run behavior of comovement using this measure is shown in Panel B of Figure 5 in Campbell, et al (2001). For each stock, the market model is estimated over the previous 60 months of consecutive monthly data, and using the CRSP value-weighted index as the market index. The lowest point in this series corresponds to January 1997. Comovement in (b) is the proportion of market and industry volatility in total volatility. This is the measure of comovement used in Brockman, Liebenberg, and Schutte (2010). I construct market, industry, and firm-level volatilities from equations (17) – (22) in Campbell et al (2001). The low point in this series corresponds to May 1995.

Series/Period	*obs.*	σ^2	*mean*	*min*	*q1*	*median*	*q3*	*max*
(a) Comovement as in Campbell et al (2000)								
December 1930 – December 2009	949	0.123	0.324	0.118	0.245	0.296	0.398	0.613
December 1930 – January 1997	794	0.117	0.350	0.118	0.275	0.324	0.433	0.613
February 1997 – December 2009	155	0.041	0.192	0.119	0.164	0.188	0.220	0.289
(b) Comovement as in Brockman et al (2010)								
January 1926 – December 2009	1,008	0.110	0.318	0.085	0.240	0.300	0.385	0.735
January 1926 – May 1995	833	0.112	0.315	0.085	0.234	0.298	0.379	0.735
June 1995 – December 2009	175	0.097	0.328	0.128	0.266	0.311	0.398	0.589

Table II
Time Trend of Stock Return Comovement

This table shows regression results of the natural logarithm of stock return comovement as a function of time using all observations in CRSP during the period January 1926 to December 2009, and for sub-periods before and after the structural break-point identified visually in Figure 1. The model is estimated by generalized least squares, using the Yule Walker algorithm. I report t-statistics in parentheses below the coefficient estimates. μ represents the intercept of the regression of comovement on time, β represents the slope of the function, *D.W.* is the Durbin-Watson statistic, and ρ_i is the ith lag autocorrelation coefficient.

				Autoregressive parameters							
Series/Period	μ	β	D. W.	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8
(a) Comovement as in Campbell et al (2001)											
December 1930 – December 2009	-0.70	$-10.45\text{x}10^{-4}$	1.86	1.04	-0.04	-0.02	0.04	-0.02	0.01	-0.01	-0.02
	(-8.61)	(-7.22)		(31.82)	(-0.95)	(-0.47)	(0.80)	(-0.34)	(0.15)	(-0.13)	(-0.49)
December 1930 – January 1997	-0.61	$-13.38\text{x}10^{-4}$	1.79	1.02	0.06	-0.00	0.05	-0.03	0.01	0.01	-0.04
	(-8.70)	(-8.99)		(28.52)	(1.13)	(-0.01)	(1.04)	(-0.54)	(0.25)	(0.24)	(-1.07)
February 1997 – December 2009	-5.60	$44.99\text{x}10^{-4}$	1.92	1.06	-0.13	-0.02	0.05	-0.02	0.04	-0.04	-0.05
	(-14.28)	(10.02)		(12.73)	(-1.11)	(-0.19)	(0.45)	(-0.15)	(0.29)	(-0.35)	(-0.58)
(b) Log of comovement as in Brockman et al (2010)											
January 1926 – December 2009	-1.01	$-3.69\text{x}10^{-4}$	2.01	0.33	0.15	0.06	0.08	0.10	0.05	0.02	0.05
	(-10.76)	(-2.30)		(10.58)	(4.57)	(1.70)	(2.30)	(3.05)	(1.41)	(0.54)	(1.71)
January 1926 – May 1995	-0.86	$-8.60\text{x}10^{-4}$	2.00	0.30	0.14	0.05	0.06	0.08	0.04	0.02	0.02
	(-14.60)	(-7.05)		(8.65)	(3.72)	(1.43)	(1.64)	(2.20)	(1.01)	(0.58)	(0.62)
June 1995 – December 2009	-4.92	$40.65\text{x}10^{-4}$	1.94	0.38	0.12	0.02	0.07	0.13	0.02	-0.15	0.18
	(-4.90)	(3.73)		(4.97)	(1.50)	(0.19)	(0.82)	(1.58)	(0.27)	(-1.82)	(2.36)

Table III
Unit Root Tests for Stock Return Comovement

This table reports unit-root tests for monthly stock return comovement in the US, measured using two alternative methods. I compute these measures using all available daily returns in CRSP for the period January 1926 to December of 2009. Comovement in (a) is the monthly equally-weighted average market model R^2 of individual stocks. For each stock, the market model is estimated over the previous 60 months of consecutive monthly data, and using the CRSP value-weighted index as the market index. Comovement in (b) is the proportion of market and industry volatility in total volatility. This is the measure of comovement used in Brockman, Liebenberg, and Schutte (2010). I construct market, industry, and firm-level volatilities from equations (17) – (22) in Campbell et al (2001). The unit-root tests are based on the regression $y_t = \mu + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-1} + e_t$, where y_t is comovement at time *t*, *t* is the count dummy, and Δy_{t-i} is the first difference of comovement lagged *i* times. To test for the presence of a unit-root in the series I test the null hypothesis that α=1. The significance probabilities of this test are calculated using the PROBDF function in SAS. The PROBDF function derives its probabilities from approximating functions fit to empirical quantiles that are produced by a Monte Carlo simulation that employs 10^8 replications for each simulation. The number of lags is chosen based on the lowest AIC among models with lags ranging from 0 to 24 months.

Random walk with Drift and Linear Trend $y_t = \mu + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} \Delta y_{t-1} + e_t$

	obs.	*k*	μ	t_μ	β	t_β	α	t_α	$t_{Ho:\alpha=1}$	$p_{Ho:\alpha=1}$
(a) Comovement as in Campbell et al (2001)										
December 1930 – December 2009	949	9	0.006	2.13	$-0.4\text{x}10^{-5}$	-1.73	0.987	189.95	-2.46	0.13
December 1930 – January 1997	794	0	0.007	2.05	$-0.6\text{x}10^{-5}$	-2.07	0.987	165.47	-2.21	0.20
February 1997 – December 2009	155	12	-0.101	-3.98	$16\text{x}10^{-5}$	4.12	0.794	15.60	-4.04	0.002
(b) Comovement as in Brockman et al (2010)										
January 1926 – December 2009	1008	5	0.076	5.38	$-2\text{x}10^{-5}$	-2.60	0.805	24.17	-5.84	<.001
January 1926 – May 1995	833	5	0.165	7.32	$-11\text{x}10^{-5}$	-5.83	0.625	12.60	-7.55	<.001
June 1995 – December 2009	175	4	-0.104	-0.84	$21\text{x}10^{-5}$	1.41	0.735	7.88	-2.84	0.06

Table IV
Structural Break Point Identification

I test for the presence of a structural break using unit-root tests that allow for the presence of a single break in the series. The functional forms of the models are:

Model 1: $y_t = \mu + \beta t + \gamma DT_t^* + \widetilde{y_t}; \widetilde{y_t} = \alpha\widetilde{y_{t-1}} + \sum_{i=1}^{k} c_i\, \Delta\widetilde{y_{t-i}} + e_t;\ DT_t^* = 1(t > T_b)(t - T_b)$

Model 2: $y_t = \mu + \theta DU_t(\lambda) + \beta t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i\, \Delta y_{t-i} + e_t; DU_t(\lambda) = 1 \qquad if\ t > T\lambda$

Model 3: $y_t = \mu + \beta t + \gamma DT_t^*(\lambda) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i\, \Delta y_{t-i} + e_t; DT_t^*(\lambda) = t - T\lambda \qquad if\ t > T\lambda$

Model 4: $y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t;\ DU_t(\lambda) = 1\ and\ DT_t^*(\lambda) = t - T\lambda \qquad if\ t > T\lambda$

Model 1 is Perron's (1989) Additive Outlier Model. This model is estimated in two steps. First the series is detrended and then the detrended value is used to perform the Augmented Dickey-Fuller test. μ is the equation's intercept. *t* is a count variable for time. DT_t^* is a count variable for the post-break period. $\widehat{y_t}$ is the comovement series after controlling for higher-order serial correlation. α is the first-order autocorrelation coefficient, used to test for the presence of a unit-root. The unit-root test consists in testing the null $H_o: \alpha = 1$. T_b is the series' break point, assuming the break to be known. In our case, I choose T_b to be the smallest comovement value in the series, which corresponds to May 1995 Models 2, 3, and 4 are the Zivot and Andrews's (1992) Data-driven Break Models. Model 2 allows for a change in the comovement function's intercept; Model 3 allows for a change in the slope; and Model 4 allows for a change in both, the intercept and slope.

Model	*k*	μ	θ	β	γ	α	$t_{Ho:\alpha=1}$	$p_{Ho:\alpha=1}$	AIC	$T_b/T\lambda$
1	5	0.42		$-2.5\text{x}10^{-4}$	$15.4\text{x}10^{-4}$	0.652	-8.03	<0.01	-4974.04	May, 1995
		(68.48)		(-20.72)	(17.16)	(15.06)				
2	5	0.14	0.06	$-0.9\text{x}10^{-4}$		0.678	-7.85	<0.01	-4965.60	
		(7.53)	(5.20)	(-5.70)		(16.55)				
3	5	0.15		$-9.6\text{x}10^{-4}$	$6.6\text{x}10^{-4}$	0.667	-7.98	<0.01	-4967.53	
		(7.66)		(-5.86)	(5.39)	(16.01)				
4	5	0.16	-0.30	$-1.1\text{x}10^{-4}$	$3.9\text{x}10^{-4}$	0.638	-8.24	<0.01	-4970.05	Jan, 1997
		(7.94)	(-2.11)	(-6.23)	(2.53)	(14.55)				

Table V
Structural Break Points in Six International Markets

The comovement measure is built following Brockman, Liebenberg, and Schutte (2010) using all available daily returns in Thomson Financial Datastream for the period January 1980 to May 2010. Market, industry, and firm-level volatility estimation follows equations (17) – (22) in CLMX. *ADF* is the t-statistic of the Augmented Dickey-Fuller test with drift and linear trend. *Perron (1989)* is the Additive outlier Model of Perron (1989). The structural break point in this model is the lowest value of the MA(12) transformation of comovement in each market. *Chow (1960)* is the F-statistic for Chow's test for structural breaks in the linear trend. The structural break point, $\max_{k,n_1+n_2-2k} F$, is the point with the highest F-statistic. *Zivot and Andrews (1992)* is Model (3') in Zivot and Adrews (1992). I fit 25 different ADF model specifications, including the first difference lags of order one through 24 on each possible structural break point. The break point is the date with the ADF t-statistic of the model with the lowest Akaike Information Criterion (AIC). The structural break point is identified as the point with the lowest ADF-t statistic. $T_b/T\lambda$ denotes the structural break date as identified by each of the tests.

Country		Chow (1960)		Perron (1989)			Zivot and Andrews (1992)			
	ADF	$\max_{k,n_1+n_2-2k} F$		β	γ		θ	β	γ	
	(p-value)	(p-value)	$T_b/T\lambda$	(t-stat)	(t-stat)	$T_b/T\lambda$	(t-stat)	(t-stat)	(t-stat)	$T_b/T\lambda$
Germany	-3.04	226.49	Sep 01	$-22.6\text{x}10^{-4}$	$60.2\text{x}10^{-4}$	Apr 00	-0.32	$-7.1\text{x}10^{-4}$	$15.2\text{x}10^{-4}$	Aug 01
	(0.03)	(<0.001)		(-22.74)	(20.34)		(-2.93)	(-4.88)	(3.85)	
Italy	-2.62	290.65	Sep 01	$-21.7\text{x}10^{-4}$	$60.3\text{x}10^{4}$	Feb 00	-0.14	$-5.8\text{x}10^{-4}$	$9.0\text{x}10^{-4}$	Jun 01
	(0.09)	(<0.001)		(-22.28)	(20.90)		(-1.58)	(-4.27)	(2.67)	
Japan	-3.27	160.8	Nov 95	$-20.8\text{x}10^{-4}$	$44.7\text{x}10^{-4}$	Dec 96	-0.24	$-2.6\text{x}10^{-4}$	$10.2\text{x}10^{-4}$	May 95
	(0.02)	(<0.001)		(-17.07)	(17.75)		(-4.31)	(-1.53)	(3.80)	
South Africa	-3.04	168.46	Oct 97	$-20.2\text{x}10^{-4}$	$37.7\text{x}10^{-4}$	Sep 97	-0.11	$-7.77\text{x}10^{-4}$	$8.9\text{x}10^{-4}$	Aug 97
	(0.03)	(<0.001)		(-16.57)	(13.86)		(-2.00)	(-4.07)	(3.35)	
Switzerland	-2.75	197.92	Nov 01	$-26.7\text{x}10^{-4}$	$46.1\text{x}10^{-4}$	Nov 96	-0.10	$-5.0\text{x}10^{-4}$	$6.7\text{x}10^{-4}$	Jun 01
	(0.07)	(<0.001)		(-22.67)	(19.15)		(-1.18)	(-3.86)	(2.11)	
United Kingdom	-3.21	73.51	Dec 98	$-15.6\text{x}10^{-4}$	$31.2\text{x}10^{-4}$	Jul 00	-0.26	$-0.53\text{x}10^{-4}$	$8.0\text{x}10^{-4}$	Nov 98
	(0.02)	(<0.001)		(-13.04)	(8.47)		(-3.40)	(-0.45)	(3.01)	

Table VI
Descriptive Statistics for Cash Flows and Cash Flow Shock Comovement

This table shows summary statistics for quarterly cash flows and cash flow comovement in the US, measured using the unanticipated cash flow shock volatility decomposition in Irvine and Pontiff (2009) and the comovement measure construction in Brockman, Liebenberg, and Schutte (2010). I compute these measures using all quarterly cash flow information in Standard & Poor's Compustat for the period from q2 1962 to q4 2010. Earnings, cash flows and sales must have a minimum of twelve consecutive quarters of data to be included in the sample. If the ratio of any of these variables divided by price is in the top or bottom 1% of the distribution, the variable is trimmed by setting the price normalized value the 1% value and multiplied by price.

series	*sample period*	*obs.*	*mean*	σ^2	*q1*	*median*	*q3*
Earnings per share ($)	Jul 1962 – Dec 2010	839,291	0.20	0.64	-0.02	0.13	0.44
Cash-flow per share ($)	Jul 1962 – Dec 2010	839,291	0.42	0.82	0.00	0.24	0.67
Sales per share ($)	Jul 1962 – Dec 2010	839,291	6.95	10.67	0.79	3.22	8.48
Earnings per share shock ($)	Jan 1964 – Dec 2010	782,718	0.00	0.56	-0.09	0.01	0.10
Cash-flow per share shock ($)	Jan 1964 – Dec 2010	782,718	0.00	0.60	-0.09	0.01	0.12
Sales per share shock ($)	Jan 1964 – Dec 2010	782,718	0.00	2.86	-0.22	0.00	0.33
Comovement of quarterly unanticipated cash flow shocks:							
of earnings per share	q1 1964 – q4 2010	188	0.11	0.12	0.03	0.06	0.13
of cash flows per share	q1 1964 – q4 2010	188	0.12	0.11	0.04	0.08	0.15
of sales per share	q1 1964 – q4 2010	188	0.07	0.06	0.04	0.07	0.10

Table VII
Time Trends and Autocorrelations for Cash Flow Shock Comovement

This table shows regression results of the natural logarithm of cash flow shock comovement as a function of time. Cash flow shock comovement is built from the unanticipated cash flow shock volatility decomposition in Irvine and Pontiff (2009) and the comovement measure in Brockman, Liebenberg, and Schutte (2010). I compute these measures using all quarterly cash flow information in Standard & Poor's Compustat for the period from q2 1962 to q4 2010. Earnings, cash flows and sales must have a minimum of twelve consecutive quarters of data to be included in the sample. If the ratio of any of these variables divided by price is in the top or bottom 1% of the distribution, the variable is trimmed by setting the price normalized value the 1% value and multiplied by price. The model is estimated by generalized least squares, using the Yule Walker algorithm. I report t-statistics in parentheses below the coefficient estimates. μ represents the intercept of the regression of comovement on time, β represents the slope of the function, *D.W.* is the Durbin-Watson statistic, and ρ_i is the ith lag autocorrelation coefficient.

Series/Period				Autoregressive parameters							
	μ	β	Durbin-Watson	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8
of earnings per share	-1.06	-0.02	1.99	0.14	-0.13	-0.24	-0.20	-0.27	-0.03	0.10	0.04
	(-3.38)	(-6.84)		(1.84)	(-1.69)	(-3.12)	(-2.69)	(-3.54)	(-0.45)	(0.33)	(0.54)
of cash flows per share	-1.08	-0.02	2.00	0.16	-0.09	-0.23	-0.26	-0.28	0.00	0.13	0.08
	(-3.89)	(-7.06)		(2.26)	(-1.26)	(-3.11)	(-3.52)	(-3.76)	(-0.05)	(1.69)	(1.18)
of sales per share	-1.88	-0.01	1.95	0.03	-0.18	-0.10	0.10	--0.20	-0.14	0.08	0.15
	(-9.51)	(-6.78)		(0.39)	(-2.44)	(-1.29)	(1.41)	(-2.70)	(-1.85)	(1.16)	(2.03)