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Abstract

This paper examines the evolution of risk in the U.S. financial sector using firm-level equity market data from 1975 to 2005. Over this period, financial sector volatility has steadily increased, reaching extraordinary levels from 1998 to 2002. Much of this recent turbulence can be attributed to a series of major financial shocks, and we find evidence of an upward trend in volatility only for the common component that affects the entire financial sector. While idiosyncratic volatility remains dominant, a combination of common shocks, deregulation, and diversification has reduced its relative importance since the early 1990s. Within the financial sector, commercial banks show the largest rise in volatility, which also reflects industry shocks and not the idiosyncratic component. Despite these changes, we find that the links between the financial sector and economic activity have declined in recent years. These results have implications for investors, bank regulators, and other policymakers concerned with the origins of financial sector risk and with the links between the financial markets and real activity.

Key words: financial sector, volatility, risk

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I. Introduction

Over the past three decades, the U.S. financial sector has rapidly increased in relative size as measured by the share of corporate profits and market value.[1] Over the same period, deregulation, consolidation, financial innovation, and technological progress have interacted to fundamentally change the nature of risks faced by the firms within the sector and to allow the transfer of those risks among firms both within and outside of the financial system.[2] The five largest financial holding companies, for example, now control nearly half of U.S. banking assets and while these mega-banks face increased competition from across traditional industry lines, they are also freer to engage in a much broader set of financial activities such as insurance and underwriting.

Not surprisingly, academics and policymakers are assiduously assessing the impact of the evolution of the financial sector on financial stability and the overall economy.[3] Rajan (2005), for example, has raised the possibility that recent financial developments amplify business cycle fluctuations and increase the likelihood of a low-probability, high-cost financial crisis ("tail risk").

This paper studies the evolution of risk within the U.S. financial sector. We focus on equity market volatility as our primary indicator of risk and develop a framework based on the variance decomposition of Campbell, Lettau, Malkiel, and Xu (CLMX, (2001)). This allows us to decompose financial sector risk consistently over three decades and to examine how the underlying sources – common financial sector shocks, industry-specific shocks, and idiosyncratic shocks – have evolved and changed in relative importance. We then examine the effects that these changes have had on the links between the financial sector and the real economy.

We first document that financial sector volatility has increased over the past thirty years, particularly between 1998 and 2002. Our CLMX-style decomposition indicates a fundamental shift in the source of volatility with idiosyncratic risk falling since the mid-1990s, in both

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[1]The financial sector's share of total profits of U.S. firms increased from 21% to over 30% during the last decade, while the market value of financial stocks now represents more than 20% of the overall market, up from around 10% fifteen years ago.
[2]See Carey and Stulz (2005) for a discussion of the evolution of the financial sector.
[3]See Ferguson (2002), Rajan (2005), Greenspan (2005) and Geithner (2004), and Kohn (2005) for some policy-makers' views on evolving financial markets and their economic impact.

absolute and relative terms, while common financial sector risk and industry-specific risk have risen. Increased sectoral risk is consistent with Hartmann et al. (2005), DeNicolo and Kwast (2002), and Bartram et al. (2005), who report evidence of increased systemic risk in banking due to increased inter-bank spillovers and higher aggregate risk. Declining idiosyncratic risk for the financial sector as a whole supports the firm-level work of Demsetz and Strahan (1997), Morgan and Samolyk (2005), and Stiroh (forthcoming), who conclude that larger, more diversified (across products and markets) banks are less exposed to idiosyncratic shocks.[4] Our analysis extends this to the broader financial sector, provides an internally consistent framework for measuring these components, and quantifies the relative importance of each over a long time span of dramatic financial sector change.

A fundamental question is whether the sharp increase in financial sector volatility for 1998-2002 reflects a series of large, but temporary, shocks, or is more representative of the level of volatility and risk that might be the norm in the new financial environment. To investigate this, we estimate dynamic trend regressions both with and without controls for major financial shocks such as the Russian bond default and the collapse of hedge fund LTCM in 1998, the bursting of the NASDAQ bubble in 2000, the September 11 terrorist attack in 2001, and corporate scandals in 2002. Including these controls considerably flattens estimates of the underlying trends and only the common financial sector trend remains statistically significant. We find no evidence of a trend in idiosyncratic risk. We conclude that there has been an upward trend in common financial sector risk over the past three decades as financial firms become more similar and increasingly exposed to common shocks.

We also examine the evolution and sources of risk in four industries that comprise the financial sector - commercial banks, savings institutions, insurance firms, and other financial firms (investment banks, investment firms, finance companies, government-sponsored enterprises (GSEs), and other "non-bank" financial institutions). A closer analysis of these industries shows that a substantial portion of the rising volatility stems from increased industry-specific risk for commercial banks. This is reasonable, as commercial banks operated in a

[4]These results counter CLMX, who report that industry-level risk for financial services has fallen significantly over time while the relative importance of idiosyncratic risk has remained unchanged. This apparent divergence stems from our different time periods with an important shift in the composition of volatility since 1997 when their sample ends.

tumultuous environment since the mid-1990s, first with considerable uncertainty over how deregulation might play out and then with the subsequent shake-out and consolidation. By contrast, risk has been declining for savings institutions, and has remained flat for insurance and other financial firms. Finally, we find an increased correlation in the returns across financial industries, indicating a growing convergence among financial service providers.

This suggests that risk in the financial sector has evolved due to financial innovation and structural change and was exacerbated by a series of large shocks from 1998 to 2002. Increased volatility, driven by common shocks and rising cross-industry correlations within the financial sector, suggests that the financial services industry has indeed become riskier over time. At a fundamental level, this likely reflects the deregulation and financial innovation that have enabled financial institutions to evolve towards a greater mix of riskier assets with common exposures as they exploit their diversification gains. The period since 2002, however, has been relatively quiescent and supports the view that the extraordinary volatility from 1998 to 2002 had an important transitory component.

We also examine how the evolution of the financial sector compares to the rest of the market by decomposing the overall market into two broad sectors, our constructed financial sector and a non-financial remainder. In addition to growing in relative size, the financial sector shows increased volatility in both absolute and relative terms. The correlation between the financial sector and non-financial sector, however, has declined. This suggests that financial shocks have not been transmitted to the rest of the economy, which is consistent with the classical view that finance is primarily a “veil” with little effect on the real economy.

Finally, we examine the link between real activity and financial sector volatility over the full period and three sub-periods: 1975-1984, 1985-1994, and 1995-2005. We find that financial market volatility had a large negative (highly significant) impact on economic growth only for 1985-1994. This period was one of substantial turbulence for the U.S. banking sector, e.g., large money-center banks were saddled with enormous losses from loans to developing countries, small bank failures peaked in 1988 and 1989, and consolidation accelerated. This interpretation is supported by industry-level results that show volatility within the commercial bank industry was particularly important during this period. One interpretation, albeit speculative, is that only significant disruptions in the allocation of credit impact real economic activity.

In terms of the fundamental questions surrounding the stability of the U.S. financial sector, our results can be interpreted in different ways. In one respect, it appears that the increased volatility of the financial sector has had little impact on the real economy to date. In fact, the increase in financial sector volatility occurred while the macro-economy has become increasingly stable.[5] Indeed over the past decade the macro-economy has withstood a number of major financial sector events that might have been expected to be destabilizing. This suggests that shocks to the financial sector, while not unimportant, may not have the severe negative consequences that some fear.

At the same time, our results do offer some cause for concern. Even as firms become more diversified, the U.S. financial sector appears riskier than in the past as firms are increasingly exposed to common shocks and larger. This raises the possibility of systemic risk if all firms respond similarly to market events, and makes the collapse of a major financial institution more likely to lead to a more significant financial crisis, i.e., the tail event described by Rajan (2005). While such a scenario is not likely in any given year, the economy may be more vulnerable to this type of widespread financial crisis.

The remainder of the paper is organized as follows. Section II lays out our primary methodology and data for quantifying the evolving risk of the U.S. financial sector. In Section III we describe our methodology and present results concerning the decomposition of broadly defined financial sector volatility into an overall financial sector component, specific industry components, and idiosyncratic components. In Section IV we assess the role the financial sector plays in the overall stock market. Here we explore the interaction between the financial and non-financial sectors, and highlight how the links between the two sectors have evolved over the past three decades. Section V presents evidence on the linkages between equity market performance and real economic activity. Section VI concludes.

II. Defining the U.S. Financial Sector

This section develops and presents our primary indicators of financial sector risk. We begin with firm-level stock market data for all financial firms from 1975 to 2005 and generate

[5] See McConnell and Perez-Quiros (2001) for early evidence and Stiroh (2005) for a discussion of alternative explanations.

measures of return and volatility for four industries (commercial banks, savings institutions, insurance, and other financial firms) and for the financial sector as a whole. We aggregate firm-level data for each of the four component industries and we obtain returns and volatility for the financial sector by aggregating returns and volatility of the four industries. This aggregation scheme allows us to sort out precisely where returns and volatility in the financial sector originate, and to implement the CLMX decomposition, which helps us better understand whether this volatility reflects firm, industry, or sector shocks.

We note that our use of equity market volatility as a measure of risk, while standard practice, has some limitations. First, we are constrained to the publicly traded portion of the financial sector. Thus, we are unable to directly measure the impact of certain key players in the financial sector that are not publicly traded, e.g., hedge funds or mutual insurers. Moreover, our approach does not capture the impact of financial activities within the non-financial sector like GE Capital or the financial subsidiaries of the auto companies. There is also some noise as new companies enter the universe of publicly traded firms, e.g., Goldman Sachs had its initial public offering in May 1999. While this affects the composition of firms over time, including all publicly traded firms ensures that we have the most comprehensive measure of financial sector risk.

Second, equity volatility may not capture all relevant aspects of risk. For example, high-frequency volatility may be less useful in measuring the type of high-severity, low-probability "tail event" discussed by Rajan (2005). Nonetheless, our variance decomposition and study of how the correlation of certain risks has evolved in recent years provide us with clear insights into whether there has been a shift in systemic risk, which in turn may shed some insights into the financial sector's vulnerability to tail-risk. At the same time, it is possible that the financial sector may be more or less vulnerable to certain unforeseen events whose potential impact is not fully captured by equity volatility.

A. Sample Construction

We began by collecting stock market data from the Center for Research in Security Prices (CRSP) for all firms that are included in the Standard Industrial Classification (SIC) Division H, "Finance, Insurance, and Real Estate." While this is an obvious starting point, this sector is defined quite broadly and includes a number of firms that are not financial in nature. For example, at different points in our sample period, SIC 6711 “Holding Offices” includes a broad range of firms such as insurance companies like American International Group, banks like Citicorp, utilities like Bell-South, and retailers like Toys-R-Us. An important part of our effort included identifying financial firms and assigning them to appropriate component industries within the financial sector.

We used SIC codes as the primary classification mechanism to identify commercial banks, savings institutions, insurance, and other financial firms. To classify financial institutions more precisely, we also relied on data from Flannery and Rangan (2004), who identified publicly traded bank and financial holding companies based on regulatory data, and on data from Bank Compustat.

We then classified the remaining firms based on 4-digit SIC codes. In some cases, we were able to classify all firms into a particular sub-industry based on the SIC. In other cases, it was clear that all of the firms with a particular SIC were non-financial; these were dropped. Finally, there were some cases where there was ambiguity and/or it appeared that different categories of firms had the same 4-digit SIC, e.g., SIC 6711. In these instances, we examined the firms individually and placed them into the appropriate industry. Firms that could not be classified were dropped, and firms within these ambiguous SIC industries with market value less than $300m were also dropped.[6]

Several specific decisions are worth noting. We include the GSEs such as Fannie Mae in the other financials industry. We also dropped financial institutions that were primarily foreign in nature. Finally, we dropped all observations that were security specific, e.g., the exchange-traded funds and the closed-end mutual funds in SIC 6726. Details about our classification strategy can found in the Appendix.

B. Summary Statistics

To get a quick picture of the evolution of the financial sector, we divide our sample into three distinct time periods: 1975-1984, 1985-1994 and 1995-2005. The dates are arbitrarily chosen to yield periods of approximately equal length, and subsequent analysis will also examine continuous measures of performance to avoid any problems with the sample periods selection.

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[6]This should not affect the primary results because our analysis focused on market value-weighted decompositions.

Table 1 reports the average number of firms, market value, and market value share for the four financial industries and the financial sector as a whole.[7]

Table 1 clearly illustrates the steady growth in the size of the financial sector, where the average number of firms rose from 423.2 during 1975-1984 to 1,025.9 for 1995-2005 and the market value of the sector increased from an average of $83.4 billion to an average of $2,060.7 billion. This rise in market value represents both the steady increase in value of the largest financial firms, particularly over the last decade, and the IPOs of firms in the financial sector. For example, the financial sector now includes a number of large firms like Goldman Sachs and John Hancock, which went public within the past decade.

A closer look at the four industries shows some interesting changes and confirms some well-known trends. In terms of market value shares, other financials, largely due to the GSEs, experienced the largest increase, from 9.3% of the financial sector for 1975-84 to over 21.7% for 1995-2004. This increase reflects both the relative performance of the firms in that industry and the changing composition of the financial sector. Insurance firms, in contrast have seen their financial sector share drop from 38.8% in 1975-84 to 27% for 1995-2005 in spite of the demutualization and concurrent IPOs of several large insurance firms such as John Hancock. This decline partially reflects consolidation among firms within the financial services industry, e.g., when Citicorp and Travelers merged, the combined Citigroup is included in the commercial bank industry. For commercial banks, the number of firms rose through the 1980s and then declined as the industry consolidated after deregulation removed interstate branching restrictions. Interestingly, despite all of these changes within the financial sector over the past three decades, commercial banking's share of the total financial sector is about where it was thirty years ago (slightly less than 50% of the total financial sector).

C. Returns and Volatility by Industry

We employ a bottom-up approach where we use the firm-level data described above to generate indices of returns and volatility for each of the four component industries and then for the financial sector as a whole. Although our primary unit of analysis for returns and volatility

[7]Precise definitions of the market value construction are provided in the following sub-section.

will be months, m, we first create measures of return and volatility for individual firm j on date t using daily equity market observations.

For each firm, we estimate a daily excess return, $R_{j,t}$, as the difference between the daily return from CRSP and the risk-free return, defined as the daily return on the 30-day U.S. Treasury bond. Monthly (excess) returns, $R_{j,m}$, are calculated as the product of the daily excess returns over the period. We also calculate, for each month, the mean and variance of a firm's daily returns, denoted as $\mu_{j,m}$ *and* $\sigma^2_{j,m}$, respectively. All return estimates are annualized and expressed in percentages. We calculate the firm's daily market value as the price of equity times the shares outstanding, and define its monthly market value as the arithmetic mean of the daily market values within a month.

We proceed in a similar fashion for each of the four component industries i. We define industry returns as the value-weighted average of the firm-specific returns for all firms within that industry. Returns are always computed over the same period, i.e., industry daily return, $R_{i,t}$, is a value-weighted average of the daily returns for firms in industry i on date t and the industry monthly return, $R_{i,m}$, is a value-weighted average of the returns for the all of the firms in industry i in month m. To be consistent in the decomposition, we use the monthly weights in defining the industry returns as value-weighted returns:

$$\text{(1)} \quad \begin{array}{l} R_{i,t} = \sum_{j \in i} R_{j,t} w_{j,m} \\ R_{i,m} = \sum_{j \in i} R_{j,m} w_{j,m} \end{array} \qquad \sum_{j \in i} w_{j,m} = 1 \ \forall \ m$$

where we define a firm's weight in its industry for a month, $w_{j,m}$, as the firm's monthly market value divided by the sum of all firms' monthly market values in that industry. Weights for all firms in an industry sum to one in each period. We also calculate the industry's mean and variance of daily returns within a month, $\mu_{i,m}$ *and* $\sigma^2_{i,m}$, respectively, as the arithmetic mean and the variance around that mean. All estimates are annualized and expressed in percentages.

Figure 1 plots the smoothed mean monthly returns, for each industry from 1975 to 2005. To focus on the long-run trends, we made two adjustments when presenting these data. First, we follow CLMX and "down-weight" the October 1987 stock market decline by replacing its value in each series with the next largest observation of that series. Second, we present backwards, twelve-month moving averages of each underlying series. Neither adjustment changes the long-run perspective, but simply makes the results easier to interpret. One could use more sophisticated frameworks, e.g., GARCH models, to estimate time-varying volatility, but we use the simple variance to be consistent with the subsequent decompositions that allows us to allocate expected volatility into the underlying sources.

Figure 1 suggests that the returns of the four industries are highly correlated. To examine this issue more completely, we estimate the average pair-wise correlation of the daily returns for each industry over the three sub-periods. These estimates are presented in Table 2. To estimate these correlations for a given industry pair, we calculated the correlation of daily returns in a month for two industries, and then averaged those monthly correlations for each period. For all industry pairs there is steady rise in the correlations with estimates between 0.53 and 0.76 for 1975-1984 and between 0.65 and 0.84 for 1995-2005. The change in correlation between 1985-1994 and 1995-2005 is significantly different from zero at the 5% level for five of the six industry pairs.

This increasing correlation likely reflects convergence within the financial services industry. Beginning in 1987 and culminating with Gramm-Leach Bliley in 1999, commercial banks saw a steady increase in their ability to engage in underwriting activities and many large commercial banks now routinely offer investment banking and insurance activities.[8] Similarly, massive deregulation in the 1970s and 1980s allowed savings institutions to become more involved in corporate lending, like commercial banks. Our results suggest that as the financial sector has evolved, the various component industries have become more similar with an increased exposure to common shocks.

Figure 2 plots the variance of daily returns for the four industries over the same time period, where we again smooth the monthly variances using a backwards 12-month moving average of the down-weighted series. Most notably, we observe an enormous surge in volatility in 1998 that persists through 2002, particularly for commercial banks and other financial firms. The level and breadth of sustained volatility during this five year span was unprecedented over the last three decades.[9] More recently, however, volatility has declined to levels comparable to earlier periods in all four industries. A critical question is whether the increased volatility from

[8]See Strahan and Sufi (2000), particularly Table 1, for a summary of the evolution of commercial bank operating restrictions.

1998 to 2002 or the lower volatility since then is more representative of the current environment and more likely to reflect the future.

Finally, there are large differences in the trends in variance across the industries, which reflect familiar industry trends and events. Savings institutions, for instance, saw high volatility during the 1970s as inflation and rising interest rates fundamentally altered their business model and increased uncertainty, but less volatility since then. More recently, volatility has been particularly high for other financial firms and commercial banks. The increased volatility for the other financial firms can likely be attributed to the large capital market fluctuations associated with the 1990s boom and subsequent decline in stock prices and capital market activity. Similarly, the increased volatility for commercial banks can be linked to the industry's massive deregulation during the 1990s.[10]

III. Decomposing Financial Sector Risk

We now turn to our methodology for quantifying and evaluating the evolution and sources of risk within the U.S. financial sector. The methodology was developed by CLMX, who showed how aggregate equity return volatility can be decomposed into three components: overall market volatility, industry-specific volatility, and idiosyncratic volatility. A key advantage of their approach is that aggregation across firms and industries allows one to quantify these components without estimating industry or firm-specific "betas," which are difficult to estimate and could vary over time.[11]

While our methodology follows CLMX, our focus is quite different. CLMX decompose aggregate volatility across all U.S. industries into market, industry, and idiosyncratic components. In contrast, we focus on the U.S. financial sector and decompose broadly-defined financial sector volatility into an overall financial sector component, specific industry components, and idiosyncratic components. This allows us to identify the specific sources of evolving risk in U.S. financial institutions.

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[9]Using data that does not down-weight October 1987 introduces a very large, but transient volatility spike.

[10]See Strahan and Sufi (2000) for an event study of how financial stock prices reacted to the Citicorp/Travelers announcement in 1998 and the agreement on Gramm-Leach-Bliley in 1999.

[11]Schuermann and Stiroh (2005) provide evidence on the instability and heterogeneity of market betas for U.S. commercial banks.

A. Methodology

We decompose equity market volatility for U.S. financial firms into factors that represent the financial sector, *F*, the four component industries, *i*, and an idiosyncratic component for each firm, *j*. To define the financial sector, we use the same process to generate financial sector returns and market values from the component industries as when we generated industry aggregate from firm measures. We define the daily and monthly financial sector returns, $R_{F,t}$ and $R_{F,m}$, respectively, as the value-weighted average of the component industry returns:

$$(2)\quad \begin{aligned} R_{F,t} &= \sum_i R_{i,t} w_{i,m} \\ R_{F,m} &= \sum_i R_{i,m} w_{i,m} \end{aligned} \qquad \sum_i w_{i,m} = 1 \; \forall \; m$$

where we define an industry's weight in the financial sector for a month, $w_{i,m}$, as the industry's monthly market value divided by the sum of all industry's monthly market values. Weights for all industries sum to one in each period. We also calculate the financial sector's mean and variance of daily returns within a month, $\mu_{F,m}$ *and* $\sigma^2_{F.m}$, respectively, as the arithmetic mean and the variance around that mean. All estimates are annualized and expressed in percentages.

The volatility decomposition in CLMX is based on a "market-adjusted-return model," detailed in Campbell et al. (1997). This is a simplified return decomposition where industry-specific returns equal market returns plus an industry-specific component. In our decomposition, we relate industry returns to returns for the financial sector as a whole, so our market-adjusted-return model is:

$$(3)\quad \begin{aligned} R_{i,t} &= R_{F,t} + \varepsilon_{i,t} \\ \sigma^2_{i,m} &= \sigma^2_{F,m} + \sigma^2_{\varepsilon,i,m} + 2 \cdot C(R_{F,t}, \varepsilon_{i,t}) \end{aligned}$$

where $\varepsilon_{i,t}$ is the difference between financial sector returns and industry returns, $\sigma^2_{\varepsilon,i,m}$ is the variance of those differences, and *C(.,.)* is the covariance of the daily arguments. All variances and covariances are calculated over the daily observations within a month.

Similarly, we can decompose firm-specific returns into a common industry component and a firm-specific component as:

$$(4)\quad \begin{aligned} R_{j,t} &= R_{i,t} + \varepsilon_{j,t} \\ \sigma^2_{j,m} &= \sigma^2_{i.m} + \sigma^2_{\varepsilon,j,m} + 2 \cdot C(R_{i,t}, \varepsilon_{j,t}) \end{aligned}$$

where $\varepsilon_{j,t}$ is the difference between industry and firm-specific returns and $\sigma^2_{\varepsilon,j,m}$ is the variance of those differences.

A difficulty with the variance decompositions in Equations (3) and (4) is that because the errors are not orthogonal (as they would be in a traditional CAPM decomposition), there is a covariance term. CLMX show, however, that weighting over firms and industries can eliminate these covariances, which in turn leaves a simpler variance decomposition.[12] In particular, one can weight each industry in Equation (3) by its market value share and sum over all industries to obtain a decomposition of financial sector volatility:

$$(5)\quad \sum_i w_{i,m}\sigma^2_{i,m} = \sigma^2_{F,m} + \sum_i w_{i,m}\sigma^2_{\varepsilon,i,m}$$

and similarly weight each firm in Equation (4) by its market value share and sum over all firms to obtain a decomposition of industry volatility:

$$(6)\quad \sum_{j\in i} w_{j,m}\sigma^2_{j,m} = \sigma^2_{i,m} + \sum_{j\in i} w_{j,m}\sigma^2_{\varepsilon,j,m}$$

for each industry *i*.

It is useful to discuss the interpretation of these decompositions. Beginning with the decomposition of industry volatility in Equation (6), the left-hand side is the weighted-average of firm-level volatility, which reflects the expected volatility of a firm in that particular industry, with probabilities equal to the firm's market share. This measure of expected volatility reflects two components – a common industry factor and idiosyncratic factors (appropriately weighted by the firm's market share). Similarly, the financial sector decomposition in Equation (5) shows that the weighted average of industry volatility, interpreted as the expected value with probabilities equal to market share, reflects a common financial sector factor and industry specific factors (appropriately weighted). In each case, the weighting and summing has removed the covariance terms.

The final step is to combine the industry and firm decomposition by weighting each firm in Equation (6) by the share of its industry, summing across industries, and substituting in Equation (5). This yields the following financial sector decomposition:

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[12]See CLMX, particularly pp. 4-6, for details on the derivation and elimination of the covariances. The intuition is that the covariances essentially represent the betas in a traditional CAPM decomposition and the weighted sum of the betas from a CAPM estimate, with market returns defined as the weighted sum of firm returns, equals one.

$$(7)\ \sum_i w_{i,m} \sum_{j \in i} w_{j,m} \sigma^2_{j,m} = \sigma^2_{F,m} + \sum_i w_{i,m} \sigma^2_{\varepsilon,i,m} + \sum_i w_{i,m} \sum_{j \in i} w_{j,m} \sigma^2_{\varepsilon,j,m}$$

The interpretation of this final decomposition parallels the earlier ones. The left-hand side is again expected volatility, i.e., the weighted-average of firm-level volatility, where firms are now weighted by both the share in the industry and the industry's share in the financial sector. This can be interpreted as a measure of overall volatility, defined as the expected volatility of a given firm with probabilities equal to the firm's weight in the financial sector as a whole. Expected volatility reflects common factors for all firms in the financial sector, $\sigma^2_{F.m}$, factors specific to the industry in which the firm operates (weighted by the industry's market share), $\sum_i w_{i,m} \sigma^2_{\varepsilon,i,m}$, and idiosyncratic factors that are specific to the particular firm (again weighted by the firm's market share), $\sum_i w_{i,m} \sum_{j \in i} w_{j,m} \sigma^2_{\varepsilon,j,m}$.

We refer the left-hand side of Equation (7) as "expected volatility" and to each of the three right-hand side components as "financial sector volatility," "industry volatility," and "idiosyncratic volatility," respectively. It is worth that emphasizing that both expected volatility and the idiosyncratic component are firm-level measures, e.g., weighted average of firm-specific total and residual volatility. In contrast, the financial sector and industry components reflect volatility of aggregates and can be thought of as a portfolio measure that includes diversification effects.

Our methodology closely follows CLMX, but our approach differs in three specific ways. First, we use the contemporaneous monthly weight, while CLMX use the lagged monthly weight. This difference doesn't matter quantitatively, as long as weights are consistently used when defining aggregate returns and the estimating the volatility decomposition. Second, we estimate the variances of residuals in each month around the mean for that month, while CLMX define the variance of returns around the sample mean. Again, this does not matter quantitatively. Third, we follow the decomposition exactly and use the variance of residuals in Equation (4) and (5), while CLMX use the sum of the squared residuals. These are very highly correlated, but they are not the same because the errors from the market-adjusted-return model need not be mean-zero in a given month. Our use of the actual variance of returns makes the decomposition exact.

B. Financial Sector Volatility Decomposition

Table 3 reports mean returns from Equations (1) and (2) and the volatility decomposition in Equation (7). Note that our references to volatility mean variance, rather than the more frequently-used measure of standard deviation. This simply reflects the decomposition described above. To make the results easier to interpret, we also report standard deviation of expected volatility.[13] Once again, we split our sample into three sub-periods to highlight how the sources of volatility in the U.S. financial sector have evolved over the past three decades. Figure 3 reports the same volatility data in a continuous fashion by reporting the smoothed, down-weighted values of all four elements in Equation (7). Figure 4 reports the relative contribution of each type of volatility, i.e., the share of that component in expected volatility.

We first observe that the U.S. financial sector experienced relatively strong returns over this period rising from around 12 percent prior to 1995 to 18 percent afterward. Expected volatility for financial sector firms has risen substantially over time, rising from 788.5 for 1975-1984 to 1043.7 for 1985-1994 and to 1162.1 for 1995-2005. In terms of standard deviations, the expected volatility increased from 27.6% to 31.2% to 32.2% for the same periods. This upward trend in volatility primarily reflects the weighting within the financial sector as the relatively large commercial bank and other financial industries have seen increased volatility over time.

This rise in expected volatility in the financial sector, particularly from 1998 to 2002, is unprecedented in terms of magnitude and duration. Table 3 and Figure 4 show that the common sector component has driven these volatility gains as it more than doubled from 190.0 for 1985-1995 to 429.8 for 1995-2005 and accounted for more than a third of volatility in the last period. Idiosyncratic volatility, in contrast, declined after 1995, following increases the 1980s and early 1990s. The evidence of increased sensitivity to common shocks is consistent with the analysis of return correlations in Table 2, which showed that returns across all pairs of financial industries have become more correlated over time.

Finally, we examine the components of volatility in each of the four financial industries from Equation (6). Table 4 reports the mean returns, expected volatility (both variance and

[13]To be clear, all measures are estimated from the daily returns in a month, annualized and reported as percentages, and averaged over the months in a period.

standard deviation), and volatility decomposition for each industry and time period.[14] Figure 5 reports the components of the decomposition and Figure 6 plots idiosyncratic volatility as a percentage of total expected volatility for each of the four financial industries. Both figures report smoothed, down-weighted data. As a reminder, Figure 2 reports the industry component separately, $\sigma_{i.m}^2$.

As in the financial sector as a whole, we find that idiosyncratic volatility accounts for the majority of expected volatility in all industries, ranging from 55% in commercial banks to 74% in savings institutions in the last period. We also see that relative importance of idiosyncratic volatility has declined since the mid-1990s, although there has been a slight increase since 2003 when industry volatility declined.

The declining importance of idiosyncratic risk has been particularly notable in the commercial bank industry, where the share of idiosyncratic volatility fell from 85% during the 1985-1994 period to 56% for 1995-2005. In terms of absolute volatility, both the insurance and other financial industries saw an increase in idiosyncratic volatility even as its relative importance declined. This dichotomy seems reasonable. The post-1995 period was relatively strong for commercial banks and there were not large bank-specific shocks.[15] In contrast, many firms in the insurance and other financials industries have been exposed to specific shocks such as hurricanes, the collapse of LTCM, and corporate scandals.

C. *Trend Analysis*

The previous section presented evidence of a steady rise in financial sector risk with a particularly strong increase during the period 1998-2002 that was driven by the common financial sector component. This section examines the nature of the underlying trend, e.g., deterministic or stochastic, and gauges the relative importance of specific events in determining both the direction and the magnitude of any trend. This sub-section presents the results, and the following sub-section presents a discussion and interpretation.

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[14]As with the financial sector as a whole, these returns are quite high and we compared them to returns of value-weighted indices computed by SNL Securities, LP for the U.S. banking and savings institutions industries. The results are very close in both the level and variation over time, e.g., correlation of monthly returns for 1989:m1-2005:m12 was 0.99 for commercial banks and 0.98 for thrifts.

[15]See Schuermann (2004) on the success of the U.S. banking system through the 2001 recession.

We first test for the presence of unit roots in the individual series by estimating augmented Dickey and Fuller tests (ADF, 1979) for each of the four main volatility estimates from Equation (7): expected volatility, financial sector volatility, industry volatility, and idiosyncratic volatility. We estimate the ADF tests with just a constant and with a constant and a deterministic time trend. Results are reported in Table 5 and reject the presence of a unit root in all four cases for both specifications.[16] We focus the remainder of our analysis on the level of volatility over time and test for the existence of a deterministic linear trend.

We are primarily interested in whether these measures of risk and volatility have been trending upward over time so we estimate variations of dynamic trend regressions, e.g., volatility regressed on a constant, its own lag, and a deterministic time trend. We do not include any other macroeconomic controls like business cycle indicators, yield information, or credit conditions because we are interested in the long-run trends of the unconditional volatility of financial sector returns. Our basic specification for a deterministic trend is:

$$(8)\quad X_t = \alpha + \rho X_{t-1} + \delta t + \varepsilon_t$$

where X is a measure of volatility, ρ measures the dependence on the first lag, and the error term, ε, is corrected for heteroskedasticity and autocorrelation using the procedure of Newey and West (1987), where we allow up to four lags in the autocorrelation structure of the error.

One obvious and important concern is how to differentiate any underlying trend from specific shocks that are temporary in nature. This is particularly relevant for the period 1998-2002, which was marked by high volatility that may reflect a series of specific events like the terrorist attach in September 2001 that are unlikely to be repeated.

We address this issue in three ways. First, we compare the basic trend regression in Equation (8) to a trend regression that controls for extreme outliers. We do this by creating a dummy variable of “extreme values” equal to 1 if the monthly observation was greater than the value of the 95th percentile of the series for the full sample and then including this dummy in the trend regression. This approach has the advantage of being agnostic, and hopefully less subjective, about the nature of particular shocks, but has the disadvantage that it does not allow

[16]As in CLMX, our results are virtually identical if we use the down-weighted data, so we do not report them here. Those results are available upon request.

meaningful economic interpretation of the shocks. This should be viewed as a parsimonious way to examine the robustness of the underlying trend.

Second, we identified several "financial shocks" that led to large spikes in volatility of the financial sector. An obvious shock was the 1987 stock market crash. More recently, since 1997, there have been shocks like the Russian bond default and the Long-Term Capital Management (LTCM) meltdown in 1998, the bursting of the NASDAQ bubble in 2000, the terrorist attacks in 2001, and corporate accounting scandals in 2002. While these shocks likely affected individually firms differently, there were clearly macroeconomic implications that affected many firms and industries and volatility spiked. To be conservative and err on the side of not finding an upward trend, in addition to October 1987, we identified shocks only in the recent period of exceptionally high volatility after 1997.

Our list of financial shocks includes:

- Stock Market Crash of 1987 – October 1987
- Russian Bond Default and LTCM – September-October 1998
- NASDAQ Collapse – March-April 2000
- September 11, 2001 – September 2001
- Corporate Scandals – July and October 2002[17]

For each financial shock, we created a dummy variable that was set equal to 1 in the months around these events, (e.g., these months, any intervening months, the preceding month, and the following month), and included these five dummy variables in the trend regression. This approach has the appealing property that we know precisely which events are being controlled for, but suffers from the obvious problem of subjectivity in identifying relevant shocks. Moreover, there is a deeper question about whether one should consider these one-time events, which we discuss at the end of the section. As a result, this exercise should also be viewed as a robustness test of the trend analysis.

Third, we estimate the basic trend regression for only the early sample of data before the volatility run-up in the late 1990s. There is some arbitrariness to the breakpoint, but we chose April 1998. This month included a watershed moment for the U.S. financial sector as The

Travelers Group and Citicorp announced their intention to merge and create the largest financial services business in the U.S. To the extent that increased volatility reflects the expansion and a broader opportunity set of large financial firms, this is a reasonable breakpoint as it anticipates subsequent deregulation and consolidation. Moreover, Strahan and Sufi (2000) show that volatility of financial stocks increased markedly after this announcement. Finally, this cut-off is consistent with our evidence that shows rising financial sector volatility beginning in 1998.

Results for each of the four trend regressions – basic trend-full sample, extreme value dummy variable, financial shocks dummy variable, and basic trend-early sample – for each of the four financial sector volatility measures are reported in Table 6. We report the coefficient on the time trend and the regression R^2; estimates of the constant and coefficient on lagged dependent variable are available upon request. In all cases, standard errors are corrected for heteroskedasticity and autocorrelation using the method of Newey and West (1987).[18]

The first conclusion is that overall volatility, measured by the expected volatility of all firms in the financial sector, shows an upward trend over the last three decades, but this trend is not particularly robust. Controlling for extreme volatility measures or the specific shocks flattens the trend substantially and eliminates statistical significance. Moreover, the explanatory power of the regressions increases greatly when the dummy variables are included, indicating that these events are quite important sources of variation. As shown in the last panel, we find evidence of an upward trend for the early period before 1998:m4. Economically, however, these trends are not large, e.g., the trend estimate is only 0.6 per month, compared to an annualized monthly volatility of 1162.1 for 1995:m1-2005:m12. We conclude that there has been a modest long-run increase in overall financial sector risk and volatility, but that a series of specific shocks in the last few years have been the primarily source of increased volatility in recent years.

Looking at the trends in individual components highlights the evolving source of financial sector volatility and shows some important differences. Most strikingly, we see a robust upward trend in the common sector component. Controlling for extreme values or financial shocks reduces, but does not eliminate, the upward trend. This is consistent with the

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[17]Volatility in the 2nd quarter of 2002 was triggered, in part, by a $3.8B restatement by Worldcom on June 25, 2002. Subsequent volatility through the fall was driven by a wave of downgrades by Standard and Poors related to unfunded pension obligations (BIS (2003)).

earlier decomposition, which shows the sector component accounting for an increasing share of overall volatility, and the rising correlation of returns across component industries.

By contrast, weighted industry volatility shows no trend for the full period, both without and with any controls, and was actually trending down prior to 1998. Similarly, idiosyncratic volatility shows no trend for the full period, although there does appear to be an upward trend prior to 1998. This rise in idiosyncratic risk in the period before 1998 echoes one of the main results in CLMX.

It is worth emphasizing that while these results indicate that there have been a significant upward trend in the sector component of volatility of the financial services industry over the past three decades, this does not mean that volatility will continue to increase in the years ahead. Our evidence suggests that specific shocks accounted for a good deal of the volatility rise and, and, as pointed out earlier, volatility has leveled off since 2002.

We now examine trends in the volatility components of the underlying industries as in Equation (6).[19] We estimated the same set of regressions described above for the expected volatility, industry component, and idiosyncratic component of each industry. Note that while the financial shock dummy variables are the same for all regressions, the extreme value dummy variables vary by series and industry by construction, so that they are more tailored to the individual industry events. Results are presented in Table 7.

The strongest result is that commercial banks show an upward trend in the common shock measured by the industry component. This is true after including either dummy controls and for the early sample before 1998. We note, however, that this is not particularly large compared to average volatility over the period. Idiosyncratic risk for banks, in contrast, seems to have leveled off after 1998, which is consistent with the idea of internal diversification and a widening of the investment opportunity set as banks expanded in a more deregulated environment. For savings institutions, both expected volatility and the industry component show strong negative trends, which reflect the dissipation of the industry problems from the 1970s.

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[18]Estimates are similar if we use the down-weighted volatility series or if we exclude, rather than dummy out, the extreme values or financial shocks. Those results are available upon request.

[19]For space reasons, we do not report estimates of the augmented Dickey Fuller tests for indidivual industries. These estimates reject the null of a unit root, so we proceed in levels throughout. Results are available from the authors upon request.

For insurance, there is some evidence of a positive trend in the industry component, but it is not particularly robust. This is reasonable as volatility in this industry is generally driven by industry-specific events, e.g., hurricanes in the mid-1990s, that are not necessarily reflective of an underlying trend. Once one controls for these events, particularly via the extreme value dummy variables, the volatility profile flattens.

For other financial firms, there is no trend for the full period for either expected volatility or its components. This likely reflects the relative heterogeneity of this industry, i.e., it is a broad industry that includes a wide range of firms from investment banks to the GSEs. As such, one would expect the common component to be small. In the early period, there is some evidence of falling industry volatility and rising idiosyncratic volatility. The upward trend in idiosyncratic volatility, however, suggests that individual firms may be engaging in more risky activities.

D. Explaining The Surge in Expected Volatility and Changes in the Sources

This section discusses potential causes and implications of the increase in financial sector volatility over the past three decades. Our results suggest that this increase is more than a series of specific financial shocks and is reflective of underlying structural changes in the U.S. financial sector, particularly within in the commercial bank industry, so we focus our attention there.

As is well-known, the U.S. banking industry experienced massive deregulation in the 1980s and 1990s. Berger et al. (1999) discuss the deregulation and document the impact on bank consolidation. Strahan and Sufi (2000) chronicle the steady expansion of bank powers and geographic reach, e.g., limited underwriting activity for a handful of banks in 1987; Riegle-Neal in 1994 that allowed interstate banking; legal rulings that allowed expanded insurance sales in 1995 and 1996; and Gramm-Leach-Bliley in 1999. The cumulative impact is that traditional commercial banks now offer a wider range of products and operate in broader geographic markets. In addition, the industry is increasingly dominated by the largest firms.

This evolution has three implications that are supported by our results. First, as industry lines blur and financial conglomerates increasingly operate across traditional business lines, one would expect common shocks to rise in relative importance. This is seen in the strong upward trend in the sector component for the financial sector (Figure 3 and Table 6). In contrast, the industry and idiosyncratic volatility components are essentially flat.

The second implication is related more specifically to commercial banks. If geographic deregulation allows banks to operate in broader markets, this should increase the exposure to common shocks and increase the ability to diversify internally. Morgan et al. (2004), for example, show that the integration of banking markets after Riegle-Neal in 1994 has led to smoother state-level business cycles, but also increased synchronization of state-level fluctuations. This is consistent with our finding of a significant upward trend in industry volatility for commercial banks (Figure 5 and Table 7).

A final implication of this deregulation is that idiosyncratic shocks should decline in importance as banks become more internally diversified and as common shocks emerge from the integration of previously disjoint markets. Demsetz and Strahan (1997) and Stiroh (forthcoming), for example, report that idiosyncratic risk for publicly traded bank holding companies tends to fall with size as they become more internally diversified, while Morgan and Samolyk (2005) show that risk-adjusted returns first fall and then rise with geographic diversification. We find, both for the financial sector as a whole and for commercial banks, evidence of rising idiosyncratic volatility only before 1998. For the full period, our estimates indicate no significant trend with idiosyncratic risk declining in relative importance in the last decade.

Our finding of declining idiosyncratic volatility since 1995 counters one of CLMX's main results – rising idiosyncratic risk for the market as a whole and for financial services firms in particular. CLMX offered a variety of possible explanations for their finding. For example, they noted that the breaking up of conglomerate firms produced more specialized firms with higher idiosyncratic risk. CLMX also suggested that there have been important changes in the life cycle properties of initial public offerings with firms issuing equity at a younger age. Fink et al. (2005) offer supporting evidence of this interpretation and report that the rise in idiosyncratic risk for the market reflects a selection phenomenon as young, risky firms were increasingly like to issue public equity at a young age.

The story in the financial sector, however, appears to be different. The U.S. financial sector, particularly on a value-weighted basis, is increasingly dominated by large institutions, so idiosyncratic risk trends are unlikely to reflect entry by young, risky firms.[20] Moreover, rather than producing smaller, younger firms, the ongoing consolidation within the financial sector has created larger, more diversified institutions that are likely to have less idiosyncratic risk (Demsetz and Strahan (1997), Morgan and Samolyk (2005), and Stiroh (forthcoming)). We conclude that these structural shifts in the size and scope of U.S. banks are driving the shift in the source of financial sector risk away from idiosyncratic to common, sectoral factors.

A second contributing factor behind the divergence with CLMX is simply the different sample periods. When we restrict our sample to end in 1998:m4 to roughly coincide with CLMX, we find evidence of an upward trend for the financial sector as a whole and all industries except insurance. While we are looking at only financial firms and CLMX examined the entire market, this suggests that the CLMX finding may indeed be sensitive to the time period examined. This issue is obviously an important question and gets at the heart of whether the changes in the sources of volatility are expected to be permanent.

We conclude this section with some speculation about both the nature of the shocks and the implications for the future. Extrapolating any estimated trend indefinitely, to be sure, is rarely appropriate and one needs to apply some caution when interpreting our results. As discussed, the period 1995 to 2005 was one of considerable turbulence for the U.S. financial sector and only some aspects may be relevant looking to the future. The uncertainty, churning, and shake-out associated with the massive deregulation of the U.S. banking industry, for example, is unlikely to be as important in the future as it was in the past. By contrast, the impact of broader financial firms with different risk preferences and continued financial innovation are likely to be relevant in the future. Gauging the relative importance of these forces, while critical for any assessment of the financial stability, is obviously difficult.

Moreover, our approach to distinguishing trend from specific shocks was to identify specific financial shocks (or extreme values) and control for them. This is clearly a two-edged sword. On one hand, this approach reduces the influence of specific events that might reflect special circumstance and thus are unlikely to have an impact in the future. One would not want to draw implications for the future from these one-off events. On the other hand, the presence,

[20]The ten largest banks held 25% of assets in 1995 and 46% in 2004 (Klee and Natalucci (2005)). Berger et al. (1999) describe this consolidation process in detail.

frequency, and magnitude of the shocks do say something important about the stability system as a whole. The last panels of Tables 6 and 7, for example, show that nearly 80% of the extreme values of expected volatility for the financial sector occurred after 1994. By simply eliminating these observations and ignoring the fact that they do not appear to be randomly distributed over time, our estimated time trends with controls may understate the true trend.

A final issue is how much subjective weight one should put on the most recent period. As indicated in Figure 3, all components of financial sector volatility have dropped precipitously since 2002. A benign interpretation is that the volatility from 1998 to 2002 was the exceptional period due to a series of specific shocks, while a more pessimistic view is that the calm since 2002 is the more exceptional period. As time passes and more data is accumulated, the relative probabilities of each interpretation will evolve.

IV. The Role of the Financial Sector in the Overall Market

We now turn our attention to the role of the financial sector in overall market movements. Our goal here is to highlight the growing importance of the U.S. financial sector as a driver of overall market activity and to identify any changes in the way the financial and non-financial sectors interact.

A. Methodology

We begin with the observed daily excess returns for the market for each day t, $R_{M,t}$, and our estimates of daily returns for the financial sector, $R_{F,t}$, created above. In both cases, these are excess returns calculated as the difference between the daily return of the index and the daily return on the 30-day Treasury bond. For the market, we use a value-weighted index of all stocks traded on the NYSE/AMEX/NASDAQ exchanges from CRSP.

Use of a value-weighted market returns ensures that these returns are a weighted average of returns in the financial sector and the returns in the implicit non-financial sector of the economy, $R_{N,t}$:

$$(9)\quad R_{M,t} = w_{F,m} R_{F,t} + \left(1 - w_{F,m}\right) R_{N,t} \qquad t \in m$$

where $w_{F,m}$ is the average market value share of the financial sector for all days t in month m. We use the monthly share rather than the daily share to be consistent with the subsequent variance decomposition.[21]

Using the imputed $R_{N,t}$ series, we estimate a corresponding variance decomposition of market returns as:

$$(10) \qquad \sigma^2_{M.m} = w^2_{F,m}\sigma^2_{F,m} + \left(1-w_{F,m}\right)^2\sigma^2_{N.m} + 2w_{F,m}\left(1-w_{F,m}\right)C\left(R_{F,t}, R_{N,t}\right)$$

where $\sigma^2_{*,m}$ is the variance of daily returns in month m and C(.,.) is the covariance of the arguments during that month. All estimates are annualized and expressed in percentages.

Equations (9) and (10) provide an obvious way to examine the impact of the financial sector on the mean and variance of market returns because they reflect both the size of the financial sector and activity within that sector. We refer to a weighted return in Equation (9) as the "contribution to market returns" from the sector and a weighted variance or covariance in Equation (10) as the "contribution to market variance" from the sector or covariance.

B. Empirical Results

We begin with the decomposition of excess market returns and market variance into the financial and non-financial sector contributions using the methodology summarized in Equations (9) and (10). Tables 8 and 9 report results for the three sub-periods and Figures 7, 8, 9, and 10 show the trends in the market value share of the financial sector, the excess returns in each sector, the variance of returns in each sector, and the share of each variance component, respectively. As above, all reported values are the arithmetic means of the monthly observations in each period.

The market value share of the financial sector, $w_{F,m}$, shows the steady rise in importance of the financial sector as the share increased from 7.1% for 1975-1984 to 16.4% for 1995-2005. Over the same period, the financial sector has outperformed the non-financial sector, often by a wide margin, e.g., annualized daily excess returns for the financial sector averaged 17.7% for 1995-2005 compared to 6.23% in the non-financial sector. Figure 8 shows the financial sector

[21]Obviously, we could construct the non-financial sector component explicitly from micro data as we do for the financial sector, but we are primarily interested in the relative importance of the financial sector here, so that is not necessary.

outperforming both the market and non-financials through the bursting of the NASDAQ in 2000 and the recession in 2001.

The middle panel in Table 8 shows the contribution to market returns from each sector from Equation (9), while the bottom panel shows the share of market returns attributable to each sector. Due to the relatively small size of the financial sector, the non-financial sector makes the larger contribution in all periods. Looking at the averages for all periods, the share of market returns due to the financial sector is about equal to the market value share. The prevalence of both positive and negative returns, however, can make this comparison misleading. Consequently, it is also useful to think about the share of average returns, i.e., the mean contribution of financial returns divided by mean market returns. In the most recent period since 1995, we see that the financial sector accounted for 16% of market value, but contributed about 34% of mean returns (2.72%/8.02%) due to the relatively strong performance of the sector.

Table 9 presents the volatility decomposition from Equation (10) for each period and Figure 9 plots this data over the three decades. The first thing to note is the high volatility from 1995 to 2005, again driven by the period 1998 to 2002, reflects increased volatility in both the financial and the non-financial sectors, as well as an increase in the covariance.

Perhaps more important, financial sector volatility has been steadily increasing, both in an absolute sense and relative to the non-financial sector. In the 1975-1984 period, the financial sector's annualized daily volatility averaged 139.0 compared to 164.5 for non-financials. Mean standard deviations were 11.3% vs.12.2%. During 1985-1994 the two sector volatilities were virtually the same. In the most recent period 1995-2005, volatility in the financial sector exceeded non-financial volatility by a wide margin, 429.8 vs. 301.7 for mean variances and 18.6% vs. 15.7% for mean standard deviations. This increase reflects the high volatility around the banking crisis of the early 1990s and during the capital market turmoil that occurred after 1997. More recently, volatility in both sectors has declined noticeably (Figure 9).

The second panel of Table 9 reports the contributions to the market variance estimate from Equation (10) for each period and Figure 10 shows the smoothed share of market variance from each component over time. As with the returns, the non-financial sector makes the largest direct contribution to overall market volatility due to its relatively large size. The covariance term makes the second largest contribution, and the financial sector makes relatively small contribution to aggregate volatility. There have been some shifts over time, however, with the non-financial contributing less to overall volatility, while the covariance and financial sectors are contributing more. This is apparent in the bottom panel of Table 9, which shows the contribution from each component to market variance.

As a final exercise, we also examined the correlation between the non-financial sector and the financial sector, and between the non-financial sectors and the four financial industries. In both cases, we calculated the correlation of daily returns in a month and then plotted the smoothed series. Figure 11 plots the smoothed correlation and covariance between the financial and non-financial sectors, while Figure 12 shows the smoothed correlation between the non-financial sector and each of the four financial industries.

The correlation between financials and non-financials in Figure 11 is large throughout the sample, near 0.85, but declines substantially in the early 1990s and in 2000 when financial institutions firms outperformed non-financials during the stock market decline that began in 2000. Figure 11 also shows some decline in the correlation but a rising covariance through 2003. This reflects the trends in underlying volatility of each series, which all rose through 2003 and then declined more recently.

The comparison between non-financials and the individual financial industries in Figure 12 shows a similar pattern of strong correlations over time, but a decline in the late 1990s and 2000 when relative returns diverged. There is systematic variation in the level of correlation across industries, e.g., savings institutions have the lowest correlation near 0.63 for the full period, while insurance and other financials show higher correlations near 0.78 for the full period. This is reasonable as savings institutions are typically small and more closely linked to their local geographic area, while the other financials are larger and more directly linked to the overall economy.

C. *Implications*

The above results indicate that over the past three decades the financial sector has become a larger part of the overall stock market and has made increasing contributions to the returns and volatility of the market as a whole. During this same time period, the volatility of the financial sector has also increased. At first glance, these patterns may be of some concern to policymakers who worry that shocks to the financial sector may create spillover effects that reduce overall economic activity. These patterns may also be alarming if recent changes in the financial sector have the potential to increase the amplitude of business cycles, e.g., Bernanke (1983) argues that financial sector frictions transformed a severe downturn into a protracted depression in the 1930s and Bernanke et al. (1996) review the literature on the "financial accelerator," where credit-market conditions amplify real shocks.

Despite these concerns, it is notable that over this same time period, the macro economy has not witnessed a dramatic increase in volatility. Indeed, the macro economy has become considerably more stable over this period while the financial sector has become more volatile. Consistent with this view, our results indicate the correlation between financial sector returns and the returns of the non-financial sector have declined steadily in recent years. This suggests that, if anything, the spillover effects between the financial sector and the real economy has weakened in recent years.

One possible explanation is that as capital markets have become more developed, firms looking for capital are less dependent on the economic viability of a single credit provider, e.g., a large bank, and are therefore more immune to shocks to the financial sector. An alternative explanation is that the same forces that have increased financial sector volatility have given financial sector firms additional tools to withstand shocks to the financial system and the real economy. Schuermann (2004), for example, discusses the risk management innovations that helped commercial banks to fare well during the 2001 recession. If so, this factor could explain why the series of shocks that we have seen to the financial sector have had limited impact on the overall economy. We explore these issues in more detail in the following section.

V. Financial Market Volatility and Economic Activity

We now turn to the relationship between equity market activity and the business cycle. A robust stylized fact is that volatility is higher during economic downturns (Officer (1973), Schwert (1989), Hamilton and Lin (1986), and CLMX). Most recently, CLMX moved beyond the correlation between equity market volatility and economic activity, and find that market volatility helps explain future GDP growth.

We extend the CLMX work on volatility and economic activity in three ways. First, we examine whether there are differences in explanatory power between the volatility of the financial sector and the non-financial sector. There is considerable evidence, for example, that the financial sector plays an important role in real economic activity via the allocation of credit, particularly to small firms.[22] If this is the true, volatility and disruptions in the financial sector may be useful predictors of real economic activity. Second, we examine two measures of output - GDP and industrial production (IP).[23] GDP obviously measures output for the entire economy, while IP includes only manufacturing, utilities, and mining. As a result, looking at the link with IP offers one way to examine the impact of the financial sector on real activity elsewhere in the economy. IP is a monthly series, so it matches our decomposition in frequency. To transform our estimates to a quarterly frequency to match GDP, we simply averaged the annualized monthly returns and variances in the quarter. Third, we examine the stability of the links over time to assess the question of whether the financial sector has become more important for economic activity.

Our basic empirical strategy is to estimate reduced-form regressions such as:

$$X_t = f(X_{t-1}, R_{t-1}, \sigma^2_{t-1}, t) \tag{11}$$

where X is measure of economic activity, e.g., GDP or IP growth, R is a measure of equity returns, and σ^2 is a measure of equity market volatility, and t is a time trend. These are obviously reduced-form regressions with possible endogeneity and a potentially complicated lagged structure, so we estimate them in the spirit of the earlier literature but emphasize that these should be thought of as conditional correlations. As above, we correct standard errors for heteroskedasticity and autocorrelation in the errors using Newey and West (1987) with up to four lags.

We estimate several versions of Equation (11) using IP growth and GDP as the measure of economic performance. These estimates are reported in Table 10 and Table 11, respectively. Our specifications vary based on how we measure returns (market, non-financial, and financial) and how we measure volatility (market, non-financial, and financial, or the sector, industry, and idiosyncratic components of financial sector volatility). For both the IP and GDP regressions, we begin with the broadest market measures and then we systematically introduce the disaggregated measures. All estimates include a time trend and use down-weighted data.

[22]See James and Smith (2000) for a review of the literature and Ashcraft (2005) for a recent example.
[23]Note that earlier work by Officer (1973), Schwert (1989), and Hamilton and Lin (1986) examined the link between industrial production and broad stock market volatility.

Column 1 of Tables 10 and 11 reports the most basic regression that includes only the lagged dependent variable, lagged returns for the market, and lagged volatility for the market. The results show that increases in overall market volatility are correlated with slower output growth in the next period. This is true for both IP and GDP. Moreover, the results using GDP growth as the dependent variable are very similar to the results reported by CLMX, Table IX, so our approach seems consistent.

We next decompose both market returns and market volatility into the separate non-financial and financial components. These results, reported in column 2 of Tables 10 and 11, show a slight increase in explanatory power, a negative coefficient on only non-financial volatility, and indicate that non-financial volatility is the most important determinant of economic activity. The coefficients are estimated imprecisely, however, and we cannot reject the null that the coefficients on non-financial and financial volatility are equal.[24] Our main conclusion is that we find no evidence that financial sector volatility is particularly linked with future output growth.

We next introduce an alternative measure of financial sector volatility, the expected volatility of a financial firm from Equation (7). These results are presented in column 3 of Tables 10 and 11. We find no evidence that this measure of financial sector volatility is informative. We then decompose the expected volatility into the three components identified in Equation (7) - financial sector, industry, and idiosyncratic - by including each component individually and all three jointly in columns 4, 5, 6, and 7.[25] Volatility in the non-financial sector remains the more consistent predictor of future economy activity.

In column 7 with all three components, non-financial sector volatility is significant at least at the 10% level in both regressions. The three financial sector volatility series are jointly insignificant in the IP and marginally significant in the GDP regression. Consistent with CLMX, we note that idiosyncratic risk has the largest t-statistic among the three components in both regressions and significant in the GDP regression.

Our final question is whether this link has evolved over time, so we estimate the broadest specification in column 7 for each of the three periods identified earlier. Results are reported for

[24]The weak significance individually likely reflects the high degree of multi-collinearity.

1975-1984, 1985-1994, and 1995-2005 in columns 8, 9, 10, respectively. Here we do see a strong impact of financial sector volatility, although it is quite unstable over time. In the first period 1975-1984, the three components are jointly significant in both regressions and we find a positive impact from industry volatility and a negative impact from idiosyncratic volatility. For the period 1985-1994, we strongly reject the null hypothesis that the three financial sector volatility components are jointly insignificant in both the IP and the GDP regressions. In particular, higher sector and idiosyncratic risk are conditionally correlated with conditional declines in output growth, suggesting that financial sector volatility leads declines in GDP growth. For the final period, financial sector volatility maintains modest predictive ability in both regressions.

These results are suggestive because the middle period 1985-1994, when we find the strongest negative link, was one of considerable turbulence for the U.S. financial sector. The banking crisis of the late 1980s, for example, led to rising bank failures and the credit crunch in the early 1990s was thought to contribute to the 1990-91 recession (Bernanke and Lown (1991)). We also note that non-financial sector volatility was positively correlated with future output growth in this period.

To explore this issue in more detail, we estimated similar regressions where we tested the separate effects of the volatilities of each of the financial industries. These results (not reported) largely confirm the above results. In each case the volatility of the non-financial sector continues to have a more important influence on economic activity. This closer look suggests that the negative links between financial sector volatility and economic activity during the 1985-1994 were driven primarily by shocks in the commercial banking industry.

On balance, these results do not suggest a particularly strong link between financial sector volatility and economic growth for the entire period 1975-2005. We find some suggestive evidence, however, that large disruptions to the financial system like the banking crisis of the late 1980s may be associated with declines in real economic activity for the economy as a whole and outside of the financial sector.

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[25]Note that columns 2 and 4 report the same results. This is because overall volatility of the financial sector is one component of the expected volatility of a financial firm. We report both regressions for ease of interpretation.

VI. Conclusions

We show that risk in the U.S. financial sector has evolved dramatically over the last three decades. Equity returns of the typical financial institution have become more volatile, mostly due to increased common shocks that have made returns more highly correlated across financial industries. Moreover, the nature of the risks has changed significantly as idiosyncratic risk, which rose in relative importance from 1975 to 1995, now plays a much smaller role. That is, the typical financial firm now bears more financial sector risk and less idiosyncratic risk. Finally, despite the increased risk and increased relative size of the financial sector, the connections between the financial sector and the real economy, if anything, have declined in recent years.

Our results suggest a number of important implications for investors, bank regulators, and other policymakers. From the investor's perspective, our results provide a useful extension to the recent findings of Campbell et al. (2001). Looking at the time period 1962-1997, they found for the overall stock market that idiosyncratic risk had increased, while total market risk had remained remarkably constant. We find a quite different result for stocks in the financial services industry – overall market risk has increased while idiosyncratic risk has fallen. The differences are likely related to the dramatic changes within the financial services industry over the past decade that created larger and more diversified firms and to a series of broad shocks after 1997 such as LTCM, September 2001, the NASDAQ decline, etc. that had a large common impact

These results also have important implications for bank regulators. Deregulation, consolidation, financial innovation, globalization, and changing technology have fundamentally transformed the banking industry. These changes have allowed banks to take on more risks, but they have also provided banks with expanded opportunities to control, share, and manage these risks. Our results suggest that over the past three decades, the stock market volatility of the average bank has increased while idiosyncratic risk has fallen and industry risk has increased. One implication is that publicly traded banks are now more exposed to common shocks. While the banking system has remained remarkably strong in the face of these changes, due perhaps to higher capital ratios and the increased ability of bank managers and regulators to manage these risks, the level of systemic risk appears to have increased significantly over the past three decades.

From a broader macroeconomic perspective, it is notable that while the financial industry has become a larger part of the overall economy, the links between financial sector volatility and economic activity have declined in recent years. This suggests that the economy has become increasingly insulated against shocks to the financial system.

Putting all of this together, it appears that the U.S. financial system has evolved toward a system with a smaller number of large, diversified financial institutions with a better set of tools to manage various risks, but whose risks are now more highly correlated with one another. These institutions have successfully handled a series of major financial system shocks in recent years, and the resulting impact on the real sector has been marginal. This is certainly encouraging, but the increasing importance of common shocks means that the sector remains vulnerable to unforeseen shocks with systemic implications if a number of large institutions are affected simultaneously.

Appendix

To obtain our initial sample of financial firms, we began with all CRSP firms that are included in the Standard Industrial Classification (SIC) Division H, "Finance, Insurance, and Real Estates." This includes SIC codes between 6000 and 6999 in the 1987 SIC codes. We classified this group of firms into the following industries: commercial banks, savings institutions (including thrifts, some savings banks, and credit unions), insurance firms, and other financial firms. A set of institutions were not classified and were dropped from our analysis.

Our classification system went as follows. We relied on four-digit SIC codes as the primary vehicle for classifying firms, but we also employed two other datasets to help us classify these firms as accurately and efficiently as possible. First, we merged our list of firms with Flannery and Rangan's (2004) list of regulated bank holding companies. All firms that are part of the regulated list, regardless of SIC, were classified as commercial banks. Second, we used the Bank Compustat database. Firms in this database with a DNUM=6035 or 6036 were classified as savings institutions. All other firms listed on the Bank Compustat database were classified as commercial banks.

We then relied primarily on SIC codes to classify the remaining firms by examining individual firms and the SIC names and descriptions. In some cases, we were able to classify all firms in an SIC industry into a particular industry. In other cases, it was clear that all of the firms within that SIC were non-financial firms in which case they were dropped from the sample.

There were some SIC industries where there was ambiguity and/or it appeared that different types of firms had the same SIC. These firms had to be examined in more detail. In these cases, we performed an Internet search to determine the appropriate industry for each firm. We restricted this detailed examination to firms with market value greater than $300m and dropped the smaller firms. Of the firms we examined, non-financial firms and firms for whom we were not able to make a definite categorization were dropped.

The Appendix Table summarizes the approach we used for categorizing each of the SIC industries.

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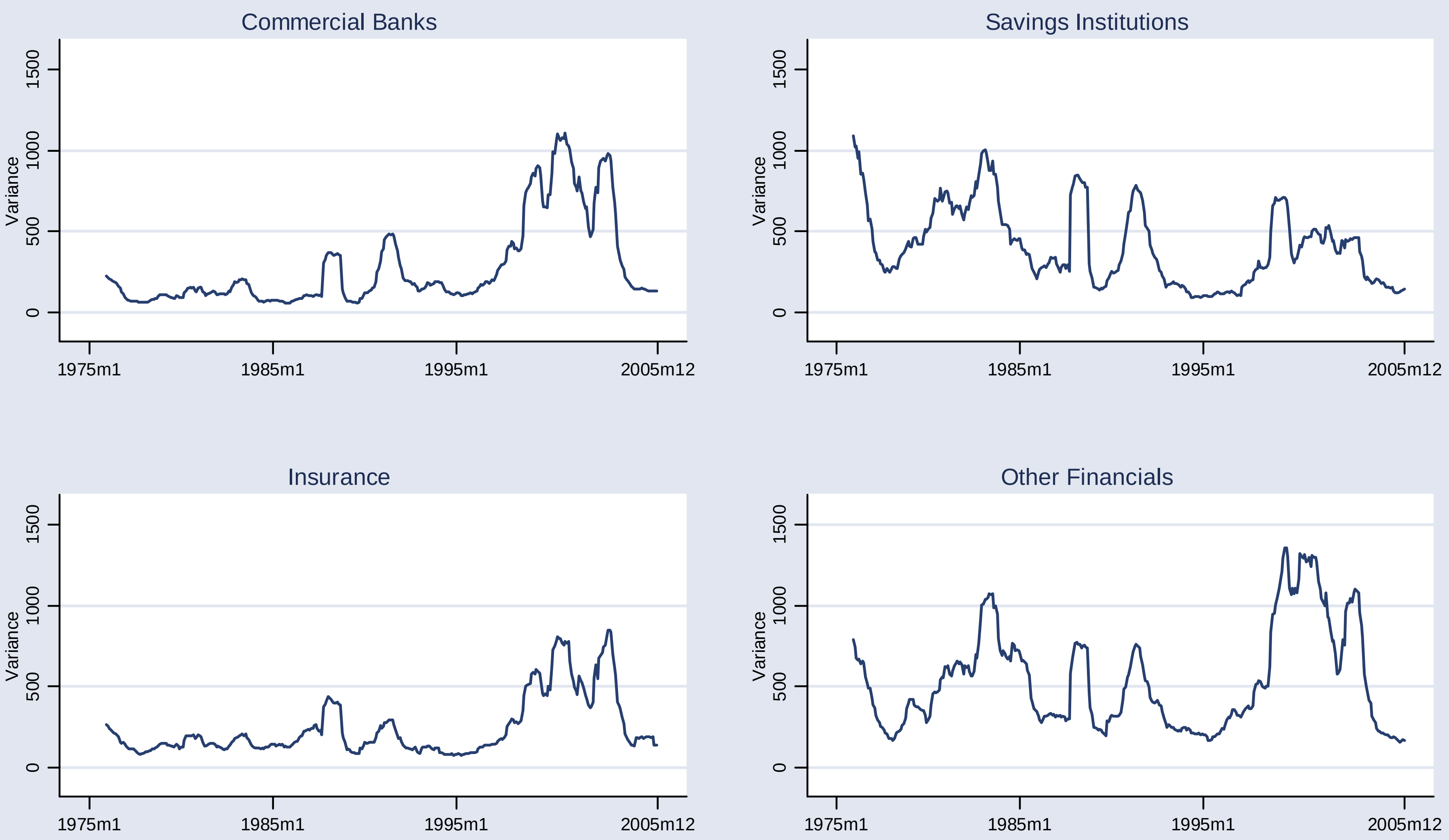
Figure 1: Mean Daily Returns for Financial Industries

1975:m1 - 2005:m12

Note: Mean of daily returns in a month for each financial industry, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 2: Variance of Daily Returns for Financial Industries

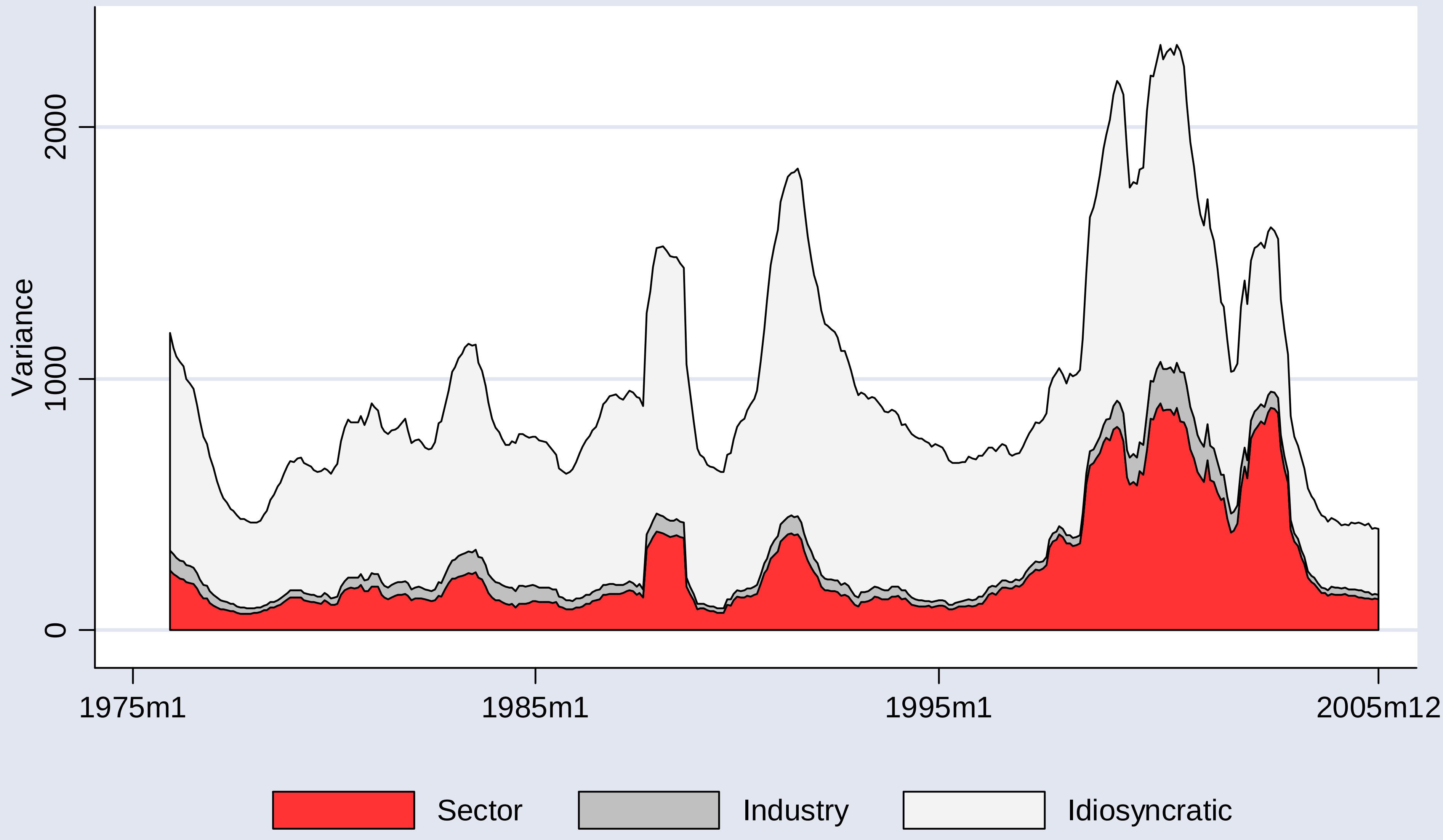
1975:m1 - 2005:m12



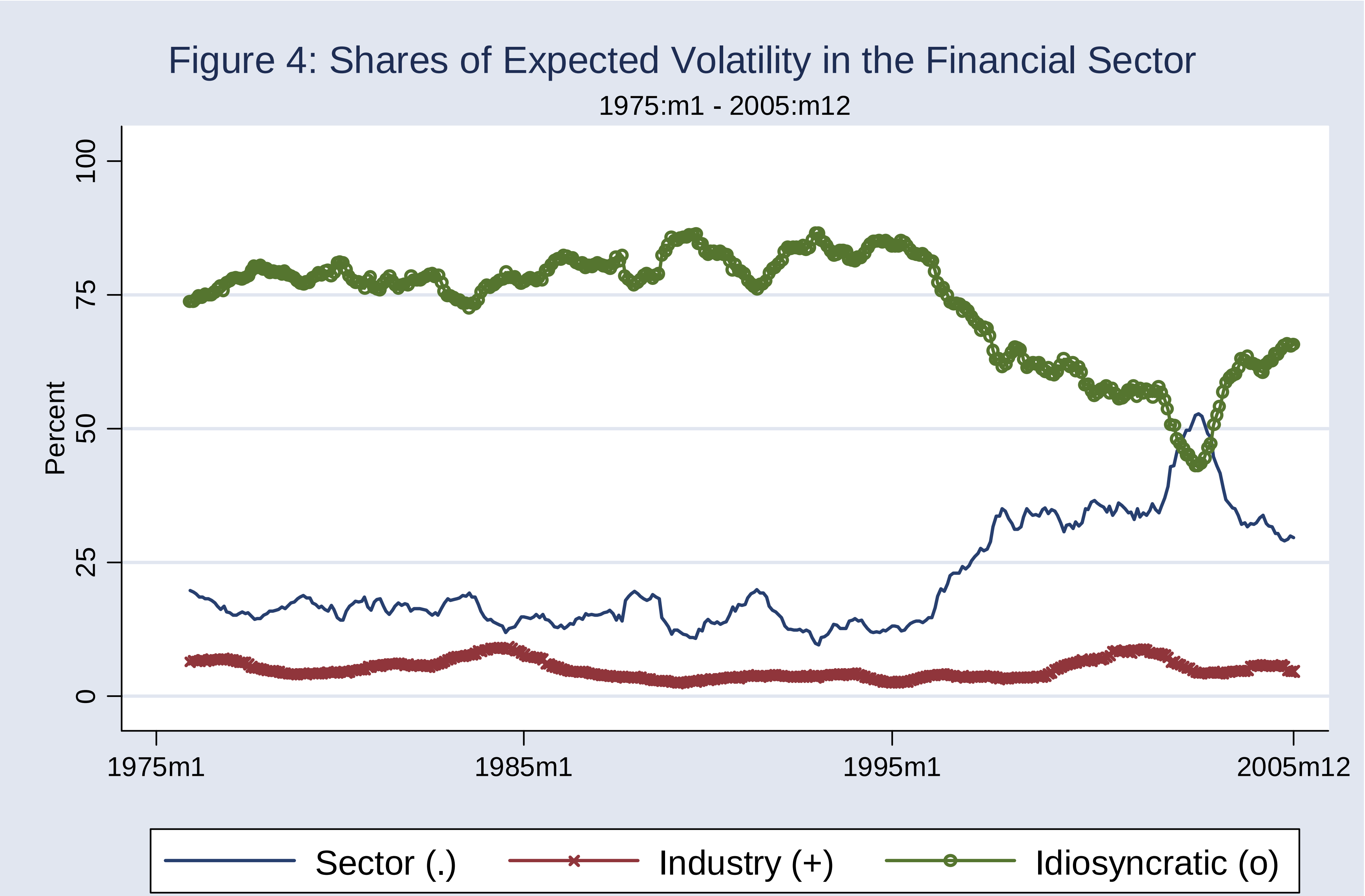
Note: Variance of daily returns in a month for each financial industry, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 3: Decomposition of Variance for the Financial Sector

1975:m1 - 2005:m12



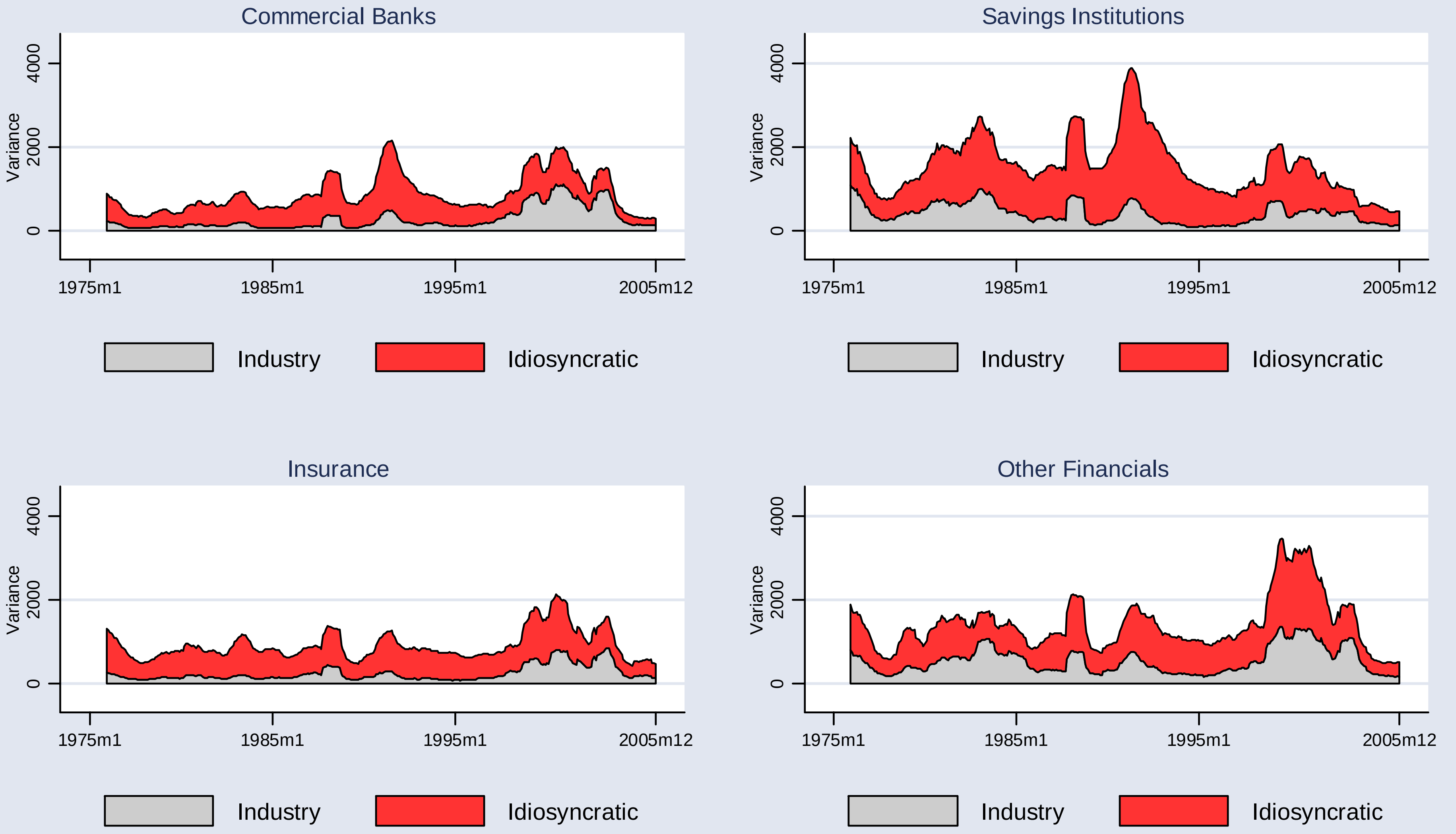
Note: Variance of daily returns in a month in the financial sector, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.



Note: Monthly observation of decomposition component as a percent of expected volatility for the financial sector.
Series are backwards 12-month moving averages of the 10/87 down-weighted data.

Figure 5: Decomposition of Variance for Financial Industries

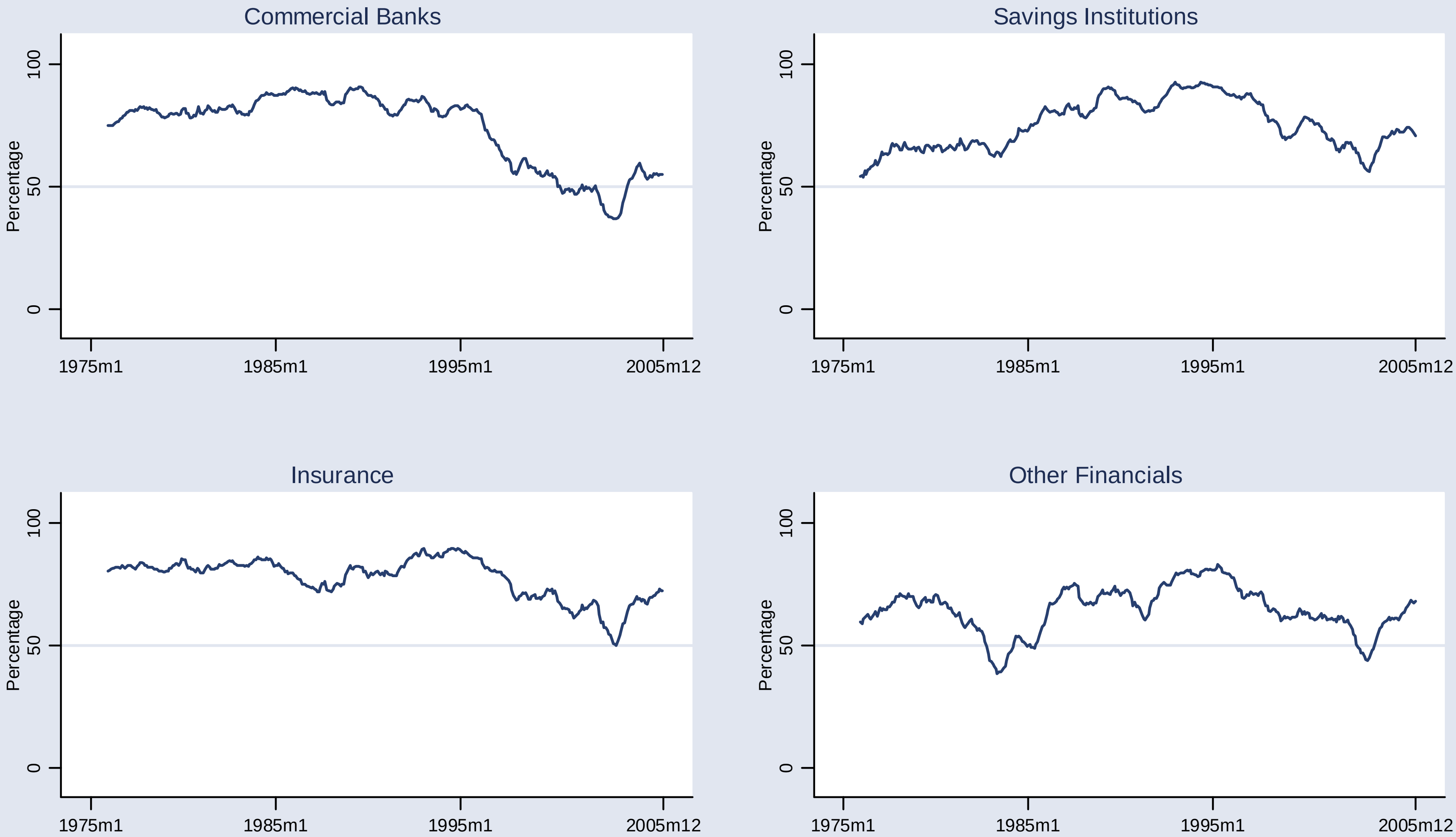
1975:m1 - 2005:m12



Note: Variance of daily returns in a month for each financial industry, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 6: Idiosyncratic Share of Expected Volatility for Financial Industries

1975:m1 - 2005:m12



Note: Monthly idiosyncratic volatility as a percent of expected volatility for each financial industry.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

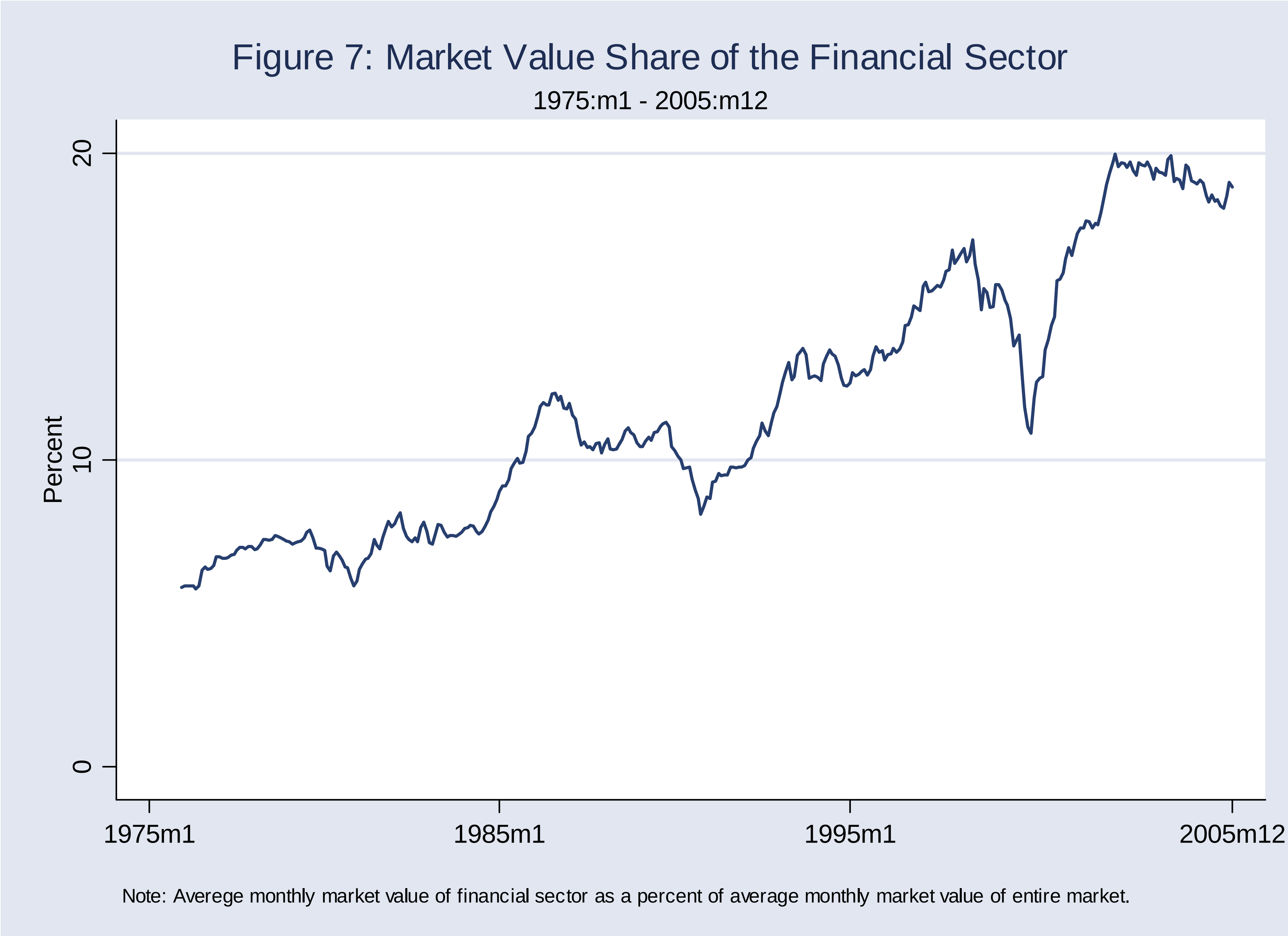
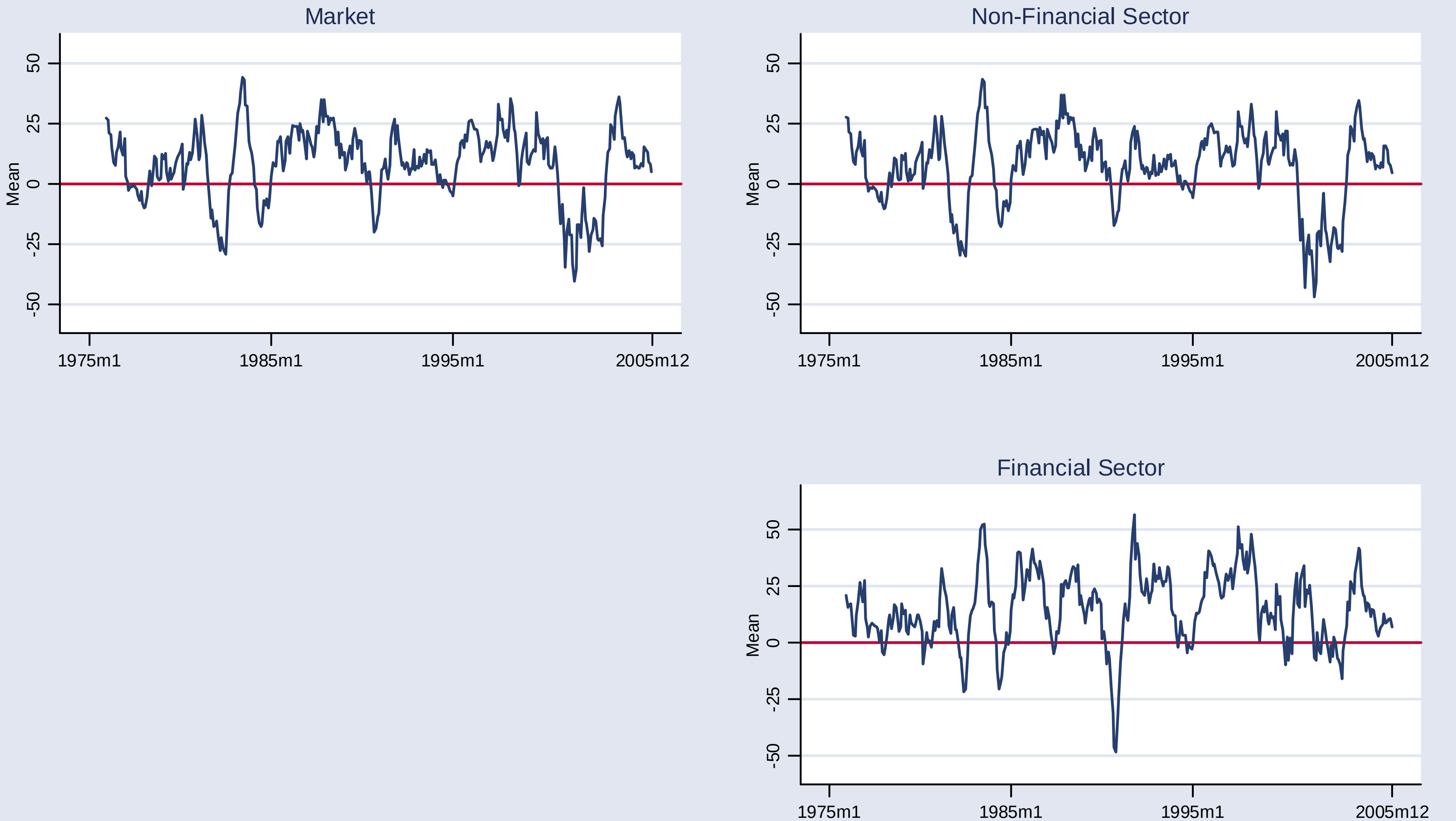


Figure 7: Market Value Share of the Financial Sector
1975:m1 - 2005:m12
Percent
20
10
0
1975m1
1985m1
1995m1
2005m12
Note: Averege monthly market value of financial sector as a percent of average monthly market value of entire market.

Figure 8: Mean Daily Returns for the Market, Non-Financial, and Financial Sector

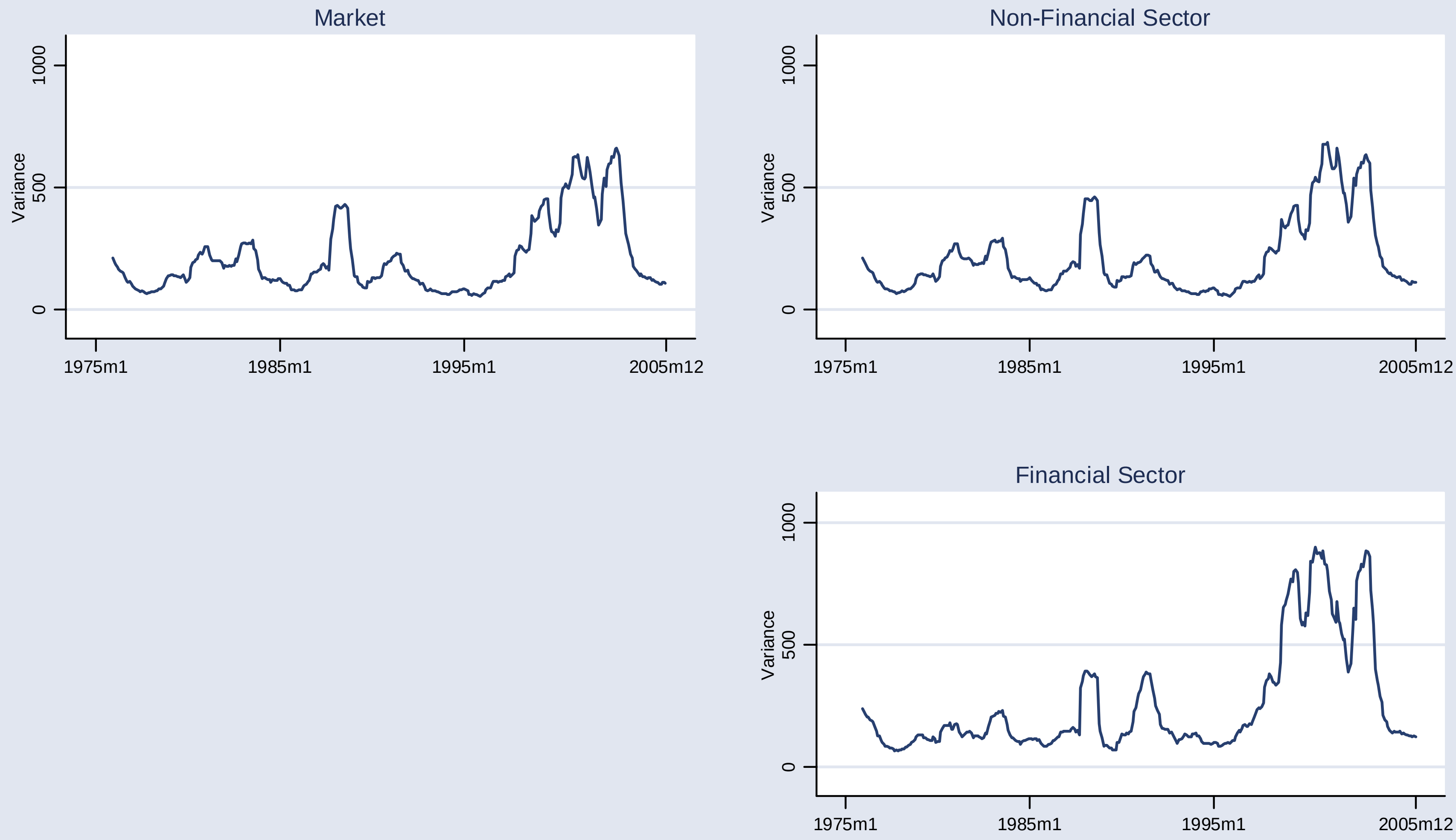
1975:m1-2005:m12



Note: Mean of daily returns in a month in each sector, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 9: Variance of Daily Returns for the Market, Non-Financial, and Financial Sectors

1975:m1-2005:m12



Note: Variance of daily returns in a month in each sector, annualized and in percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

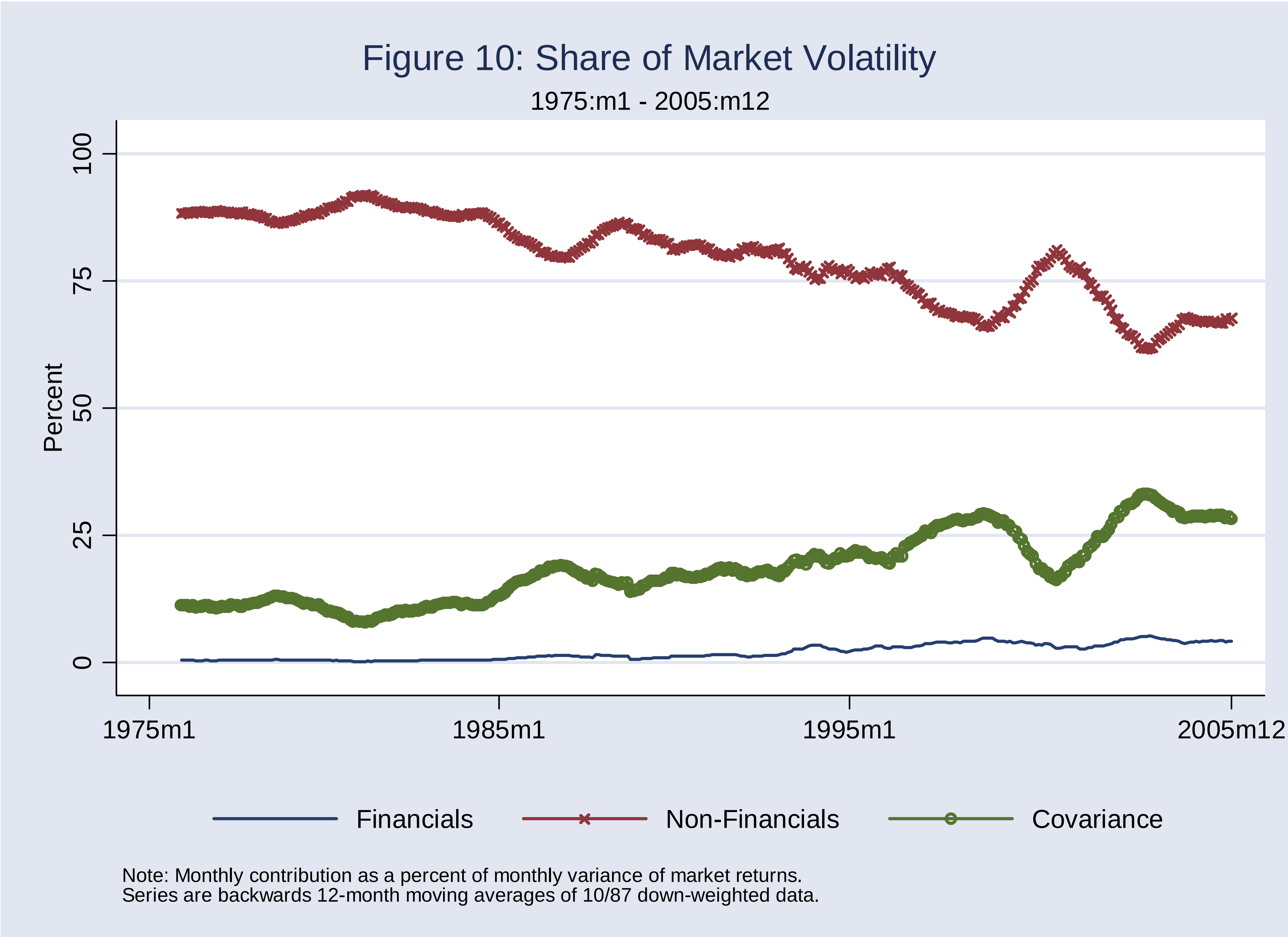
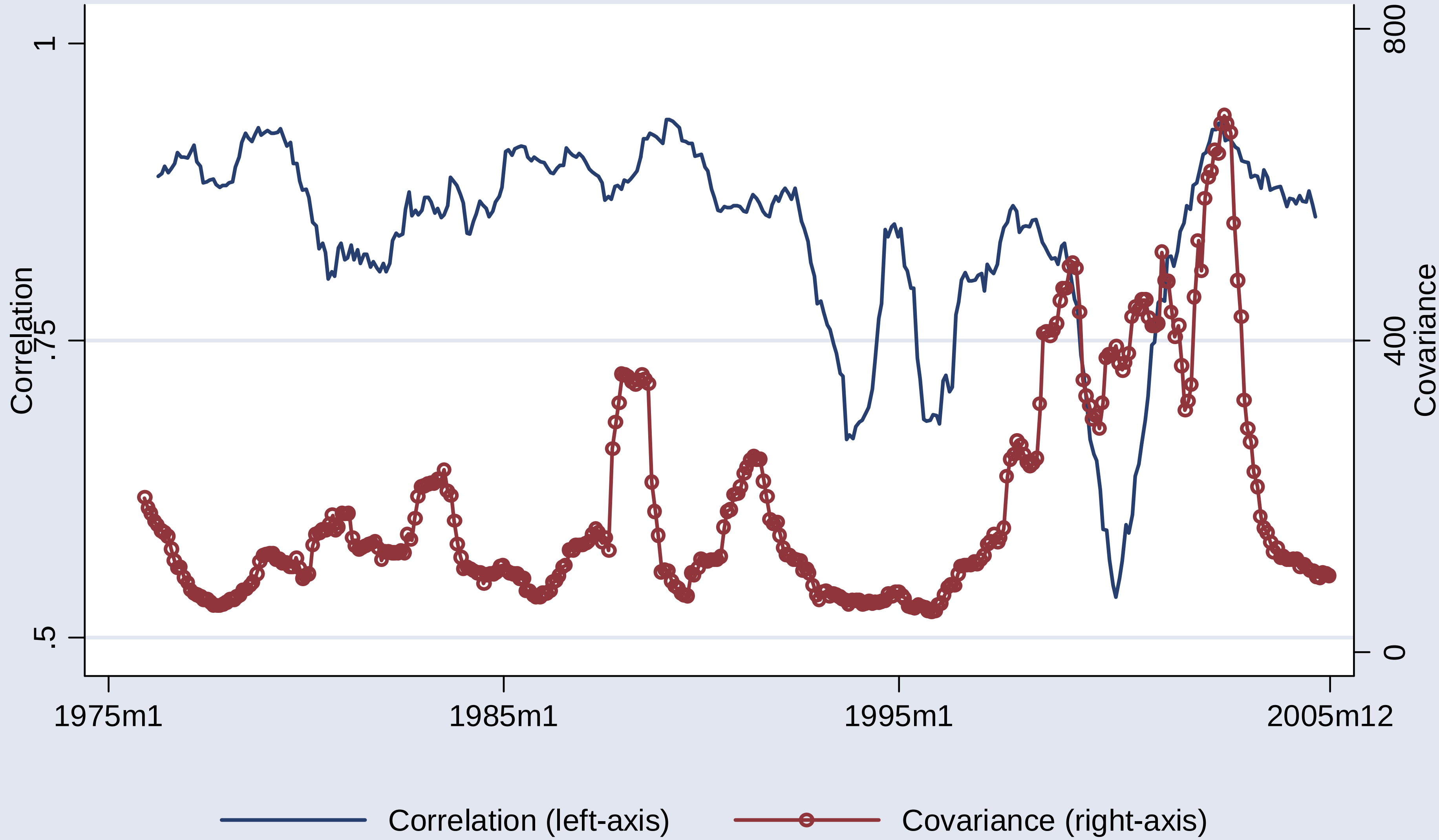


Figure 10: Share of Market Volatility
1975:m1 - 2005:m12
Percent
100
75
50
25
0
1975m1
1985m1
1995m1
2005m12
Financials
Non-Financials
Covariance
Note: Monthly contribution as a percent of monthly variance of market returns.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 11: Correlation and Covariance of Financial and Non-Financial Returns

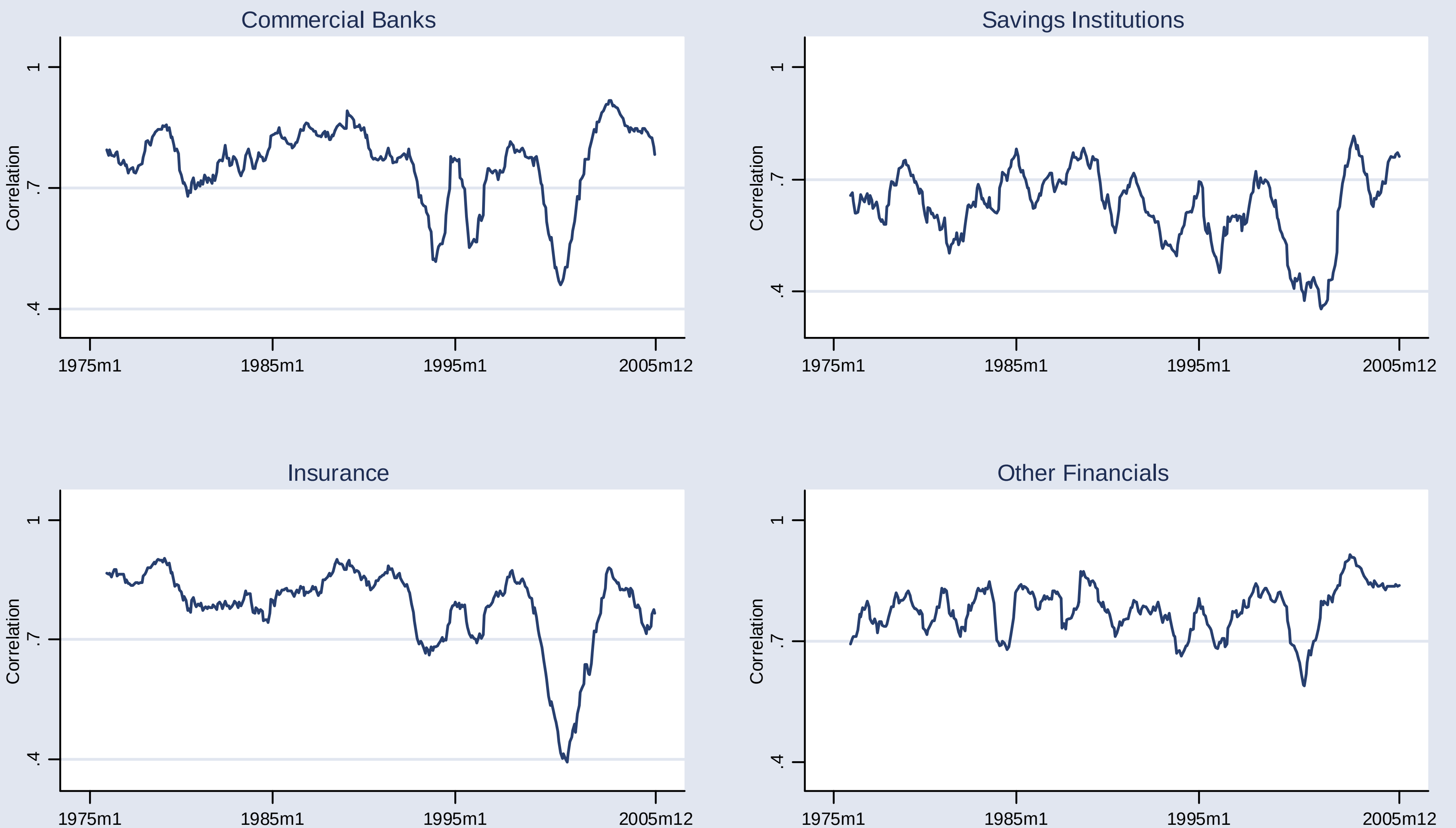
1975:m1 - 2005:m12



Note: Correlation and covariance of daily returns in a month between non-financial and financial sectors, annualized and as percentages.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Figure 12: Return Correlation of Financial Industries and Non-Financial Sector

1975:m1-2005:m12



Note: Correlation of daily returns in a month between each financial industry and non-financial sector.
Series are backwards 12-month moving averages of 10/87 down-weighted data.

Table 1: Summary Statistics

This table reports the average number of firms, the aggregate market values, and the market value shares for each of the four financial industries and the financial sector aggregate from 1975:m1 to 2005:m12. All values are means of monthly observations within the period.

Period	Commercial Banks	Savings Institutions	Insurance	Other Financials	Financial Sector
			Average Number of Firms		
1975:m1-1984:m12	213.7	31.4	140.8	37.3	423.2
1985:m1-1994:m12	533.6	143.7	190.4	104.2	972.0
1995:m1-2005:m12	449.9	227.9	202.1	146.0	1025.9
			Average Aggregate Market Value ($B)		
1975:m1-1984:m12	41.4	2.2	31.8	8.0	83.4
1985:m1-1994:m12	191.9	13.0	121.6	46.6	373.0
1995:m1-2005:m12	975.8	68.8	547.8	468.3	2,060.7
			Market Value Share (%)		
1975:m1-1984:m12	49.2	2.6	38.8	9.3	100.0
1985:m1-1994:m12	51.5	3.6	32.7	12.3	100.0
1995:m1-2005:m12	48.0	3.3	27.0	21.7	100.0

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Table 2: Financial Industry Correlation of Excess Returns over Time

This table reports the average correlation of daily excess returns (defined as the return net of the risk-free rate) across industries from 1975:m1 to 2005:m12. We first estimated the correlation of daily returns for each pair of industries within a month, and then averaged those monthly correlations for each period. Significance levels of a t-test of equal means for monthly correlations between adjacent periods are indicated by stars.

1975:m1-1984:m12

	Commercial Banks	Savings Institutions	Insurance	Other Financials
Commercial Banks	1.00			
Savings Institutions	0.62	1.00		
Insurance	0.76	0.63	1.00	
Other Financials	0.66	0.53	0.68	1.00

1985:m1-1994:m12

	Commercial Banks	Savings Institutions	Insurance	Other Financials
Commercial Banks	1.00			
Savings Institutions	0.69 ***	1.00		
Insurance	0.74	0.64	1.00	
Other Financials	0.73 ***	0.60 ***	0.71	1.00

1995:m1-2005:m12

	Commercial Banks	Savings Institutions	Insurance	Other Financials
Commercial Banks	1.00			
Savings Institutions	0.73 **	1.00		
Insurance	0.78 **	0.66	1.00	
Other Financials	0.84 ***	0.65 **	0.76 ***	1.00

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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Table 3: Decomposition of Financial Sector Volatility

This table reports mean returns and the decomposition of financial sector volatility. Returns are the mean daily excess return (defined as the return net of the risk-free rate) for the financial sector aggregate in a month, annualized and in percentages. Expected volatility is the weighted variance of daily returns in a month for all financial sector firms. Std Dev is the square root of the monthly expected volatility. Sector is the common component for all financial sector firms. Industry is the sum of the weighted industry components. Idiosyncratic is the sum of the weighted idiosyncratic components. All variables are defined in Equations (1) through (7) and reported estimates are annualized and in percentages. Share is the mean ratio of the monthly component to the monthly expected volatility multiplied by 100. All values are arithmetic means of monthly observations within the period.

		Expected Volatility		Sector		Industry		Idiosyncratic	
Period	**Returns**	**Std Dev**	**Variance**	**Variance**	**Share**	**Variance**	**Share**	**Variance**	**Share**
1975:m1-1984:m12	11.6	27.6	788.5	139.0	16.6	50.7	6.2	598.2	77.2
1985:m1-1994:m12	12.0	31.2	1043.7	190.0	14.3	38.5	3.7	815.2	82.0
1995:m1-2005:m12	17.6	32.2	1162.1	429.8	32.6	63.9	5.2	666.7	62.1
1975:m1-2005:m12	13.8	30.4	1003.4	258.6	21.5	51.4	5.0	692.5	73.4

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Table 4: Decomposition of Volatility by Financial Industry

This table reports the decomposition of volatility for each financial industry. Returns are the mean daily excess returns for the industry aggregate in a month, annualized and in percentages. Expected volatility is the weighted average of firm-level volatility in each industry. Std Dev is the square root of the monthly expected volatility. Industry is the common component for firms in that industry. Idiosyncratic is the weighted average of firm-specific volatility. All variables are defined in Equation (6) and reported values are annualized and in percentages. Share is the mean ratio of the monthly component to the monthly expected volatility multiplied by 100. All values are arithmetic means of monthly observations within the period.

		Expected Volatility		Industry		Idiosyncratic	
	Returns	Std Dev	Variance	Variance	Share	Variance	Share
Commercial Banks							
1975:m1-1984:m12	8.3	23.9	596.1	120.0	18.8	475.8	81.1
1985:m1-1994:m12	11.9	30.9	1035.9	192.5	14.8	843.9	85.1
1995:m1-2005:m12	16.8	29.6	1001.7	498.3	44.4	502.9	55.5
1975:m1-2005:m12	12.5	28.2	881.9	277.6	26.6	604.1	73.3
Savings Institutions							
1975:m1-1984:m12	16.2	40.0	1691.8	614.3	34.7	1072.9	65.1
1985:m1-1994:m12	15.0	43.1	1993.3	335.2	14.3	1655.4	85.6
1995:m1-2005:m12	20.3	31.6	1088.2	314.5	26.2	771.8	73.7
1975:m1-2005:m12	17.3	38.0	1574.9	417.9	25.1	1154.0	74.8
Insurance							
1975:m1-1984:m12	14.1	28.5	841.4	153.9	17.6	687.0	82.4
1985:m1-1994:m12	11.3	28.5	862.5	195.9	18.7	666.2	81.3
1995:m1-2005:m12	15.8	30.9	1062.7	375.7	30.3	683.1	69.6
1975:m1-2005:m12	13.8	29.4	926.8	246.1	22.4	678.9	77.5
Other Financials							
1975:m1-1984:m12	17.6	35.6	1341.1	571.9	40.5	767.7	59.4
1985:m1-1994:m12	14.0	34.7	1321.0	441.6	28.1	878.3	71.8
1995:m1-2005:m12	21.5	38.0	1634.7	649.3	36.8	984.4	63.2
1975:m1-2005:m12	17.9	36.2	1438.8	557.3	35.2	880.3	64.7

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Table 5: Unit Root Tests for Financial Sector Volatility

This table reports estimates of unit root tests for the components of monthly volatility for 1975:m1-2005:m12. Expected volatility is the weighted variance of daily returns in a month for all financial sector stocks. Sector is the common component for all financial sector firms. Industry is the sum of the weighted industry components. Idiosyncratic is the sum of the weighted idiosyncratic components. All variables are defined in Equations (3) through (7) and estimates are annualized and in percentages. T-test reports the estimate of the augmented Dickey-Fuller test statistics. P-value reports the approximate p-value based on MacKinnnon (1994). All estimates include two lags of the difference term as determined by the "general to specific" method of Campbell and Perron (1991). The 5% critical values are -2.88 for the regressions with just a constant and -3.43 for the regression with a constant and a trend.

	Expected Volatility		Sector		Industry		Idiosyncratic	
	t-test	P-value	t-test	P-value	t-test	P-value	t-test	P-value
Constant	-5.877	0.000	-6.622	0.000	-4.855	0.000	-4.873	0.000
Constant and Trend	-6.033	0.000	-7.206	0.000	-4.922	0.000	-4.868	0.000

Table 6: Tests of Time Trends for Volatility in the Financial Sector

This table reports estimates of time trend regressions for each volatility component. Expected volatility is the weighted variance of daily returns in a month for all financial sector stocks. Sector is the common component for all financial sector firms. Industry is the sum of the weighted industry components. Idiosyncratic is the sum of the weighted idiosyncratic components. All variables are defined in Equations (3) through (7) and estimates are annualized and in percentages.

Basic Trend - Full Sample includes a constant (not shown), first lag of the dependent variable (not shown), and a time trend as in Equation (8). Each regression includes 371 observations from 1975:m1 to 2005:m12. **Extreme Value Dummy Variable** also includes a single dummy variable set equal to 1 for every value above the 95th percentile; equal to 0 otherwise. **Financial Shock Dummy Variable** also includes a separate dummy variable set equal to 1 for each window surrounding the five shocks identified in the text; equal to 0 otherwise. **Basic Trend - Early Sample** restricts the regression to data before April 1998, when Citigroup/Travelers announced their merger. Each regression includes 279 observations from 1975:m1 to 1998:m4. Standard errors reported in parentheses are corrected for heteroskedasticity and autocorrelation using the method of Newey and West (1987) with up to four lags in the autocorrelation structure. **Distribution of Extreme Values** shows the number of observations above the 95th percentile in each decade.

	Dependent Variable			
	Expected Volatility	**Sector**	**Industry**	**Idiosyncratic**
		Basic Trend - Full Sample		
Time Trend	0.634*	0.694***	0.023	0.053
	(0.336)	(0.207)	(0.018)	(0.125)
R^2	0.27	0.19	0.39	0.43
		Extreme Value Dummy Variables		
Time Trend	-0.015	0.267**	-0.006	-0.085
	(0.250)	(0.120)	(0.016)	(0.107)
R^2	0.64	0.65	0.66	0.60
		Financial Shock Dummy Variable		
Time Trend	0.100	0.375**	-0.024	-0.084
	(0.364)	(0.177)	(0.022)	0.167
R^2	0.38	0.37	0.48	0.48
		Basic Trend - Early Sample		
Time Trend	0.640**	0.289**	-0.036**	0.320**
	(0.321)	(0.142)	(0.018)	(0.156)
R^2	0.13	0.02	0.22	0.37
		Distribution of Extreme Values		
1975:m1-1984:m12	0	0	2	1
1985:m1-1994:m12	4	1	2	9
1995:m1-2005:m12	14	17	14	8

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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Table 7: Tests of Time Trends for Volatility in each Financial Industry

This table reports estimates of time trend regressions for each volatility component. Expected volatility is the weighted average of firm-level volatility in each industry. Industry is the common component for firms in that industry. Idiosyncratic is the weighted average of firm-specific volatility. All variables are defined in Equation (6) and estimates are annualized variances and in percentages.

Basic Trend - Full Sample includes a constant (not shown), a lagged dependent variable (not shown), and a time trend as in Equation (8). Each regression includes 371 observations from 1975:m1-2005:m12. **Extreme Value Dummy Variable** also includes a single dummy variable set equal to 1 for every value above the 95th percentile; equal to 0 otherwise. **Financial Shock Dummy Variable** also includes a separate dummy variable set equal to 1 for each window surrounding the five shocks identified in the text; equal to 0 otherwise. **Basic Trend - Early Sample** restricts the regression to data before April 1998, when Citigroup/Travelers announced their merger. Each regression includes 279 observations from 1975:m1 to 1998:m4. Standard errors reported in parentheses are corrected for heteroskedasticity and autocorrelation using the method of Newey and West (1987) with up to four lags in the autocorrelation structure. **Distribution of Extreme Values** shows the number of observations above the 95th percentile in each decade.

	Commercial Banks			Savings Institutions			Insurance			Other Financials		
	Expected Volatility	Industry	Idiosyncratic	Expected Volatility	Industry	Idiosyncratic	Expected Volatility	Industry	Idiosyncratic	Expected Volatility	Industry	Idiosyncratic
Basic Trend - Full Sample												
Time Trend	0.659**	0.798***	-0.009	-1.099**	-0.797***	-0.342	0.413	0.555***	-0.012	0.562	0.241	0.282
	(0.330)	(0.233)	(0.115)	(0.520)	(0.272)	(0.221)	(0.281)	(0.172)	(0.126)	(0.521)	(0.302)	(0.241)
R^2	0.30	0.29	0.44	0.28	0.12	0.50	0.22	0.14	0.38	0.17	0.08	0.32
Extreme Value Dummy Variable												
Time Trend	0.286	0.470***	-0.084	-1.391**	-0.467***	-0.633**	-0.287	0.094	-0.154	-0.513	-0.234	0.068
	(0.272)	(0.124)	(0.148)	(0.474)	(0.153)	(0.287)	(0.246)	(0.122)	(0.117)	(0.526)	(0.266)	(0.232)
R^2	0.65	0.73	0.62	0.54	0.49	0.64	0.60	0.61	0.60	0.48	0.44	0.63
Financial Shock Dummy Variable												
Time Trend	0.252	0.474***	-0.056	-1.431*	-1.417***	-0.302	-0.166	0.242*	-0.220	-0.480	-0.501	-0.034
	(0.288)	(0.167)	0.142	(0.706)	(0.389)	(0.261)	(0.276)	(0.141)	(0.141)	(0.640)	(0.344)	(0.288)
R^2	0.38	0.43	0.47	0.32	0.25	0.51	0.33	0.33	0.41	0.33	0.30	0.40
Basic Trend - Early Sample												
Time Trend	1.004***	0.505***	0.452**	-0.093	-1.576***	0.596*	-0.084	0.050	-0.063	-0.106	-0.632**	0.404*
	(0.383)	(0.160)	(0.205)	(0.667)	(0.388)	(0.361)	(0.272)	(0.122)	(0.145)	(0.503)	(0.306)	(0.234)
R^2	0.24	0.06	0.44	0.21	0.13	0.43	0.08	0.02	0.26	0.06	0.03	0.16
Distribution of Extreme Values												
1975:m1-1984:m12	0	0	1	5	13	1	0	0	4	1	4	3
1985:m1-1994:m12	7	1	13	11	2	15	2	1	3	3	2	4
1995:m1-2005:m12	11	17	4	2	3	2	16	17	11	14	12	11

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Decomposition of Market Returns

This table reports the decomposition of market returns from Equation (8). Financial Share is the average market value of the financial sector in a month divided by the average market value of the market in a month, as a percentage. Returns are the mean daily excess returns (defined as returns net of the risk-free rate) in a month. Contributions to Market Returns is the share-weighted return for each sector. Share of Market Returns is the contribution to market returns divided by market returns. All return and contribution estimates are arithmetic means of the monthly observations in the period and reported at an annualized rate and in percentages.

	Financial	Returns		
Period	**Share**	**Market**	**Financials**	**Non-Financials**
1975:m1-1984:m12	7.1	7.07	11.62	6.68
1985:m1-1994:m12	10.9	8.21	12.02	7.77
1995:m1-2005:m12	16.4	8.02	17.65	6.23
			Contribution to Market Returns	
			Financials	**Non-Financials**
1975:m1-1984:m12			0.84	6.23
1985:m1-1994:m12			1.28	6.93
1995:m1-2005:m12			2.72	5.30
			Share of Market Returns	
			Financials	**Non-Financials**
1975:m1-1984:m12			9.0	91.0
1985:m1-1994:m12			10.0	90.0
1995:m1-2005:m12			15.3	84.7

Table 9: Decomposition of Market Variance

This table reports the decomposition of market volatility from Equation (9). Financial Share is the average market value of the financial sector in a month divided by the average market value of the market in a month, averaged across months and reported as a percentage. Std Dev is the standard deviation of daily excess returns in a month. Variance is the variance of daily returns in a month. Covariance and Correlation are the covariance and correlation of daily returns for the financial sector and non-financial sector in a month. Contribution to Market Variance is the weighted variance or covariance from the variance decomposition in Equation (9). Share of Market Variance is the contribution to the market variance divided by the market variance. Standard Deviation, Variance, Covariance and Contriubtions are reported at annual rates and in percentages. All values are arithmetic means of monthly observations within the period.

	Financial	Market		Financials		Non-Financials			
Period	**Share**	**Std Dev**	**Variance**	**Std Dev**	**Variance**	**Std Dev**	**Variance**	**Covariance**	**Correlation**
1975:m1-1984:m12	7.1	12.0	160.0	11.3	139.0	12.2	164.5	131.6	0.87
1985:m1-1994:m12	10.9	11.5	188.4	12.0	190.0	11.6	193.4	168.2	0.86
1995:m1-2005:m12	16.4	15.6	300.6	18.6	429.8	15.7	301.7	282.2	0.80

	Contribution to Market Variance		
	Financials	**Non-Financials**	**Covariance**
1975:m1-1984:m12	0.7	142.0	17.3
1985:m1-1994:m12	2.1	154.6	31.7
1995:m1-2005:m12	11.5	211.1	78.0

	Share of Market Variance		
	Financials	**Non-Financials**	**Covariance**
1975:m1-1984:m12	0.5	88.5	11.0
1985:m1-1994:m12	1.5	80.9	17.6
1995:m1-2005:m12	3.9	70.3	25.8

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Table 10: IP Growth and the Decomposition of Equity Returns and Volatility

$IP_t = f(IP_{t-1}, R_{t-1}, V_{t-1}, t)$

This table reports estimate of a regression of growth in industrial production (IP) on lagged growth in IP, equity market returns, equity market volatility, and a time trend for 1975:m1 to 2005:m12. R_M is market returns, V_M is market volatility, R_F is financial sector returns, V_F is financial sector volatility, R_N is non-financial sector returns, V_N is non-financial sector volatility. Exp Vol is expected volatility of a financial firm (defined in Equation (7)), which consistst of financial sector volatility V_F, industry volatility V_{IND}, and idiosyncratic volatility V_{IDIO}. H_0: reports the p-value associated with the null hypothesis that the coefficients on returns or on volatility are the same for the financial and non-financial sectors. Jt. Sig. reports the p-value associated with the null hypothesis that three components of Exp Vol are jointly zero. Standard errors reported in parentheses are corrected for heteroskedasticity and autocorrelation using the method of Newey and West (1987) with up to four lags in the autocorrelation structure.

								Split Sample Regressions		
								1975-1984	1985-1994	1995-2004
	1	2	3	4	5	6	7	8	9	10
IP_{t-1}	0.304***	0.298***	0.299***	0.298***	0.300***	0.296***	0.290***	0.342***	0.011	-0.038
	(0.075)	(0.075)	(0.074)	(0.075)	(0.075)	(0.074)	(0.074)	(0.092)	(0.087)	-0.11
$R_{M,t-1}$	0.040									
	(0.064)									
$V_{M,t-1}$	-0.038***									
	(0.013)									
$R_{F,t-1}$		-0.077	-0.074	-0.077	-0.072	-0.073	-0.074	-0.351**	-0.139	0.097
		(0.077)	(0.076)	(0.077)	(0.077)	(0.076)	(0.076)	(0.169)	(0.141)	(0.089)
$R_{N,t-1}$		0.103	0.115	0.103	0.112	0.121	0.114	0.233	0.241	0.026
		(0.09)	(0.09)	(0.09)	(0.09)	(0.089)	(0.09)	(0.189)	(0.233)	(0.095)
$V_{F,t-1}$		0.015								
		(0.018)								
$V_{N,t-1}$		-0.054**	-0.025	-0.054*	-0.031*	-0.023	-0.051*	-0.157	0.171***	-0.049
		(0.029)	(0.027)	(0.029)	(0.018)	(0.019)	(0.031)	(0.172)	(0.045)	(0.035)
Exp Vol			-0.005							
			-0.01							
$V_{F,t-1}$				0.015			0.028	-0.066	-0.082*	0.015
				(0.018)			(0.017)	(0.198)	(0.046)	(0.022)
$V_{IND,t-1}$					-0.036		0.011	0.896**	0.070	-0.271*
					(0.092)		(0.101)	(0.347)	(0.205)	(0.142)
$V_{IDIO,t-1}$						-0.014	-0.021	-0.080	-0.065**	0.033
						(0.016)	(0.016)	(0.071)	(0.027)	(0.028)
H_0: $R_{F,t-1}=R_{N,t-1}$		0.25	0.22	0.25	0.23	0.20	0.22	0.09	0.30	0.67
H_0: $V_{F,t-1}=V_{N,t-1}$										
Jt. Sig.							0.30	0.08	0.00	0.19
R^2	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.32	0.20	0.13
No. Obs.	372	372	372	372	372	372	372	120	120	132

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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Table 11: GDP Growth and the Decomposition of Equity Returns and Volatility

This table reports estimate of a regression of growth in GDP on lagged growth in GDP, equity market returns, equity market volatility, and a time trend for 1975:Q1 to 2005:Q4. R_M is market returns, V_M is market volatility, R_F is financial sector returns, V_F is financial sector volatility, R_N is non-financial sector returns, V_N is non-financial sector volatility. Exp+A19 Vol is expected volatility of a financial firm (defined in Equation (7)), which consistst of financial sector volatility V_F, industry volatility V_{IND}, and idiosyncratic volatility V_{IDIO}. H_0: reports the p-value associated with the null hypothesis that the coefficients on returns or on volatility are the same for the financial and non-financial sectors. Jt. Sig. reports the p-value associated with the null hypothesis that three components of Exp Vol are jointly zero. Standard errors reported in parentheses are corrected for heteroskedasticity and autocorrelation using the method of Newey and West (1987) with up to four lags in the autocorrelation structure.

								Split Sample Regressions		
								1975-1984	1985-1994	1995-2004
	1	2	3	4	5	6	7	8	9	10
GDP_{t-1}	0.226*	0.218	0.219	0.218	0.222*	0.211	0.195	0.077	-0.024	-0.038
	(0.129)	(0.138)	(0.135)	(0.138)	(0.134)	(0.135)	(0.131)	(0.150)	(0.137)	(0.178)
$R_{M,t-1}$	1.121									
	(0.991)									
$V_{M,t-1}$	-0.273**									
	(0.119)									
$R_{F,t-1}$		-0.036	-0.183	-0.036	-0.397	-0.137	-0.230	-2.904	-0.355	-1.541
		(1.177)	(1.231)	(1.177)	(1.216)	(1.232)	(1.124)	(3.055)	(1.555)	(1.664)
$R_{N,t-1}$		0.974	1.347	0.974	1.342	1.461	1.397	6.258	1.497	0.462
		(1.378)	(1.309)	(1.378)	(1.323)	(1.290)	(1.410)	(4.316)	(1.424)	(1.240)
$V_{F,t-1}$		0.257								
		(0.223)								
$V_{N,t-1}$		-0.581*	-0.216	-0.581*	-0.424**	-0.157	-0.725**	-2.524	1.015***	-0.725**
		(0.313)	(0.236)	(0.313)	(0.198)	(0.152)	(0.359)	(1.619)	(0.289)	(0.305)
Exp Vol			-0.026							
			(0.090)							
$V_{F,t-1}$				0.257			0.404	1.703	-1.399**	0.270
				(0.223)			(0.291)	(2.495)	(0.687)	(0.296)
$V_{IND,t-1}$					0.925		1.777	15.821**	6.246*	-1.077*
					(0.907)		(1.175)	(5.822)	(3.358)	(0.638)
$V_{IDIO,t-1}$						-0.114	-0.300**	-2.01***	-0.465**	0.221
						(0.112)	(0.138)	(0.716)	(0.202)	(0.166)
H_0: $R_{F,t-1}=R_{N,t-1}$		0.71	0.57	0.71	0.52	0.55	0.55	0.18	0.56	0.39
H_0: $V_{F,t-1}=V_{N,t-1}$		0.19								
Jt. Sig.							0.10	0.01	0.00	0.10
R^2	0.11	0.12	0.11	0.12	0.12	0.12	0.15	0.36	0.40	0.29
No. Obs.	124	124	124	124	124	124	124	40	40	44

***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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Appendix Table: Classification of SIC Industries into Financial Industries

SIC	Dropped	Examined Individually	Final Classification	SIC	Dropped	Examined Individually	Final Classification
6000		x		6162			Other Financial
6010			Commercial Bank	6163			Other Financial
6011			Commercial Bank	6170		x	
6020		x		6172	x		
6021		x		6190			Other Financial
6022			Commercial Bank	6199			Other Financial
6023			Commercial Bank	6210			Other Financial
6025		x		6211			Other Financial
6026	x			6220	x		
6027	x			6221	x		
6028			Savings Institution	6231	x		
6030			Savings Institution	6280		x	
6032			Savings Institution	6281	x		
6033			Savings Institution	6282			Other Financial
6034			Savings Institution	6289	x		
6035			Savings Institution	6300-6499			Insurance
6036			Savings Institution	6510	x		
6044		x		6519	x		
6050		x		6520	x		
6052		x		6522	x		
6059		x		6530	x		
6060			Savings Institution	6531	x		
6062			Savings Institution	6532	x		
6081	x			6540	x		
6082	x			6610		x	
6090		x		6710		x	
6091	x			6711		x	
6099		x		6712		x	
6111	x			6719		x	
6112	x			6720		x	
6120			Savings Institution	6722		x	
6122			Savings Institution	6723		x	
6123			Savings Institution	6726	x		
6124			Savings Institution	6727	x		
6125			Savings Institution	6730	x		
6140			Other Financial	6732	x		
6141			Other Financial	6733	x		
6144			Other Financial	6740		x	
6145			Other Financial	6770	x		
6146		x		6779		x	
6149	x			6790		x	
6150			Other Financial	6792	x		
6153			Other Financial	6793	x		
6159		x		6794	x		
6160			Other Financial	6798	x		
				6799	x		