Systemic Risk between Insurers and Banks: A Generalized Event Study (GES) Approach

Richard J. Butler
Brigham Young University and Southwestern University of Finance and Economics, China
richard_butler@byu.edu

Craig Merrill
Brigham Young University
craig_merrill@byu.edu

Gene Lai
University of North Carolina, Charlotte
glai@uncc.edu

Abstract: This study expands the event-study framework to develop a generalized event study framework (GES) to examine the interconnections between banks and insurers in a causal estimation model. This GES framework adds autoregressive process responses to the standard event framework and then measures the impact of large standard deviation (SD) shocks on the resulting specifications' intercept ("network shifts"), autoregressive response ("process dynamics"), and market returns ("systematic risk shifts"). Our methodology focuses on the extent to which major activity for each firm affects stability in other parts of the network. The model is estimated on 2006-2010 market data for the 25 largest publicly-traded insurers and 25 largest publicly-traded banks. The evidence shows a propensity for insurers' and banks' shocks to move in the same direction on average. We also find stability in the network overall with respect to intercept shifts. Bank return-shocks have a larger impact on the generation of potential network instability than insurer return-shocks when examining shifts in the autoregressive process. The systematic risk associated with the overall market return is also quite significant. In addition, the evidence indicates that not all network boats are lifted or sink collectively. The evidence also shows systemic risk in the presence of day fixed effects (common-date risk) is much more important during our sample periods than systemic risk without controls for day fixed effects. In addition, systemic risk accounts for about two thirds of the responses to shocks while common-date risk account for only about a third of the responses. In other words, common-date risk is important to shocks in addition to systemic risk and systematic risk. Finally, variations in firm value profoundly affects the process dynamics--that is, the larger firms are more likely to be market changers. This evidence provides indirect support for "too big to fail."

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I. Introduction

This study expands the event-study framework to develop a generalized event study framework (GES) to examine the interconnections between banks and insurers in a causal estimation model. Our study is highly related to studies of systemic risk. Perceptions as what should be counted as systemic risk are many and varied, often tied to specific theoretical constructs in finance. As one example, Billio Getmansky, Lo, and Pelizzon (2012) define systemic risk as any set of circumstances that threatens the stability of or public confidence in the financial system. We delete "of or public confidence" from their definition because our empirical model does not measure public confidence. In other words, our definition of systemic risk include circumstances that threatens the quantitative stability of the financial system, and in our empirical work below, specifically includes risk between insurers and banks.

Historically, insurance leverage, liquidity, and losses were analyzed to determine insurer risk. In recent years, the emphasis has shifted to multi-factored "linkages" as predictors of risk, including the financial crisis. In that historical tradition, we identify risk linkages in a casual estimation model just as Billio et al. (2012), in an excellent review of the emerging literature, identified three measures in the finance literature to estimate the linkages among financial institutions. The three linkages include: CoVar, systemic expected shortfall (SES), and distress insurance premium (DIP). Adrian and Brunnermeier (2010) propose CoVar, a measure of value-at-risk conditional on the financial distress of other institutions. SES (Acharya, Pedersen, Philippon, and Richarson (2011)) is an institution's "propensity to be undercapitalized when the system as a whole in undercapitalized." Huang, Zhou, and Zhu (2011) propose DIP as the third linkage measure: the insurance premium required to cover distressed losses in the banking system.

Billio et al. (2012) argue that the three measures do not predict financial stress well in recent years of rapid financial innovation, nor do they reliably predict financial distress in the presence of newly connected parts of financial system. New linkages change the financial systemic dynamics when financial institutions are simultaneously distressed. Though these measures may serve as useful early warning indicators, correlations among financial institutions during non-crisis periods may not be useful to predict a build-up of systemic risk in times of financial crisis.

Billio et al. (2012) use principal components analysis and pairwise Granger-causality tests to estimate the degree of linkages. It is important to note that they measure correlations directly and unconditionally. The advantage of unconditional measures is that they can detect new connections, even when the financial system is not suffering simultaneous losses. The disadvantage of unconditional measures is that only correlations can be measured, and underlying causal relationships may go undetected. Hence, they also perform Granger-casualty tests.

Several papers examine systemic risk in the insurance industry. They conclude that insurers and reinsurers do not pose systemic risk because primary insurers can spread their risk through several insurers or formal reinsurance contracts (Swiss Re, 2003, the Group of Thirty, 2006, Bell and Keller, 2009). American International Group (AIG) and other insurance companies were faulted for starting the financial crisis. The conclusions of Harrington (2009), Grace (2010), and Cummins and Weiss (2014) dispute this claim. Rather, they suggest that it was financial products such as credit default swaps (CDS) of AIG, not their insurance products, that were systemically important to the financial crisis. Mutenga and Parsons (2011) conclude that systemic risk is lower in the insurance industry than that of banking industry in European markets. Our model provides additional insight about the role of the insurance industry on systemic risk.

Like Chen et. al. (2014), our study focuses on the linkages between the banking industry and the insurance industry. Our alternative GES model of network linkages includes all types of events that result in large jumps in the market returns of individual financial firms. Instead of examining the impact of specific regulatory or weather-related calendar events on stock returns, as is usual in standard event studies, we use large standard deviation (SD) shocks in the returns of the individual banks and insurers as a proxy for unusual events. In addition, we include an autoregressive process in the event-studies' returns regression. The impact of SD shocks on daily returns is estimated both as shifts in the intercept and as a rescaling of the autoregressive process. These adjustments have impact on system stability. We label these later autoregressive adjustments due to major shocks as the 'process-dynamics' of the returns.

We estimate the model on 2006-2010 market data for the 25 largest publicly-traded insurers and 25 largest publicly-traded banks (and then, 2011-2016 as a robustness check). Our main findings are summarized below. First, there appears to be a propensity for insurers' and banks' shocks to move in the same direction on average. We interpret this as a reflection of banks and insurers being part of the same 'network' of financial intermediaries. In addition, the evidence indicate that (given an expectation of) positive shocks, not all network boats are lifted collectively, nor do (a given expectation of) negative shocks, sink them collectively. Second, we find that in general, the random event shocks of January, April, July and October are larger and statistically significant than other months. These results are consistent with the argument of Ball and Kothari (1991) who state that "earnings announcements resolve some uncertainty about future cash flows, but the concurrent price reactions increase the variability and covariability of securities' return during the announcements." Third, bank shocks are relatively destabilizing compared to insurer shocks while we find stability in the network overall. Bank return-shocks have a larger impact on network instability than insurer return-shocks, and the differential impact of banks over insurers increases when restricting the estimates to systemic risk only, that is, after controlling for systematic risk and common-date risk. Common-date risk is related to day fixed effects and represents network simultaneous exposure and response which are not fully anticipated in the market returns. Fourth, we also find systemic risk in the presence of day fixed effects (common-date risk) is much more important during our sample periods (2006-2010, and also for 2011-2016) than systemic risk without controls for day fixed effects. In addition, systemic risk accounts for about two thirds of the responses to shocks while common-date risk account for only about a third of the responses. In other words, common-date risk is important to shocks in addition to systemic risk and systematic risk. Fifth, changes in firm value is consistently affects the process dynamics--that is, the larger firms are more likely to be market changers. This evidence provides indirect support for "too big to fail."

Our study differs from the literature in several aspects. First, this study expands the event-study framework to develop a generalized event study framework (GES) to examine the interconnections between banks and insurers in a causal estimation framework. Our framework can be viewed as a rough analogue to error correction models (for co-integrated time series), but our study focuses on interconnected financial activity on network stability with autoregressive processes instead of cointegrated regressors moving together over time. Second, while Billio et al. (2012) examine the impact of returns of one financial institution (e.g., banking) on other financial institutions (e.g., insurance companies), our paper investigates the impact of shocks (volatility) of returns of individual banks/insurer on other banks/insurers. The impact of an individual firm on the systemic risk on related financial entities is an interesting and important issue. Finally, we also provide evidence about the speed at which firms return to their network stability after major shocks.

II. General Empirical Model

To the standard event study model, we add an autoregressive process for the returns (which if it is sufficiently small excludes arbitrage opportunities for most investors), which we denote generically as $\sum_{j=1}^{J} \theta_j r_{i,t-j}$, with J indicating the order of the autoregressive process in the returns (the autoregressive order as well as coefficient variables were determined empirically):

$$r_{i,t} = \gamma_{0,i} + \gamma_{1,i} R_t + \sum_{j=1}^{J} \theta_j r_{i,t-j} + \sum_t \sum_k \tau_{k \neq i} Event_k(k,t) + \mu_{i,t} \quad (1)$$

where $r_{i,t}$ is rate of return of a stock i at time t; R_t is the market rate at time *t*; $\sum_{j=1}^{J} \theta_j r_{i,t-j}$, is autoregressive process in daily returns with J indicating the order of the autoregressive process in the returns; and $\sum_t \sum_k \tau_{k \neq i} Event_k(k,t)$ are the major events. We employ "large" standard deviation shocks (big jumps) in returns as the relevant "events" that affect the returns of firm *i* at day *t*. As indicated in Equation 1, all firms have their own intercept values in the returns equation (the $\gamma_{0,i}$ vector of coefficients), and their own market betas (the $\gamma_{1,i}$ vector of coefficients). All firms are assumed to be subject to the same unspecified, empirically determined, autoregressive process in their daily returns (the $\sum_{j=1}^{J} \theta_j r_{i,t-j}$ terms in Equation 1).

For our shocks to the system, we generated two standard deviation jumps in the firms specific returns for each firm for each day (based on the last 20 trading days, roughly the monthly number of trades), and then created the treatment "event" variables as follows:

SD2— there was a two standard deviation jump, or shock, in market returns relative to the last 4 weeks (20 trading days), with the variable = 0 if there was less than a 2 SD jump, and equaled to the standard deviation shock if there was a more than 2 standard deviation shock (say, -3.1for a large negative decline of 3.1 standard deviations, 2.7 when there is a positive 2.7 standard deviation jump, and 0 if the standard deviation jump is less than 2 in absolute value).[1]

SD3—similar for 3-standard deviation jumps.

SD4—similar for 4-standard deviation jumps (hence, any SD4 jump is also included in SD3 and SD2 shocks, but not necessarily vice versa).

Using standard deviations as the shock "events" provides a firm-specific "normalization" of the treatment inasmuch as each firm has an equal likelihood of generating a SD2, SD3, or SD4 event in any specified period of time. That is, the implicit threshold for an "event shock" is relative to each firm rather than an absolute threshold for all firms. The GES approach indicates that the market reveals information on each firm's outlier-returns to every other firm in the network. All firms have a sense of what is 'unusual' to each firm and what is not. This approach also allows all firms within the network an equal chance within a month/quarter/year to have an event (SDs) shock. Hence, this puts all firms on the same relative basis for impacting the rest of the network, and a standard derivation shock-event is akin to a quasi-random event. Absolute thresholds would predictably generate many more events among some firms than others.

Network Shifts vs. Process-dynamics

Equation 1 is a firm fixed-effects model, with an assumed common overall autoregressive process for returns within this financial network of insurers and banks (the firm fixed effects specification is one of our identifying conditions for the generalized event), along with an exclusion restriction to be discussed below. We refine the general 'event' specification given next to the far right hand side of equation 1, by allowing SD shocks to affect network stability in one

[1] For robustness, we use other variable lengths for the standard deviation model (10 days or 30 days). The results are qualitatively similar.

of three ways--either via overall network one-time adjustment to daily returns ($\sum_k \alpha_{k\neq i} SD_k$), or as changes in the autoregressive process-dynamics ($\sum_k \pi_{k\neq i} SD_k(\sum_{j=1}^{J} \theta_j r_{i,t-j})$) or as a vector of shifts in systematic risk (($R_t * SD_{k,t-1}$) $\gamma_{2,i}$), – as given in equation 2 below:

$$r_{i,t} = \gamma_{0,i} + \gamma_{1,i} R_t + \sum_k \alpha_{k\neq i} SD_{k,t-1} + + \sum_{j=1}^{J} \theta_j r_{i,t-j} + \sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j}) +$$

$$(R_t * SD_{k,t-1})\, \gamma_{2,i} + \mu_{i,t} \qquad (2$$

Equation 2 shows the intercept shifts, standard deviation shocks ($\sum_k \alpha_{k\neq i} SD_{k,t-1}$), the autoregressive shifts ($\sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})$, abd changes in the systematic risk ($R_t * SD_{k,t-1}$) $\gamma_{2,i}$ represent systemic risk in our causal framework, after controlling for systematic risk (the $\gamma_{1,i}$ vector of coefficients in equation 2), with and without controls for common date risk (the day fixed effects).

Network Shifts

Network shifts are measured as the shifts in the *i*th network firm's returns given by a shock from one of the *other k*th firm's SD shocks (standard deviation shock, SD_k). As each firm has an equal chance, on any given day of a given-sized SD shock, we treat these events as random relative to the network (and hence, exogenous). Firm *i* finds out about its shock as it occurs, while the other networked firms (all $j, j \neq i$) find out about the shock on the next business day (equivalently, overnight), with the network reaction recorded as the shift in returns for all $j \neq i$. Firm *i* is not surprised (as the other *j* firms are) by its own shock that occurred yesterday. This is our exclusion restriction: that a SD shock yesterday by a firm potentially shifts returns for all *others* (excluding yesterday's shocked firm) today.

These *network shift responses* to shocks are measured as the $\alpha_{k \neq i}$ coefficients in the following expression: $\sum_k \alpha_{k \neq i} SD_k$ ($k \neq i$ in the subscript is due to the exclusion restriction). This shift in returns due to a specific shock (given by the α-coefficient of the SD variable), we denote as a network shift—a one-time shift up or down due to a SD shock elsewhere in the network. Hence, the $\alpha_{k \neq i}$ estimated coefficients from Equation 2 indicate whether the particular shocking firm is a complement ($\alpha > 0$) or a substitute ($\alpha < 0$) to other firms in the network. If our financial firms are network stable, a shock on average should not drive the whole system up or down. At the extensive margin of impact (i.e., a simple unweighted count of the number of firms that are complements relative to those that are substitutes), the number of complement firms should "roughly" equal the number of substitute firms.

For example, if all firms were complements, then a static-baseline positive shock (where 'static-baseline' positive shock means a shock that is positive in expectation, so firms' shocks are expected to be positive) would bring returns across the whole network up, while a static-baseline negative shocks would bring returns across the network down. If all firms were either complements to all other firms in the network, or if all firms were substitutes to all other firms in the network, then the network would not return towards its original stability for such static-baseline shocks. Static-baseline shocks (imagine some subset of firms perturbed simultaneously) would bring the *rest* of the network up or down. This yields our first hypothesis:

Hypothesis 1a, extensive margin (number): For short-term stability relative to a static-baseline shock, there will be an approximately equal number of complement and substitute responses to SD shocks in the system, such that the number of network complement responses ($\alpha > 0$) roughly equals the number of network substitute responses ($\alpha < 0$). Hence, in expectation, the system will retain roughly the same "static-baseline" stability.

The extensive margin of complementarity in Hypothesis 1a is a good measure of tendency to the baseline static-stability if market presence alone is important, rather than market-weighted influence. As an alternative measure of network influence, we also report the cumulative sum of coefficient responses for firms that are complements (hence, the cumulative response if all complementary firms simultaneously presented the network with a SD shock) as measured against the cumulative sum of coefficient responses for firms that are substitutes. We call this cumulative response comparison the intensive margin of complementarity. We expect that the positive cumulative sum will roughly equal the negative cumulative sum if the network is in baseline static-stability:

Hypothesis 1b, intensive margin: For short-term stability relative to a static-baseline shock, the sum of positive responses to shocks will roughly equal the sum of negative responses to shocks, namely, $|\sum_k \alpha^{+}_{k\neq i}| \approx |\sum_k \alpha^{-}_{k\neq i}|$, where α^{+} indicates summation a positive network shift response, and α^{-} indicates a negative network shift response.

Process-dynamics

In Equation 2, we also model shocks as affecting the speed at which firms return to their network stability, conditional on standard deviation (SD) shocks. Empirical estimates show that the autoregressive responses ($\sum_{j=1}^{J} \theta_j r_{i,t-j}$) in daily returns indicate regression towards the mean, as the $\sum_j \theta_j \leq 0$ for the three lags in the empirical model.[2] Our empirical speed of adjustment results of three lagged days is consistent with Gottardo's Italian stock market results (2011, p. 739) that complete price adjustments are completed "between three and five days of trading, this is true for the index and the futures but also for every single stock," and also consistent with the empirical results of Damodaran (1993), Patell and Wolfson (1984), and Hasbrouck and Lo (1987).

Hence, the term, $(\sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j}))$, in Equation 2 represents how shocks affect the stability of dynamic process—that is, how quickly, if at all, the network returns towards

[2] In the initial estimates, we experimented with an up to 8 lagged values in the autoregressive process, but only the first three reported here were statistically significant.

its original stability given a shock. The nonlinear specification in Equation 2 allows this regression-towards-the-mean pattern for the network to be altered by SD shocks from other firms within the network. For example, looking at the π term in Equation 2, it's clear that when $\pi_{k \neq i} = 0$ there is no change in the baseline regression towards network stability, given a shock for firm k. Otherwise, the degree of shifting towards stability depends on the value of the SD shock. If $\pi > 0$, then the return to the stability speeds up. For example, if $\pi = .5$ then for the smallest standard deviation shock of 2 ($SD_k = 2$) in our study, the speed to stability doubles as follows:

$$r_{i,t} = other\ terms_{i,t} + \sum_{j=1}^{J} \theta_j r_{i,t-j} + \sum_k (.5)\, SD_{k,t-1} (\sum_{j=1}^{J} \theta_j r_{i,t-j})$$

$$= other\ terms_{i,t} + (1 + .5 * SD_{k,t-1})(\sum_{j=1}^{J} \theta_j r_{i,t-j})$$

$$= other\ terms_{i,t} + (1 + .5 * 2)(\sum_{j=1}^{J} \theta_j r_{i,t-j}) \qquad (3)$$

(when $SD_{k,t-1} (= 2) and\ \pi_{k \neq i} = .5$)

Hence, for a given SD shock, the speed to equilibrium is doubled where $\pi = (\frac{1}{SD})$ (as illustrated in Equation 3, and more than doubled when $\pi > (\frac{1}{SD})$). If $0 > \pi > -(\frac{1}{SD})$, then the speed of the return to stability is slowed down.

Going further, if $\pi < -(\frac{1}{SD})$, then the return-to-mean process becomes destabilizing relative to the initial stability conditional on the respective shock. Suppose a given bank has $\pi = -.5$ for a SD shock of three ($SD = 3$), then the net adjustment to the new stability is, given our results above, $(1 + (-1.5))(\sum_{j=1}^{J} \theta_j r_{i,t-j}) = -.5(\sum_{j=1}^{J} \theta_j r_{i,t-j})$, so that returns are no longer converge back towards the original stability. Rather, they are moving towards a new stability that reflects the sign of the SD shock: a positive shock for a firm with a sufficiently negative value of the parameter, π, will tend to rise the network stability returns to a higher level. If that same bank with the sufficiently negative value of the parameter π had a large negative shock, then the network stability returns would be lowered. Hence, banks and insurers with larger (in an absolute value sense) negative π will be market changers in the sense of driving the network to a new stability.

On the basis of prior literature (Cummins, Lewis, Wei, 2006; and especially Chen et al, 2014, who find that banks have a stronger impact on insurers than vice versa, and that banks create significant systems risk for insurers but not vice versa, using a very different approach than the one employed here), we expect that there will be more market changers ($\pi < -(\frac{1}{SD})$) among banks than insurers:

Hypothesis 2a: We hypothesize that market changers among our sample of larger banks and insurers will be in the minority of all network firms (that is, there are relatively few firms with $\pi < -(\frac{1}{SD})$), but that—given the prior literature—more of these will be banks than insurers.

Hypothesis 2b: As shown above, that firms with $0 > \pi > -(\frac{1}{SD})$ in the network will be slower to reach stability than other firms (outside of market changers). If additional regulatory constraints limits the financial flexibility of banks or insurers, differential regulatory pressures will affect speed of adjustments. However, as none of the firms in our sample changed domicile during the sample period, time-invariant regulatory differences will be held constant in the analysis by our firm fixed effects, which we expect to the statistically significant.

Systematic Risk Shifts

Given the discussion above regards the prior empirical literature on the importance of banks relative to insurers in generating market risk, we expect the following:

Hypothesis 3: The SD shock shifts associated with banks to be greater than the SD shock shifts associated with insurers, or that $|\sum_k \gamma_2^{banks}| > |\sum_k \gamma_2^{insurers}|$.

Separating out Common-Date Risk from other forms of Systemic risk

As discussed above, measures of systemic risk in the GES framework have already accounted for systematic risk (again, the $\gamma_{1,i}$ vector of coefficients in equation 2). Thus, our measures of systemic risk are made independent of systematic risk. What about common-date risk, which captures the common shocks that are not fully captured by the market return: is that different from systemic risk (we think so), and should it be confounded with systemic risk (we think probably not)? Hence, we examine results without day fixed effects (in which case, our systemic risk may be confounded with common-date risk which captures the common shocks that are not fully captured by the market return on the daily basis), and results with day fixed effects which eliminates common-date risk, leaving a cleaner estimate of systemic risk only. For example, if a hurricane hits East Coast, it may severely affect an insurer which underwrites heavily on the coastal area of East Coast, but it may only lightly affect insurers which underwrite nationally. In addition, the hurricane may not affect banks at all. Comparing the coefficients of these two alternative specifications (with, and without, day fixed effects) allows us to discern something about the relative importance of systemic risk, given our model-specific definitions. The reason that the systematic risk variables are not perfectly collinear with day fixed effects is that systematic risk is measured in Equations 1 and 2 as *interactions* with firm fixed effects (that is, other variables multiplied by the firm fixed effects), and hence not collinear with any subset of them (since not all firm FEs can be in the model simultaneously when the model contains an intercept).

Again, the key difference between systemic risk and common-date risk—within the structure of our model—is that systemic risk evolves over time differentially across firms *within* the network, while common-date risk represents network *simultaneous* exposure and response (and, hence, controlled by our day fixed effects). Hence, we propose the following additional hypothesis:

Hypothesis 4. We hypothesize that systemic risk remains, even after controlling for daily FEs (i.e., controlling for common-date risk).

III. Descriptive Statistics

Stock Returns

The daily returns and shocks in Table 1 summarize, in board terms, trends in the data. The average returns in 2006 and 2007 is small. For example, the mean of daily return is 0.0004 and 0.0010 for insurers and banks, respectively. The mean returns declined in 2008 for both insurers and banks then rebounded in 2009 and 2010. For example, the mean of daily return is 0.0022 and 0.0021 for insurers and banks, respectively in 2009. The spread in the returns was greatest for these firms in 2008, mirroring more general market responses. Specifically, the spread in the returns is 0.0034 and 0.0033 for insurers and banks between 2008 and 2009, respectively.

Standard Deviation (SD) Shocks

Table 1 also presents the results of standard deviation shocks over time. Recall that "shocks" in this paper are measured in deviations up or down. The shocks are much higher for insurers in the first three years of our sample than in 2009 and 2010. For insurers the 2 standard deviation (return) is 0.79, 0.89, and 0.90 in 2006, 2007, and 2009, while the standard deviation is 0.67 and 0.73 in 2009 and 2010. For banks, the results are similar.

The distribution of shocks in Table 2 indicate some bunching of both positive and negative shocks over the sample period. We first examine month-by-month patterns between insurers and banks. Note for the SD2 and SD4 (and to a lesser extent, the SD3) shocks-by-month data, there appears to be a propensity for insurers and banks shocks to move in the same direction. We interpret this as a reflection of banks and insurers being part of the same 'network' of financial intermediaries. In particular, whenever the positive shocks outweigh the negative shocks for insurers, the banking pattern has a tendency to move in the same direction.[3] Likewise, when

[3] For example, see February – May in 2009.

negative shocks outweigh positive shocks for one of the two paired industries, negative shocks tend to outweigh positive shocks for the other industry. We denote such examples as ‘similar patterns’. So for February 2006 (January is excluded as it provides the initial baseline to measure standard deviations based on the last 20 trading days), insurers have 15 positive shocks and only 10 negative shocks (15>10), and banks have 27 positive shocks and only 1 negative shock. For March, insurers are 14>11 while banks are 11=11, so we count this also as a ‘similar pattern’ (as the banking pattern does not contradict the insurer pattern). For May 2006, for insurers it is 12<19, while for banks, it is similarly 20<23.

The first dissimilar pattern for SD2 shocks is February 2008, where insurers have slightly fewer positive than negative shocks (8<9), but banks have more (5>4). When closely examining all the SD2 shock patterns between insurers and banks, a second aspect of similar vs. dissimilar shocks seems apparent (as evident in the February 2008 example): the absolute differences between positive and negative shocks tends to be larger for similar patterns than they are for dissimilar patterns. For example, the absolute difference for the February 2006 similar pattern is |15-10| + |27-1| =31, while the absolute difference for the February 2008 dissimilar pattern is |8-9| + |5-4|=2.

Note the prevalence of similar patterns. Of the 59 complete months (January 2006 is excluded as the initial baseline required for the computation of shocks), almost five-sixths of the time, SD2 shocks are similar—there are only 10 of the 59 shocks that are definitely dissimilar. SD4 shocks are similar about four-fifths of the time—there are only 12 of the 59 patterns that are definitely dissimilar.   The least strong similarity relationships are for SD3 shocks, where about three-fourths of the patterns are similar—there are only 14 of the 59 patterns that are definitely dissimilar.

To examine whether the absolute differences are related to the similarity patterns for both banks and insurers, we need to look at the 'means' of absolute values of positive-negative differences for banks and insurers. As there is no reason to suppose that such absolute differences will be unimodal, let alone normally distributed, we employ the Wilcoxon rank-sum test (with exact probability significance computations for our smaller samples), a nonparametric test of absolute differences between similar and dissimilar patterns for the combined bank/insurer sample. This test does not rely on normality, even asymptomatically. The mean of absolute differences for similar patterns are 22.8 for similar patterns, but only 11.4 for definitely dissimilar patterns. The differences are statistically significance at the 5 percent level (1.7%). This reinforces, in an alternative dimension, our findings that banks and insurer patterns of shock move together.

The quarterly and annual shocks are best summarized by the regression of the number of shocks on annual dummy variables and monthly dummy variables (Table 2a). We first focus on January, April, July, and October. Earnings for publicly traded companies are released a week or two after each quarter ends—in general, one or two weeks after each December, March, June and September. That is, the companies in this sample will tend to release their earnings data by the middle of January, April, July and October. Hence, the greater number of statistical shocks, upwards and downwards, during those periods. We find that in general, the coefficients of January, April, July and October are larger in magnitude and more statistically significant than other months, on average. These results are consistent with the argument of Ball and Kothari (1991) who state that "earnings announcements resolve some uncertainty about future cash flows, but the concurrent price reactions increase the variability and covariability of securities' return during the announcements."

IV. GES Model Results: Estimated Network Shifts and Process-dynamics

Estimation

Equation 2 is nonlinear in its parameters. Given the term, $\sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})$, an iterative process was necessarily employed when using our linear econometric models (Garch and clustered standard error models) for the error structure. The θ_j coefficients in $\sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})$ were initially set on the basis of a nonlinear OLS procedures that did not account for any special restriction on the error structure. Then, with the θ_j fixed a priori in the process-dynamics terms, the other parameters were initially estimated a Garch model, and the autoregressive process θ_j in the term, $(R_t * SD_{k,t-1})\,\gamma_{2,i} + \sum_{j=1}^{J} \theta_j r_{i,t-j}$, were estimated, along with the other parameters: $\gamma_{0,i}$, $\gamma_{1,i}$, $\alpha_{k\neq i}$, $\pi_{k\neq i}$. The converged values from the term, $(R_t * SD_{k,t-1})\,\gamma_{2,i} + \sum_{j=1}^{J} \theta_j r_{i,t-j}$, for θ_j, were fixed as values for θ_j in $\sum_{j=1}^{J} \theta_j r_{i,t-j}$, and then the model was refitted. The convergence criteria were that none of the estimated θ_j (those given in Tables 3 and 4, and the appendix tables) varied from the initial fixed θ_j by more than 2 integer values in the third decimal place. This iterative process steadily converged, except for Garch models with daily fixed effects (there was no convergence for the FE Garch models employing either STATA or SAS software). So the estimated Garch models (Appendix Tables B3 and B4) could not differentiate systematic from systematic risk for our model in Equation 2. Tables 3 and 4 where estimated with standard errors clustered by day—specifications employed along with Garch models to estimate returns. Comparing Tables 3 and 4 (clustered standard error models) to Table B3 and B4 (Garch estimates), signs and magnitudes of estimated coefficients are roughly the same (compare especially the other magnitudes of the estimated shifts in 3a relative to B3a, and 4a relative to B4a). The same are true for the 2011-2017 models, as well: compare 6a to B6a, and 7a to B7a, for example. However, the standard errors are much more conservative for the clustered standard error estimators both in terms of joint significance of the effects as well as the individual t-statics. (That is, there are far fewer statistically significant results for the clustered standard error estimators, which we focus on here, than for the Garch estimators in the appendices).

Network Shifts

Table 3 reports estimates of the α coefficients from Equation 2, the 'network shift' effects due to return shocks. Consistent with Hypothesis 1 on the effect of shocks on network stability, there are approximately the same number of complements ($\alpha > 0$) as there are substitutes ($\alpha < 0$) in the network, within either financial group and across all specifications of shock types (SD2, SD3, and SD4). For example, there are 23 complements and 25 substitutes in 2 Stand Dev Shocks (No day FE) column (two firms, CINF and CMA, are left off due to collinearity restrictions).

Table 3a reports the sums of coefficients. There are two comparisons to keep in mind in reviewing the intensive margins in Table 3a, summarizing the coefficients in Table 3. The first comparison is the shifts of *positive vs. negative* cumulative shock-adjustments (these *cumulative sums* form the *intensive* margin of the value of shock adjustments, whereas the *number* of positive and negative estimated firm responses reflect the *extensive* margin is reported Table 3 above). The second comparison is the *between sector* movements in the cumulative absolute shifts, which reflect the relative importance of banking vs insurance.

With respect to the first comparison on the intensive margin (positive vs. negative shocks), we expect the absolute value of positive shifts should roughly balance the absolute value of negative shifts. These "intercept" shifts due to shocks are measured as the coefficients in $\sum_k \alpha_{k\neq i} SD_{k,t-1}$in Equation 2 (which again, are significantly different from zero as indicated by the last row of joint-F values in Table 3). Focusing on the "No Day FE" column, derived from

Table 3 coefficients, not only are the positive and negative coefficients of roughly equal count (the extensive margin of impact as shown above), overall, they have collectively almost an identical coefficient-sum of positive and negative responses. For example, for SD2 insurer results in specifications without day FEs, as given in the upper left hand section of Table 3a, .0069 (sum of positive coefficients) is approximately equal in magnitude to -.0073 (sum of negative coefficients). SD2 bank shifts given just below these insurer shifts, indicate a cumulative value of .0050 positive shifts for banks, approximately equal in magnitude to a -.0048 negative shifts for banks during the same 2006-2010 period. The "No Day FE" columns across Table 3a reflect similar equalities for SD3 and SD4 shifts as well. This supports Hypothesis 1b, For short-term stability relative to a static-baseline shock, the sum of positive responses to shocks will roughly equal the sum of negative responses to shocks.

Results with the day FEs in the model removes the common-date risk component, leaving only the systemic risk component of network shifts, process-dynamics, and *network shifts* in systematic risk. This helps distinguishing results between insurers and banks in terms of systemic risk without common-date risks effect, the second comparison represented in Table 3a. For the SD2, SD3 and SD4 shifts in the "*No Day FE*" cumulative totals, insurers always have a greater impact than banks. Overall for the SD2 (two-standard deviation) shocks, the cumulative absolute values of insurer shifts is .0142, compared to .0098 cumulative shifts for banks (the fourth versus sixth row of the left hand column in Table 3a). That insurer shifts are at least as large as bank shifts when systematic risk is included in the estimates, is also true for SD3 shocks (roughly equal, .0157 vs .0163) and for SD4 shocks (.0199 vs. .0185). However, when common-date risk is removed, the systemic risk results reverse this trend and now banks are systemically more important than insurance for shift responses. For SD2 shocks, banks cumulative network effects on static-baseline stability adjustments (.0128) are only slightly higher than insurers cumulative network effects (.0119), but the reversal nearly doubles for SD3 and SD4 systemic risk adjustments as well (for SD3, banks cumulative is .0227 while insurers is only .0115). These results are consistent with the literature that systemic risk is lower in the insurance industry than that of banking industry (Swiss Re, 2003, the Group of Thirty, 2006, Bell and Keller, 2009).

In summary, the results of Table 3 and Table 3a indicate that static-baseline upward shocks do not lift network boats collectively, nor does a static-baseline downward shock sink them. With respect to collective shocks, about half the firms in the networks act as 'substitute'-inducing downward shifts, and about half the firms in the networks act as 'complements'-inducing upward shifts in returns. This is true overall, and it is true within the insurance and banking sectors as well (Tables 3 and 3a). Finally, we find systemic risk is lower in the insurance industry than that of banking industry. (This is true for the Garch estimators in the appendix as well.)

Process-dynamics

Process dynamics in this model are estimated by the baseline process-dynamics term ($\sum_{j=1}^{J} \theta_j r_{i,t-j}$), and changes in the speed to convergence according given a SD shocks (changes in process dynamics are given by the $\pi_{k\neq i}$ terms in the vector of effects measuring changes in process-dynamics: $\sum_k \pi_{k\neq i} SD_k(\sum_{j=1}^{J} \theta_j r_{i,t-j})$). The results are given in Table 4. Again, Table 4 contrasts the "No day FE" results (on the left hand side of each paired set of models, that includes systemic with common-date risk) with the day fixed-effect results (on the right hand side that controls for common-date risk, so only records the systemic risk response). Overall, the results describe a financial network that returns to stability after a SD shock, though bank shocks are relatively more destabilizing than insurer shocks—that is, there are more market changers among banks than among insurers for SD2 and SD3 shocks, consistent with our hypothesis 2a (though about an equal number of market changes for banks and insurers in the SD4 shocks). As indicated by the F-statistic near the bottom of Table 4 for the joint significance of the process dynamic shifts, they are quite significant overall in 2006-2010.

The first three lagged terms in Table 4, estimating the common tendency of past returns affecting future returns. We find those significant coefficients are negative, indicates a network generally returning to stability. The results indicate a given positive prior return tends to be mitigated to a lower present return through these lagged effects and a negative prior return tends to be followed by upward movement in the present returns, again, as reflected by the negative coefficients on lagged returns.

Note two important patterns in the autoregressive terms. First, across all standard deviation shock types, there seems to be this common relative stability also in the effect of shocks on lagged coefficients when they are significant. SD2 coefficients are very similar to SD3 process shock coefficients, which in turn are not so similar to SD4 process shocks. Second, regression to the mean (via the autoregressive structure) is stronger holding common-date risk constant: for the SD2 shifts, -.0389, -.0137, and -.0333 yields a stronger regression to the mean propensity than -.0213, .0021, and -.0316. Hence, it cannot be common-date risk (or the volatility of simultaneous, common risk) that is driving the process dynamics that we observe in the network.

Again, we find bank shocks are relatively more process destabilizing for SD2 and SD3 shocks, that is, there are more market changers among banks than among insurers. For example, in the far left hand column there are only two insurers during the 2006 to 2010 period that are statistically significant market changers: HUM and MFC, but five banks that are statistically significant market changers: BAP, BBT, CM, , KEY and RY. Again, these firms are market changes as the estimated $\pi < -\left(\frac{1}{SD}\right)$ or $\pi < -\left(\frac{1}{2}\right)$ in the case of SD2. Note that there are many other firms, in both sectors, estimated to have large negative process dynamic effects but are not statistically significant.

To summarize the network dynamic process effects, we tabulate the relative size of the positive and negative shock coefficient values, by financial firm type in Table 4a, in the same way that Table 3a sums the intensive margin of the results in Table 3. If all of the positive insurers coefficients are summed (for the "No Day FE" specification for SD2 in the far left hand column, .257 + .874 + .280 + .2891+ 1.614 + …= 9.647), they collectively are greater than the sum of all positive bank coefficients for the "No Day FE" model (8.184). Recall that a higher sum of positive coefficient means that the return to the stability speeds up, for those firms represented in the summation. Negative bank responses (-13.125, for SD2 shocks in the No Day FE model) are greater in absolute impact than negative insurer responses (-8.702, for SD2 shocks). In other words, the return-to-mean process associated with bank shocks becomes destabilizing because the average coefficient (-13.125/24 = -0.55) is less than -0.5. So bank shocks are relatively destabilizing compared to insurers shocks—consistent with prior research (Chen et al, 2014), for SD2 and SD3 shocks. For the relatively rare SD4 shocks (see Table 2), the two sectors are equally destabilizing. The relative destabilizing influence of banks over insurers holds for SD2 and SD3 shocks, whether or not we control for common-date risk (note this pattern also holds for the Garch estimates in Table B4a).

Comparing the results with and without the day fixed effects (Day FE), we see that most of the risk observed for our process dynamic responses is systemic risk, accounting for about two thirds of the responses, with common-date risk accounting for only about a third of the responses. For the SD2 cumulative responses, given in the left two hand columns, the ratio of systemic risk to total risk (systemic plus systematic) is 13.302/18.349= .72 for insurers; while for banks, 14.473/21.309=.68. Hence, these SD2 and SD3 results are consistent with the literature about systemic risk in the US (Swiss Re, 2003, the Group of Thirty, 2006, Bell and Keller, 2009, Harrington (2009), Grace (2010), and Cummins and Weiss (2014)), and with Baluch, Mutenga and Parsons (2011) which conclude that systemic risk is lower in the insurance industry that that of banking industry in European markets, even after we adjust for common-date risk. Moreover, we find that systemic risk is much more important than common-date risk, at least for this period.

V. Firm characteristics and Adjustment Speeds

Gottardo (2011) finds that firm size (measured by the log of capitalization at the end of the sample period, and by a dummy variable for being one of the six largest firms), has the largest and only statistically significant impact on adjustment speeds for his sample of Italian firms. In addition to firm value (*Value*, the capitalized value of each firm at the end of each trading day), we also include a variable for the volume of shares traded each day for each firm (*Volume*), and a variable for the number of analysts following each firm each day of our sample period (*Analysts*). The number of analysts following is obtained from I/B/E/S. As we include a dummy variable for each firm, we implicitly control for all time invariant, geographic specific, regulatory pressures as none of the firms in our sample changed their regulatory domicile during the sample period.

Table 5 reports the results of stock returns on all the variables employed in our prior models, plus the additional parameterization of firm-associated characteristics within our model, even though only the parameters of the firms' characteristics are included in this table (other variables not shown here, have the same rough magnitude and statistical significance as indicated in the earlier tables). As is obvious, the impact of these firm characteristics show a remarkably stable influence on the market returns across our various specifications of type of firm shocks and treatment of common-date risk.

As can be seen in the first three rows of Table 5, increases in firm value or volume of daily trades are associated with higher daily stock market returns. Number of analysts following a given firm has no discernible impact on the firm's returns. These are the "main" effects of these firm characteristics, in addition to the interactions of these variables with the process dynamic interactions included in the last three rows.

However, our main interest with Table 5 is in the last three rows, which indicate the common change in process dynamics with respect to daily market returns associated with the indicated variables. Interestingly enough, changes in firm value is the only thing that consistently affects the process dynamics--that is, the daily capitalized value of our sample firms make them more likely to be market changers (as indicated by the negative coefficients). This evidence provides indirect support for "too big to fail." We also find firm trading volume has some effect on a firm's propensity to be a market changer.

VI. 2011-2016 Estimates, Robustness Checks

For robustness, we analyze the data in 2011-2016, a period of relative financial stability after the financial storms of 2006-2010. Appendix Table A2, reproduces the pattern of SD shocks for 2011-2016, that was given in Table 2 for the 2006-2010 period. The results and discussion of Table 2 holds for Table A2 (Appendix A): most SD2, SD3, and SD4 shocks are recorded in the month after the quarterly earnings reports'—January, April, July, and October.

To see if our model fits the data in 2011-2016, we re-estimate our clustered standard error models for the later period with the results given in Tables A3 and A4 in Appendix A. The results of Garch models without day Fes are provided in Tables B3 and B4 (Appendix B). Our expectation was that the responses would be somewhat muted in this later calmer period with less variance in the returns, but follow the same general patterns we found in the 2006 to 2010 period. Specifically, we expected to estimate an autoregressive process that tended to return to a network stability, and that although banks return shocks would continue to be relatively important to our network than insurers' return shocks, that banks' collective role as market changes would be mitigated. This suggests the following hypotheses:

Hypothesis 4a: Given the financially calmer period of 2011 to 2016, we expect the estimated network shifts and process dynamic effects to be relatively smaller in value than they were for 2006-2010, though still important.

Hypothesis 4b: We expected that systemic risk would be relatively more important (as part of total risk), since 2006-2010 was a period of unusual systematic risk in the economy.

Hypothesis 4c: We expect that banks will be relatively more important than insurers as market changers in 2011-2016, though their relative role in changing markets will be smaller during 2011-2016 than during the turmoil that prevailed in 2006-2010.

The network shifts in Table A3 follow the same general pattern as estimated in Table 3 for the earlier period, though the relative magnitude of network adjustments in the intercepts given a SD shock has shifted away from its stability tendencies somewhat. Like the 2006-2010 sample, the 2011-2016 static-baseline stability results approximately hold (with respect to SD shocks on the model intercepts), as substitutes and complements are roughly evenly balanced across all specifications in that there are roughly as many complements as substitutes. Table A3a indicates that the network shift effects tend to be balanced overall even though they are not balanced within each sector. Note for example, that for all specifications, the sum of positive coefficients for insurers is always less than the sum of all negative coefficient in absolute value, while banks exhibit the opposite trend. These sectoral differences tend to cancel each other (see for example, the 3SD results with Day FEs: .0017 + .0059$\approx$ .0043 + .0032) such that that overall effect is close to zero. This evidence partially and weakly supports Hypothesis 4a.

Comparing Table A3a to Table 3a, both insurers' shifts due to shocks and banks' shifts due to shocks are lower in magnitude (both positive and negative shifts) in 2011-2016 than they were in 2006-2010. This also supports hypothesis 4a.

Comparing cumulative jumps pairwise ("No Day FE" vs. "Day FE" for SD2 shocks, then the same comparison for SD3, and for SD4 shocks), we find common-date risk in network shifts is at least as important in Table A3a as they were in Table 3a, but the relation is reversed. For all types of shocks, the insurer results show that systemic risk without controlling for common-date risk is now larger than systemic risk controlling for common-date (common-date risk in 2011-2016, apparently offsets part of the systemic risk). For insurers, for example, .0043 (systemic risk cumulative network response controlling for common-date risk) > .0036 (systemic risk cumulative network response not controlling for common-date risk). This result supports hypothesis 4b. Moreover, holding common-date risk constant, banks exhibit much more systemic risk through network shifts than insurers (.0074 > .0043, for SD2 cumulative network shifts, for example, the second column from the left). This supports Hypothesis 4c. This result is expected because banks influence on the economy seems to be much higher than insurers, based on prior research and our general findings here.

Upon reflection, it is not too surprising that the cumulative process dynamic coefficients in Table A4a (2011-2016) are cumulatively larger than the coefficients in Table 4a (2006-2010). That is, while *network shifts* are much less pronounced post 2010 than prior to 2010 (tables 3a vs. A3a), *process dynamics* continues to be important (the sums in A4a are larger than the sums in Table 4a). Table A4a are effects are larger in part because of the mechanical effect of a diminished autoregressive process, so that larger coefficients in A4a is still consistent with hypothesis 4a. That is, banks still appear to have a greater propensity to be network market changers, but that changing via SD shocks takes place with respect to a lowered autoregressive returns to the mean function.

VII. Concluding Comments

The purpose of this study is to examine networks of interconnected major activity between banks and insurers. Specifically, our paper develops new methodological tools that offer insight into the explicit nature of systemic risk in the first investigation of the impact of shocks (volatility) of returns of banks on insurers and vice versa. Volatility of returns are important because volatility is the number one concern of investors other than returns.

We estimate the model on 2006-2010 market data for the 25 largest publicly-traded insurers and 25 largest publicly-traded banks and summarize our findings below. First, there appears to be a propensity for insurers and banks move in the same direction after a major shocks. We interpret this as a reflection of banks and insurers being part of the same 'network' of financial intermediaries. Second, we find that in general, the coefficients of January, April, July and October are larger and statistically significant than other months. These results are consistent with the argument of Ball and Kothari (1991). Third, bank shocks are relatively destabilizing compared to insurer shocks for the turmoil of 2006-2010, but the pattern is not so clear cut for the calm that followed (2011-2015). But through both periods, and across all specifications, we find systemic risk is much more important during these periods than common-date risk.

Results from the 2011 to 2016 varied somewhat from the 2006-2010 results: the network shifts still suggest a static-baseline stability in the presence of shocks, though the results were not as large as they were in the earlier (financially tumultuous) period. The relative calm of 2011 to

2016 period yielded common autoregressive processes that were less significant by themselves (less chance of “arbitrage” opportunities in the absence of large shocks), though the importance of shocks to that process remained important in the latter period. Systematic risk is even less important, and the systemic SD shock responses more muted. It would be interesting to know whether these muted responses were an adaptive-markets response (Lo, 2004; Lo, 2005).

In terms of the robustness of the results, note common “lead” values of the shocks (without the exclusion restriction that identifies past effects), would be controlled by the daily fixed effects (common-date risk). Recall that common-date risk is defined as the network exposure and response which are not fully captured by the market return during that specific date. Hence, the identification of systemic risk and the control for lead shocks are both accomplished by the daily FEs specification. Interestingly, daily FEs (and hence, controlling for common-date risk) mattered a great deal to the estimated responses in 2006-2010, but mattered relatively little in the 2011-2016 period.

Though we developed the estimators here as an extension of event study framework, our models can be approached from an econometric perspective as well. In particular, the impulse-response function literature (Lütkepohl, 2008; Hamilton, 1994) has focused on how a dynamic system (such as autoregressive stock returns for a firm) reacts to a brief signal (here the SD shocks elsewhere in the network), called the impulse. Future research may benefit from examining the synergies between that econometric literature and the event study framework developed here.

Our research suggest other issues to be explored. Are insurers, like AIG, that are also important entities in the banking sector, behaving differently than insurers that provide insurance services exclusively? What would happens if 2006-2016 were treated as a single stable period of response except for subperiod crisis of 2007-2008? Do the network dynamics change mid crisis?

Are the same firms that are systemically important outside the crisis also important mid crisis? These would interesting issues to be taken up in future research.

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Table 1. Daily Returns and Standard Deviation Shocks by Financial Firm Type

		Insurers				Banks			
		Mean	S.D. (ret)	Minimum	Maximum	Mean	S.D. (ret)	Minimum	Maximum
2006	Return	.0004	.0129	-.2031	.1019	.0010	.0125	-.0689	.1375
	2SD shock	.0300	.7906	-13.0303	7.8774	.0645	.7670	-7.1141	16.8305
	3SD shock	.0051	.6101	-13.0303	7.8774	.0289	.5577	-7.1141	16.8305
	4SD shock	-.0053	.5135	-13.0303	7.8774	.0201	.4359	-7.1141	16.8305
2007	Return	.0004	.0157	-.0832	.1049	.00001	.0183	-.1083	.1326
	2SD shock	.0030	.8859	-9.5849	16.3182	-.0153	.8421	-7.3925	5.2474
	3SD shock	.0075	.6947	-9.5849	16.3182	-.0147	.5775	-7.3925	5.2474
	4SD shock	.0152	.5379	-9.5849	16.3182	-.0174	.4178	-7.3925	5.2474
2008	Return	-.0012	.0586	-.5441	1.0236	-.0012	.0511	-.4107	.5782
	2SD shock	-.0134	.8979	-13.2292	9.5202	.0106	.8484	-7.176	10.9268
	3SD shock	-.0071	.6650	-13.2292	9.5202	.0278	.6200	-7.176	10.9268
	4SD shock	-.0091	.5215	-13.2292	9.5202	.0127	.4400	-7.176	10.9268
2009	Return	.0022	.0481	-.3819	.6138	.0021	.0522	-.5904	.4841
	2SD shock	.0150	.6681	-7.7444	7.1658	.0123	.7106	-14.3282	4.9929
	3SD shock	.0042	.4560	-7.7444	7.1658	-.0024	.5069	-14.3282	4.9929
	4SD shock	-.0003	.3430	-7.7444	7.1658	-.0072	.3716	-14.3282	4.9929
2010	Return	.0008	.0187	-.1400	.1266	.0009	.0216	-.1079	.2299
	2SD shock	.0075	.7319	-7.1133	6.7334	. 0199	.7353	-6.086	7.1754
	3SD shock	-.0009	.4887	-7.1133	6.7334	.0154	.4687	-6.086	7.1754
	4SD shock	-.0021	.3184	-7.1133	6.7334	.0053	.2946	-6.086	7.1754

Notes:

Table 2: Bunching of Standard Deviation Shocks over Time

		2 Std. Dev. Shocks				3 Std. Dev. Shocks				4 Std. Dev. Shocks			
Year	month	insurers		Banks		insurers		banks		insurers		banks	
Year	month	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
2006	Feb	15	10	27	1	4	5	4	1	2	3	1	0
	Mar	14	11	11	11	3	5	3	2	1	1	2	0
	Apr	30	20	29	14	9	5	16	4	3	4	8	1
	May	12	19	20	23	3	5	4	6	2	2	2	1
	June	20	16	22	16	4	3	4	6	0	0	2	1
	July	23	14	27	4	5	4	10	0	1	4	4	0
	Aug	12	8	14	3	6	2	1	1	2	2	1	1
	Sept	22	8	19	9	5	1	3	1	0	0	1	0
	Oct	32	17	23	15	8	8	10	3	4	4	1	1
	Nov	9	8	25	20	2	0	1	3	2	0	0	0
	Dec	23	2	20	5	7	0	5	0	3	0	3	0
2007	Jan	23	23	21	21	6	6	5	5	2	1	2	1
	Feb	18	26	13	35	6	11	2	25	2	6	1	20
	Mar	7	22	18	25	0	4	0	2	0	0	0	0
	Apr	33	3	17	4	15	2	2	2	7	0	0	2
	May	15	8	21	9	8	5	7	2	3	2	2	0
	June	14	24	16	25	5	7	3	1	5	0	1	1
	July	23	51	26	42	7	20	9	10	3	6	1	2
	Aug	31	28	32	28	9	11	11	6	2	2	2	0
	Sept	18	1	24	0	6	0	11	0	0	0	1	0
	Oct	30	20	31	24	8	5	3	4	5	0	1	1
	Nov	16	29	25	42	4	4	1	12	1	0	0	3
	Dec	5	10	3	10	0	1	0	0	0	1	0	0
2008	Jan	23	42	28	34	4	12	14	7	0	3	3	4
	Feb	8	9	5	4	1	3	0	0	0	2	0	0
	Mar	29	26	44	29	7	6	22	5	2	5	9	0
	Apr	21	5	14	1	6	2	0	0	0	1	0	0
	May	18	10	8	9	3	1	4	2	0	0	0	1
	June	4	40	10	51	2	10	0	7	0	3	0	2
	July	45	31	51	28	10	9	21	7	2	4	11	2
	Aug	7	3	8	0	1	0	1	0	0	0	0	0
	Sept	48	62	45	46	20	17	18	18	12	7	4	7
	Oct	29	40	17	15	12	14	7	1	5	9	1	0
	Nov	23	14	12	19	5	5	6	5	2	0	3	0
	Dec	5	5	1	13	2	0	0	0	1	0	0	0

Table 2 continued: Bunching of Standard Deviation Shocks over Time

		2 standard deviation shocks				3 standard deviation shocks				4 standard deviation shocks			
Year	month	insurers		Banks		insurers		banks		insurers		Banks	
Year	month	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
2009	Jan	22	42	19	46	1	11	6	21	0	0	2	11
	Feb	13	10	15	10	4	4	1	1	3	3	1	0
	Mar	24	16	32	10	6	0	8	2	1	1	1	1
	Apr	8	3	16	4	0	1	6	0	0	0	0	0
	May	12	6	20	2	4	1	4	0	0	0	2	0
	June	6	13	3	9	1	3	2	0	1	1	0	0
	July	31	19	30	12	9	5	4	2	2	2	0	1
	Aug	11	4	15	10	4	3	4	1	1	1	1	0
	Sept	29	11	14	13	7	1	4	0	2	2	1	0
	Oct	19	12	21	22	5	1	3	6	2	2	1	0
	Nov	4	9	8	9	1	1	1	2	0	0	0	0
	Dec	11	8	7	10	1	2	1	3	1	1	0	0
2010	Jan	27	24	26	32	7	5	8	8	3	3	2	0
	Feb	6	18	4	15	2	5	0	3	0	0	0	2
	Mar	20	7	13	8	2	1	4	2	0	1	2	0
	Apr	30	44	42	29	12	17	11	8	3	5	2	1
	May	35	31	24	32	13	8	8	4	2	1	3	0
	June	3	12	3	16	0	2	1	2	0	0	0	0
	July	20	15	15	11	2	1	8	1	0	1	2	1
	Aug	16	25	12	19	1	3	5	1	1	2	1	1
	Sept	26	0	30	4	0	0	3	1	0	0	1	0
	Oct	8	15	20	15	0	4	2	3	0	2	0	1
	Nov	24	12	30	18	9	4	8	1	2	1	2	0
	Dec	11	3	23	6	1	0	3	2	0	0	0	2

Table 2a. Regression Shocks by Month and Year, Based on Table 2 Shock Data

	2 Std. Dev. Shocks				2 Std. Dev. Shocks				3 Std. Dev. Shocks			
	Insurers		Banks		insurers		banks		Insurers		Banks	
	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
Inter	10.74*	5.24	11.05*	8.81	1.29	0.04	1.51	0.14	0.25	-0.10	0.27	-0.18
Jan	12.90*	26.11*	13.20*	23.27*	2.31	7.66*	6.56*	9.04*	0.28	1.64	1.84	3.45
Feb	1.00	9.00	2.00	4.20	1.20	5.00*	-0.40	5.00	0.40	2.40*	0.00	4.00*
Mar	7.80	10.80	12.80*	7.80	1.40	2.60	5.60*	1.60	-0.20	1.00	2.20*	-0.20
Apr	13.40*	9.40	12.80*	1.60	6.20*	4.80*	5.20*	1.80	1.60	1.60	1.40	0.40
May	7.40	9.20	7.80	6.20	4.00	3.40	3.60	1.80	0.40	0.80	1.20	0.00
June	-1.60	15.40*	0.00	14.60*	0.20	4.40	0.20	2.20	0.20	0.40	0.00	0.40
July	17.40*	20.40*	19.00*	10.60	4.40*	7.20*	8.60*	3.00	0.60	2.80*	3.00*	0.80
Aug	4.40	8.00	5.40	3.20	2.00	3.20	2.60	0.80	0.20	1.00	0.40	0.00
Sept	17.60*	10.80	15.60*	5.60	5.40*	3.20	6.00*	3.00	1.80	1.00	1.00	1.00
Oct	12.60*	15.20*	11.60*	9.40	4.40*	5.80	3.20	2.40	2.20	2.60*	0.20	0.20
Nov	4.20	8.80	9.20	12.80*	2.00	2.20	1.60	3.60	0.40	0.00	0.40	0.20
2006	0.87	-3.78	1.75	-4.71	0.96	-0.39	0.73	0.01	0.86	0.68	1.10	0.02
2007	0.58	3.25	0.41	5.00	2.08	2.16	-0.58	2.75	1.58*	0.33	0.33	1.83
2008	2.83	6.75	0.08	3.66	2.00	2.41	2.66	1.33	1.08	1.66*	1.33	0.66
2009	-3.00	-4.41	-3.50	-4.00	0.50	-1.41	-1.41	0.16	0.16	-0.16	0.50	0.41
R-sq	.4343	.3269	.3350	.3316	.2980	.3093	.3706	.2367	.2097	.3100	.3229	.2364

Notes: *=significant at the 10 percent level or better. This Table reports coefficients from the regression of shocks of on month (December is baseline) and Year (2010 is the baseline) dummy variables.

Table 3. Stock Market *Shifts* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects (Clustered SEs)

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.0010**	-0.0001	-0.0007+	-0.0000	-0.0013*	-0.0017**
AET	0.0005+	0.0001	0.0007+	-0.0003	0.0001	-0.0001
AFL	0.0001	0.0006+	0.0010+	0.0008*	0.0004	-0.0002
ALL	0.0008+	-0.0004	0.0001	-0.0005	0.0011	0.0003
AON	0.0007+	0.0004	0.0002	0.0004	0.0008**	0.0010
BRK	-0.0000	-0.0006*	-0.0004	-0.0006*	0.0005	-0.0002
CB	0.0006	0.0004	0.0001	-0.0001	0.0015***	0.0011**
CI	0.0001	-0.0005+	0.0000	-0.0003	0.0006	-0.0012
CNA	-0.0007	-0.0005	0.0001	0.0000	0.0009	0.0005
GNW	0.0001	0.0006	-0.0002	0.0000	-0.0003	-0.0003
HIG	-0.0011**	-0.0016***	-0.0013**	-0.0020***	-0.0005	-0.0005
HUM	-0.0000	-0.0000	0.0002	0.0004	-0.0010+	-0.0001
LNC	0.0010+	0.0007	-0.0006	-0.0008	0.0011	-0.0003
MFC	0.0003	0.0003	-0.0001	0.0006	-0.0015*	-0.0008
PFG	-0.0009*	0.0004	-0.0019***	-0.0001	-0.0010*	0.0003
PGR	-0.0005	-0.0004	-0.0004	-0.0005	0.0000	-0.0003
PRE	-0.0004	-0.0003	0.0007+	-0.0000	0.0005	0.0001
PRU	0.0007	-0.0003	0.0011+	-0.0002	0.0010*	-0.0004
RE	-0.0002	-0.0001	-0.0004	-0.0002	-0.0006**	0.0003
SLF	-0.0010*	0.0003	-0.0015*	0.0004	-0.0007	0.0036
TRV	-0.0008+	-0.0011**	-0.0008	-0.0010*	-0.0017***	-0.0011**
UNH	0.0016***	0.0007	0.0015*	0.0002	0.0010	0.0010
UNM	-0.0007*	-0.0008**	-0.0008*	-0.0005	-0.0005+	0.0001
XL	0.0004	0.0007+	0.0009	0.0016*	0.0013	0.0025+
BAC	0.0009+	-0.0004	0.0002	-0.0008	-0.0008	-0.0005
BAP	-0.0004	-0.0004	-0.0001	0.0003	0.0007	0.0003
BBT	-0.0004	0.0007	-0.0011	-0.0001	-0.0009	0.0021
BK	-0.0001	0.0003	0.0003	0.0008**	0.0001	0.0006
BMO	-0.0002	-0.0004	0.0009	0.0011	0.0001	0.0024
BNS	0.0006+	-0.0007	0.0025**	-0.0001	-0.0015	-0.0034
BSBR	-0.0001	-0.0020	0.0000	-0.0037**	0.0009**	-0.0031+
C	-0.0010**	-0.0011*	-0.0008	-0.0015+	-0.0005	0.0005
CM	0.0007+	0.0006	-0.0009	0.0008	0.0026*	0.0005
HBC	0.0004	0.0005	0.0004	0.0007	0.0008	0.0013
HDB	0.0003	0.0004	-0.0003	0.0004	-0.0009+	0.0018***
IBN	0.0001	0.0000	0.0006	0.0007	-0.0006+	0.0001
KEY	-0.0001	-0.0001	0.0005	0.0009	-0.0002	0.0011
MTB	0.0003	-0.0001	-0.0001	0.0002	0.0009	0.0004
PNC	-0.0005	-0.0002	-0.0003	-0.0009	0.0005	-0.0006
RF	0.0002**	-0.0000	-0.0002	-0.0004	0.0004	-0.0005
RY	0.0012	0.0010+	0.0026*	0.0033**	0.0013+	0.0007
STD	-0.0014**	-0.0012*	-0.0016**	-0.0015+	-0.0016**	-0.0002+
STI	0.0003	-0.0001	0.0006	0.0008	0.0001	0.0026
STT	0.0004	0.0006	0.0007	0.0010+	-0.0003	0.0009

TD	-0.0001	0.0009	0.0006	-0.0004	0.0003	-0.0010**
UBS	-0.0005	-0.0006	-0.0002	-0.0007	-0.0004	-0.0010
USB	0.0002	-0.0004	-0.0002	-0.0013+	-0.0009	-0.0014+
WFC	0.0003	0.0001	0.0006	0.0003	0.0012+	-0.0009+
F-joint statistic	1.52 (.0134)	1.86 (.0004)	1.76 (.0012)	1.66 (.0041)	2.81 (<.0001)	3.50 (<.0001)

Notes: ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. All specifications included firm specific intercepts and firm specific market returns (firm FE*market returns, yielding the firm's beta in a CAPM model), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated with clustered standard errors at the day level.

Table 3a. Network Shifts: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	0.0069	0.0052	0.0066	0.0044	0.0108	0.0108
Ins: ∑ neg coeff	-0.0073	-0.0067	-0.0091	-0.0071	-0.0091	-0.0072
Ins: ∑|coeff|	0.0142	0.0119	0.0157	0.0115	0.0199	0.018
Bank: ∑ pos coeff	0.005	0.0051	0.0105	0.0113	0.0099	0.0153
Bank: ∑ neg coeff	-0.0048	-0.0077	-0.0058	-0.0114	-0.0086	-0.0126
Bank: ∑|coeff|	0.0098	0.0128	0.0163	0.0227	0.0185	0.0279

Notes: Cell entries are the respective sums from Table 3.

Table 4. Stock Market *Process-dynamics* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.0213	-0.0389**	-0.0206	-0.0348*	-0.0095	-0.0188
Lag2	0.0021	-0.0137	-0.0033	-0.0162	0.0001	-0.0116
Lag3	-0.0316*	-0.0333**	-0.0317*	-0.0323**	-0.0201	-0.0248*
ACE	0.257	0.362	0.634	0.846+	-0.397	-1.432
AET	0.874	-0.150	2.711**	0.093	1.577	0.851
AFL	0.280	0.115	-0.365+	0.264*	-0.688**	-0.052
ALL	1.614*	1.740**	1.860*	1.966**	2.098*	2.398*
AON	0.400	0.454	0.521	-0.005	0.474	-0.340
BRK	0.938*	0.339	-0.285	-0.023	1.545***	0.460
CB	-0.175	0.451	0.753	0.048	0.681	0.768
CI	-0.431	-0.104	-0.015	0.775	-1.249	0.891
CNA	0.552	0.103	2.394+	0.447	1.346	-0.294
GNW	0.942+	0.566*	0.920	0.485+	-0.882+	0.836+
HIG	-0.018	0.273	0.574	0.342	2.125+	1.660*
HUM	-3.345***	-2.407**	-3.915***	-2.409**	-5.125**	-3.382*
LNC	0.690	0.670	1.573	1.376+	4.521***	3.685**
MFC	-1.223+	-0.706*	-1.088	-0.666	-3.849**	-2.735**
PFG	0.585	0.328	0.354	0.389**	0.049	-1.459**
PGR	-0.275	-0.087	0.301	-0.588	-0.357	-0.928
PRE	0.805+	0.536*	-1.643	-0.216	-0.216	0.051
PRU	0.168	0.108	0.568	0.292	0.704	0.426
RE	-0.857	0.726	-0.237	0.888	-1.241	0.534
SLF	-0.382	-0.853+	-0.893	-1.123+	-1.088	-1.610+
TRV	-0.550	-1.174**	0.871	0.568	-0.719	0.012
UNH	-0.639	-0.289	-2.068***	-0.894*	-2.371***	-1.118+
UNM	-0.807	-0.494*	-1.357+	-0.908*	-0.937*	-0.902***
XL	1.542	0.267	1.707+	0.620	1.484	0.606
BAC	-0.974	-0.916+	-0.977	-1.041+	-0.494	-1.129**
BAP	-1.134***	-0.466+	-1.189***	-0.925*	1.371+	1.544**
BBT	-2.077***	-0.801**	-2.710***	-1.178	-4.630***	-2.494
BK	1.366**	0.700**	1.511**	0.876***	1.337+	0.926
BMO	2.506**	1.065**	1.240	-0.088	10.051***	3.729***
BNS	0.400	0.278	0.356	0.639	-3.397***	0.331
BSBR	-0.514	0.430	0.146	0.445	0.791	0.893
C	1.399**	0.760*	2.184***	1.128***	5.113***	3.685***
CM	-2.603***	-2.025***	3.295***	0.952+	2.903	0.344
HBC	1.073**	0.670**	0.212	0.048	0.326	0.079
HDB	-0.060	-0.649	-0.125	-0.756*	-0.108	-0.160
IBN	-0.255	0.144	-0.418	-0.136	-0.245	-0.266
KEY	-1.264**	-0.743**	-1.634***	-0.855***	-5.136***	-4.033***
MTB	-0.258	-0.049	-0.066	0.349*	1.249**	0.966**
PNC	-0.107	-0.129	0.425	0.078	0.607*	0.679***
RF	-0.130	-0.670	0.134	-0.501	0.892	0.142
RY	-0.954+	-0.702	-1.010+	-1.090*	-0.737	-1.380+
STD	-0.014	0.131	-0.185	-0.141	-0.207	-0.342
STI	-1.067	-1.183+	-1.204	-1.247+	-1.203	-1.471
STT	-0.428	-0.457***	-0.647*	-0.408*	-1.738***	-1.282***

TD	-0.655	0.021	-0.870	-0.513	2.328	0.228
UBS	-0.631	0.316	-1.939***	-0.303	0.757	0.498
USB	0.002	0.121	-0.479	-0.414	-1.535	-1.600
WFC	1.438*	1.047*	1.489*	1.021+	1.692+	1.395+
F-joint statistic	5.43 (<.0001)	11.07 (<.0001)	18.20 (<.0001)	15.68 (<.0001)	51.69 (<.0001)	37.83 (<.0001)

Notes: 61,069 observations. ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. Joint F-tests on all the coefficients in each column indicated significance at the <.0001 level, for all specifications. All specifications included firm specific intercepts and firm specific market returns ("firm FE*market returns", yielding the firm's beta from a CAPM perspective), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated with clustered standard errors at the day level. We estimated our model using 5 alternative ways of measuring market returns---none of them made any difference for the results, so we present the results with only the VWRETD variable (VWRETD is the Value weighted return with dividends for all CRSP stocks).

Table 4a. Process-dynamics: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	9.647	7.038	15.741	9.399	16.604	13.178
Ins: ∑ neg coeff	-8.702	-6.264	-11.866	-6.832	-19.119	-14.252
Ins: ∑|coeff|	18.349	13.302	27.607	16.231	35.723	27.43
Bank: ∑ pos coeff	8.184	5.683	10.992	5.536	29.417	15.439
Bank: ∑ neg coeff	-13.125	-8.79	-13.453	-9.596	-19.43	-14.157
Bank: ∑|coeff|	21.309	14.473	24.445	15.132	48.847	29.596

Notes: Cell entries are the respective sums from Table 4.

Table 5. Firm Characteristics and Network Stability Shifts: Main Effects and Process Dynamic Shifts

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Value						
Volume						0.0491***
Analysts						0.0141*
Value*Process	0.0369**	0.0472***	0.0392**	0.0465***	0.0423***	-0.0000
Dynamics	0.0176**	0.0145*	0.0171**	0.0139*	0.0175**	-1.3099*
Volume*Process	-0.0001	-0.0000	-0.0001	-0.0000	-0.0001	-
Dynamics	-0.9485+	-0.4030+	-2.7870**	-1.3074***	-3.0247	0.7047***
Analysts*Process	0.0317	0.0338	-0.3603	-0.1585	-1.3001*	
Dynamics	0.0049	0.0001	0.0165**	0.0061	0.0374+	0.0194***

Notes: Firm Value (Value) and Daily Volume of Trades (Volume) are measured in billions. Number of analysts (Analysts) following the firm are measured as integers. All models also include all previous independent variables: the autoregressive process with three lags, firm fixed effects, separately betas from market returns, standard deviation network shifts, standard deviation process dynamic shifts, as well as the interactions listed above (and in half the models, fixed effects for each day). As the network process dynamic response variable for firm *i* given a shock in firm *k* at time *t* is $SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})$, (the corresponding coefficients for these process dynamic variables are given in Table 4), we measure the response variable for the interaction of the variable ($X_{i,t}$) with the network process dynamics as $X_{i,t}[\sum_k SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})]$. That is, we assume the value, volume, and analysts effects act uniformly on all process dynamic shifts (though the process dynamic shifts are estimated separately, as indicated in Table 4). Means (standard deviations) are as follows: value, .0291 (.0393); volume, .0134 (.0674); analysts, 13.272 (7.7754).

Appendix A: Standard Deviation Jumps in 2011-2016

Table A2: Bunching of Standard Deviation Shocks over Time

		2 Std. Dev. Shocks				3 Std. Dev. Shocks				4 Std. Dev. Shocks			
Year	month	Insurers		Banks		insurers		banks		insurers		banks	
Year	month	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
2011	Feb	19	14	16	16	0	3	2	3	4	1	1	1
	Mar	13	13	18	11	6	1	5	0	0	0	1	0
	Apr	28	9	15	16	1	2	2	3	7	0	1	0
	May	6	15	9	22	9	3	1	3	0	1	0	1
	June	19	30	5	34	0	7	1	16	1	1	0	7
	July	9	21	15	17	1	5	1	3	0	3	1	0
	Aug	34	73	22	75	2	34	8	40	6	22	2	15
	Sept	6	11	6	16	16	0	0	2	1	0	0	0
	Oct	16	6	23	7	1	1	2	0	0	0	0	0
	Nov	8	9	2	12	0	0	0	1	0	0	0	0
	Dec	21	3	21	2	0	0	4	0	0	0	0	0
2012	Jan	11	16	15	11	4	5	0	3	1	2	0	0
	Feb	25	6	11	5	1	3	3	0	1	1	0	0
	Mar	33	14	30	14	5	6	9	5	1	2	0	0
	Apr	14	17	9	19	6	3	2	2	3	3	1	0
	May	7	24	2	28	6	4	0	0	0	3	0	0
	June	22	21	13	25	2	5	3	8	1	1	0	5
	July	11	13	23	8	4	4	1	2	1	0	0	0
	Aug	14	6	14	4	5	3	3	1	2	2	1	0
	Sept	47	10	52	4	5	1	21	0	5	0	7	0
	Oct	26	6	19	18	19	0	6	4	5	0	3	1
	Nov	12	25	16	18	6	9	3	4	1	2	3	1
	Dec	17	7	20	2	2	1	7	0	2	0	1	0
2013	Jan	32	6	34	7	5	2	16	0	5	1	4	0
	Feb	22	37	16	34	11	10	3	12	2	2	0	4
	Mar	13	1	14	6	6	0	3	0	0	0	0	0
	Apr	35	34	27	35	1	11	4	12	3	4	0	1
	May	13	5	13	3	10	2	4	0	0	0	0	0
	June	16	25	15	32	5	1	0	8	0	1	0	1
	July	14	9	19	7	0	3	4	2	3	0	0	0
	Aug	15	22	18	26	4	3	4	12	3	0	0	4
	Sept	18	13	14	6	6	3	5	2	1	0	1	0
	Oct	34	11	30	13	3	3	10	1	2	0	1	1
	Nov	24	5	16	9	8	0	9	1	2	0	4	0
	Dec	17	11	22	8	5	1	6	1	0	0	0	1

Table A2 continued: Bunching of Standard Deviation Shocks over Time

		2 Std. Dev. Shocks				3 Std. Dev. Shocks				4 Std. Dev. Shocks			
Year	month	Insurers		Banks		insurers		banks		insurers		Banks	
Year	month	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.
2014	Jan	15	57	22	41	1	15	7	11	0	2	4	4
	Feb	9	18	7	10	5	5	2	0	4	2	0	0
	Mar	11	9	22	7	1	3	4	1	0	1	0	0
	Apr	22	32	13	21	3	7	1	7	1	1	1	1
	May	8	4	16	8	4	1	8	1	1	0	5	0
	June	18	9	24	8	2	0	4	1	1	0	0	0
	July	19	34	18	23	3	13	3	10	0	7	1	4
	Aug	9	18	10	19	2	3	3	4	2	1	1	0
	Sept	28	28	16	27	4	6	3	10	1	0	0	2
	Oct	31	27	21	45	1	3	1	14	0	0	1	3
	Nov	3	4	8	4	0	3	2	2	0	2	0	1
	Dec	44	46	36	43	12	10	9	12	3	5	2	6
2015	Jan	29	8	19	40	2	2	4	5	1	0	2	2
	Feb	12	6	13	10	2	3	1	5	1	1	0	4
	Mar	23	20	15	22	1	8	6	4	0	2	0	0
	Apr	9	18	18	6	4	6	5	1	2	2	3	0
	May	11	11	16	15	0	2	2	2	0	2	0	0
	June	36	22	14	26	10	9	0	13	3	1	0	5
	July	17	8	12	16	6	4	3	4	4	0	0	1
	Aug	27	56	30	60	5	28	6	24	2	14	1	14
	Sept	1	11	1	14	0	3	0	0	0	0	0	0
	Oct	19	7	25	2	5	3	2	0	0	1	1	0
	Nov	9	11	6	8	2	2	0	1	0	0	0	0
	Dec	22	26	23	28	5	3	2	9	1	1	0	1
2016	Jan	10	28	11	44	2	4	3	9	0	0	0	1
	Feb	26	17	19	18	5	8	0	1	0	3	0	0
	Mar	9	1	15	0	2	0	2	0	0	0	0	0
	Apr	9	23	25	12	0	12	11	3	0	6	2	1
	May	17	9	21	9	8	2	7	2	2	0	0	0
	June	26	41	17	42	7	20	2	25	2	16	0	19
	July	10	3	2	0	3	1	1	0	1	1	1	0
	Aug	25	10	29	6	3	6	10	2	1	2	3	0
	Sept	21	22	22	41	3	14	3	11	1	5	0	0
	Oct	20	19	19	8	8	6	3	2	2	3	1	0
	Nov	43	4	48	13	14	1	22	2	9	0	12	0
	Dec	14	7	8	4	1	1	4	1	1	0	2	0

Table A3. Stock Market *Shifts* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects ; 2011-2016, Clustered SEs

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.0004*	-0.0003+	-0.0002	0.0000	0.0002	0.0004
AET	0.0001	-0.0001	0.0003+	0.0001	0.0003***	0.0000
AFL	-0.0001	-0.0002	-0.0006**	-0.0004+	-0.0004*	-0.0003
ALL	0.0001	0.0001	0.0002	0.0001	-0.0001	-0.0001
AON	0.0002	0.0001	0.0001	0.0001	-0.0002	-0.0001
BRK	-0.0001	-0.0002	-0.0001	-0.0005*	0.0005**	0.0000
CB	-0.0002	-0.0000	-0.0003**	-0.0003	-0.0002*	0.0001
CI	-0.0002+	-0.0002+	-0.0006***	-0.0004*	-0.0009***	-0.0006+
CNA	-0.0002	-0.0001	-0.0001	0.0000	-0.0002	-0.0002
GNW	-0.0002	-0.0003**	-0.0003	-0.0003*	-0.0002	-0.0003*
HIG	0.0000	0.0002+	0.0002	0.0002	-0.0001	0.0000
HUM	-0.0001	0.0001	-0.0000	0.0002+	0.0001	0.0002+
LNC	0.0000	-0.0001	0.0004+	-0.0003	0.0000	-0.0003
MFC	-0.0001	0.0002	-0.0002	-0.0002	-0.0008**	-0.0004
PFG	0.0002	-0.0003	-0.0000	-0.0010***	-0.0002	-0.0013***
PGR	0.0000	-0.0001	0.0001	-0.0002	-0.0000	-0.0000
PRE	-0.0001	-0.0000	-0.0001	-0.0000	-0.0003	-0.0003
PRU	-0.0004***	0.0001	-0.0005**	0.0006**	-0.0006**	0.0002
RE	-0.0001	-0.0001	-0.0002	0.0000	-0.0003	0.0001
SLF	0.0002	0.0002	-0.0002	0.0002	0.0001	0.0002
TRV	0.0003+	0.0004**	0.0001	0.0002	0.0001	0.0001
UNH	-0.0000	-0.0002+	-0.0002	-0.0003+	-0.0001+	-0.0005+
UNM	-0.0001	-0.0002	-0.0000	-0.0002	-0.0007	-0.0010**
XL	-0.0002	-0.0005**	-0.0002	-0.0002	-0.0004	-0.0004
BAC	0.0003+	0.0002	0.0006*	0.0003	-0.0003	0.0004
BAP	0.0000	-0.0005+	0.0004*	-0.0004	0.0001	-0.0010
BBT	0.0004+	0.0005**	0.0004	0.0004	-0.0002	0.0003
BK	-0.0001	-0.0001	-0.0001	-0.0002	0.0005+	0.0006+
BMO	-0.0001	-0.0005+	0.0001	0.0004+	0.0003	0.0005***
BNS	-0.0000	-0.0010**	0.0002	0.0001	0.0002	0.0004
BSBR	0.0000	0.0011+	0.0001	0.0014	-0.0002	0.0011
C	-0.0003+	-0.0001	0.0000	0.0005	0.0000	0.0004
CM	-0.0001	0.0001	-0.0010***	-0.0000	-0.0011***	-0.0009*
HBC	0.0001	-0.0003	0.0003+	-0.0004	0.0002	0.0001
HDB	-0.0001	0.0002	-0.0004**	0.0006+	-0.0007**	0.0002
IBN	0.0000	0.0000	0.0001	0.0004	0.0005***	0.0011**
KEY	0.0001	-0.0001	-0.0001	-0.0005*	-0.0001	-0.0009**
MTB	0.0003+	0.0002	0.0002	0.0003	0.0006*	0.0006+
PNC	-0.0000	0.0001	0.0000	0.0001	-0.0002	-0.0005
RF	-0.0004*	-0.0002	-0.0004	-0.0007**	-0.0008	-0.0004
RY	0.0003+	0.0004	-0.0003	-0.0003	-0.0003*	-0.0001
STD	-0.0000	-0.0004+	-0.0000	-0.0003	0.0005+	-0.0004
STI	-0.0006***	-0.0001	-0.0004	0.0001	0.0008	0.0001
STT	0.0005**	0.0008***	0.0008***	0.0009**	0.0011***	0.0010*
TD	-0.0006	0.0002	-0.0005**	-0.0003	-0.0006*	-0.0003
UBS	-0.0000	0.0001	0.0000	-0.0001	-0.0002	-0.0003

USB	0.0004+	0.0001	0.0001	0.0003	0.0011+	0.0008
WFC	0.0002	-0.0001	0.0006**	0.0001	0.0002	-0.0002
F-joint statistic	1.38 (.0438)	1.45 (.0249)	7.66 (.0003)	1.47 (.0204)	4.12 (<.0001)	2.010 (.0001)

Notes: ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. All specifications included firm specific intercepts and firm specific market returns (firm FE*market returns, yielding the firm's beta in a CAPM model), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications clustered the standard errors at the day level. Estimates of the model from 2011-2016 daily returns, N=73,630 observations).

Table A3a. Network Shifts: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects; 2011-2016

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	0.0011	0.0014	0.0014	0.0017	0.0013	0.0013
Ins: ∑ neg coeff	-0.0025	-0.0029	-0.0038	-0.0043	-0.0057	-0.0058
Ins: ∑|coeff|	0.0036	0.0043	0.0052	0.006	0.007	0.0071
Bank: ∑ pos coeff	0.0026	0.004	0.0039	0.0059	0.0061	0.0076
Bank: ∑ neg coeff	-0.0023	-0.0034	-0.0032	-0.0032	-0.0047	-0.005
Bank: ∑|coeff|	0.0049	0.0074	0.0071	0.0091	0.0108	0.0126

Notes: Cell entries are the respective sums from Table A3.

Table A4. Stock Market *Process-dynamics*: No Day Fixed Effects vs Day Fixed Effects ; 2011-2016
Using Clustered SEs

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.0105	0.0085	-0.0127+	0.0089	-0.0104	0.0094
Lag2	0.0055	-0.0002	0.0042	-0.0007	0.0033	-0.0006
Lag3	-0.0093	-0.0136*	-0.0094	-0.0126+	-0.0102	-0.0119+
ACE	0.784	-0.534	0.055	-0.908	2.361	-4.995***
AET	0.163	0.750+	-1.113**	1.080**	-0.692	1.492**
AFL	1.048*	-0.890	0.789	-2.395**	1.883*	-0.806
ALL	2.064+	-0.484	2.202*	-0.658	2.234*	-0.805
AON	-0.057	0.818+	-0.845	0.580	-0.173	-0.085
BRK	-0.356	0.332	0.164	0.981	-0.709	1.638+
CB	-0.040	-0.204	-0.252	0.191	0.353	-0.589
CI	-0.032	0.679	-0.423+	0.991	-0.900	-0.117
CNA	1.288+	0.056	1.121	0.633	1.217	-0.255
GNW	-0.036	0.247	-0.144	0.117	-0.153	-0.292
HIG	0.734	0.631	-0.166	0.862*	-0.011	0.486
HUM	-0.975	0.552	-0.691	0.391	-1.110	0.557
LNC	-2.587***	-1.157	-2.180***	-0.885	-2.249**	-2.074+
MFC	-1.861***	-0.241	-1.844**	1.242	-2.582***	4.415***
PFG	-0.091	0.608	0.274	0.008	0.034	-0.467
PGR	-0.351	-1.117+	0.016	-0.579	-0.622	-1.175
PRE	-1.090*	1.353*	-0.097	1.942*	-0.098	3.150***
PRU	0.647	-1.139	0.839	-1.197	0.649	-1.437+
RE	2.006	-1.830	2.037	-2.312+	1.798	-2.350+
SLF	-0.954	3.870**	-0.902	4.182***	-0.665	4.259***
TRV	0.382	-0.030	1.824***	-0.879+	1.031	0.099
UNH	-0.574	0.560	-0.560	-0.028	-1.411**	1.525
UNM	0.504	0.072	0.778	-0.851	1.725+	-3.169*
XL	1.681	0.780	1.595	1.021	1.642	1.130
BAC	-0.640	-0.026	-0.955	0.280	-0.894	0.480
BAP	-0.878	0.306	-0.719	1.014	-0.492	-0.158
BBT	0.411	0.664	-0.305	1.165+	2.159**	-1.953***
BK	0.146	-0.554	0.691	-0.068	0.998	-0.822
BMO	-0.374	-0.441	1.364+	-2.022**	-1.276	-2.686*
BNS	0.962	0.206	-0.940	-0.275	-2.103	-3.096
BSBR	-2.366+	0.239	-2.221+	0.431	-2.192	0.223
C	0.716	0.010	-0.010	-0.279	0.425	-0.348
CM	0.594	-0.093	2.038***	-0.869	2.826***	-0.514
HBC	1.075*	-0.880+	0.275	0.042	1.023+	-0.737
HDB	-1.099*	0.569	-1.081**	0.097	0.294	-2.154***
IBN	-1.134	2.210+	-1.667	2.506+	-1.636	2.882*
KEY	-0.011	0.935	0.245	0.874+	0.106	0.272
MTB	0.199	-0.027	0.126	-0.738	0.358	-1.345
PNC	-0.592	-0.428	-0.527	-0.698	-1.558	1.598
RF	0.813	-0.633	0.884	-0.497	0.949	-0.596
RY	-2.037+	3.456**	-2.482*	3.945**	-2.072+	4.308***
STD	-1.778	-1.863+	-1.220	-1.756	-1.888	-1.735

STI	2.713**	-0.361	2.074*	-0.402	2.034+	-0.436
STT	-1.136+	-0.513	-1.951***	-1.292	-4.228***	1.706+
TD	1.664**	-0.289	1.989***	0.095	1.547	1.382
UBS	0.579	0.032	0.149	0.785	-1.114	0.664
USB	-0.878	-1.572+	0.121	0.082	0.468	0.471
WFC	2.870**	-0.800	2.942***	-0.706	3.050***	-0.902
F-joint statistic	4.53 (<.0001)	1.38 (.0443)	2.66 (<.0001)	2.61 (<.0001)	17.98 (<.0001)	8.35 (<.0001)

Notes: 73,630 observations. ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. All specifications included firm specific intercepts and firm specific market returns ("firm FE*market returns", yielding the firm's beta from a CAPM perspective), and firm specific market shocks on other firm. All specifications clustered the standard errors at the day level.

Table A4a. Process-dynamics: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects (Day FE); 2011-2016

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	11.301	11.308	11.694	14.221	14.927	18.751
Ins: ∑ neg coeff	-9.004	-7.626	-9.217	-10.692	-11.375	-18.616
Ins: ∑|coeff|	20.305	18.934	20.911	24.913	26.302	37.367
Bank: ∑ pos coeff	12.742	8.627	12.898	11.316	16.237	13.986
Bank: ∑ neg coeff	-12.923	-8.48	-14.078	-9.602	-19.453	-17.482
Bank: ∑|coeff|	25.665	17.107	26.976	20.918	35.69	31.468

Notes: Cell entries are the respective sums from Table A4.

Appendix B: Garch Results (Day FE Models not estimable for these Garch models)

Table B3. Stock Market *Shifts* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects (Garch)

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.00038*	NC	-0.00054*	NC	-0.00021	NC
AET	-0.00020		0.00012		-0.00003	
AFL	0.00010		0.00041		0.00071+	
ALL	-0.00007		-0.00037*		-0.00037+	
AON	0.00027		0.00008		0.00001	
BRK	0.00015		0.00006		0.00065+	
CB	0.00030		0.00083*		0.00088	
CI	0.000095		0.00012		-0.00014	
CNA	-0.00053		-0.00012		-0.00030	
GNW	0.00039***		0.00032*		0.00013	
HIG	0.000055		0.00010		-0.00009	
HUM	-0.00015		0.00009		-0.00045	
LNC	0.00043		-0.00069		-0.00032	
MFC	0.000029		-0.00040+		-0.00081+	
PFG	-0.00060***		-0.00033*		0.00009	
PGR	-0.00010		-0.00005		-0.00030	
PRE	-0.00019		-0.00023		0.00035	
PRU	0.00043***		0.00024		0.00019	
RE	-0.00011		0.000052		-0.00032	
SLF	-0.00014		-0.00030		-0.00246***	
TRV	-0.00071***		-0.00069**		-0.00120***	
UNH	0.00078***		0.00058**		0.00107**	
UNM	-0.00043**		-0.00032+		-0.00036+	
XL	0.00043**		0.00044**		-0.00067+	
BAC	0.00032**		0.00057***		0.00002	
BAP	0.000053		0.000073		0.00036	
BBT	-0.00001		-0.00043+		0.00112+	
BK	0.00012		0.00029**		0.00023+	
BMO	-0.00003		0.00064***		0.00028	
BNS	-0.00034***		0.00047**		0.00074+	
BSBR	0.000038		-0.00050**		0.00022	
C	-0.00014		0.00022		-7.09E-6	
CM	0.00059***		0.00003		0.00053+	
HBC	-0.00009		-0.00024*		-0.00038*	
HDB	-0.00008		-0.00003		-0.00040	
IBN	0.000021		-0.00012		-2.49E-6	
KEY	-0.00001		-0.00023+		-0.00107***	
MTB	0.000023		-0.00031*		-0.00026+	
PNC	0.000016		0.00026+		0.00077***	
RF	-0.00019+		-0.00044**		-0.00030	
RY	-0.00027**		0.000088		0.00025	
STD	-0.00035**		-0.00023+		-0.00029	
STI	0.00022*		0.00015		0.00043+	
STT	0.00027***		-0.00019+		-0.00061***	

TD	0.000094		0.00013		-0.00045*	
UBS	-0.00019*		0.00018		0.00036	
USB	-0.00053***		-0.00007		-0.00061*	
WFC	0.00012		0.00011		0.00062**	
F-joint statistic	4.61 (<.0001)		2.42 (<.0001)		2.48 (<.0001)	

Notes: ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. Joint F-tests on all the coefficients in each column indicated significance at the <.0001 level, for all specifications. All specifications included firm specific intercepts and firm specific market returns (firm FE*market returns, yielding the firm's beta in a CAPM model), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated as Garch(1,1) processes (on the error terms).

Table B3a. Network Shifts: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	0.003459	NC	0.003442	NC	0.00408	NC
Ins: ∑ neg coeff	-0.00361	NC	-0.00404	NC	-0.00803	NC
Ins: ∑|coeff|	0.007069	NC	0.007482	NC	0.01211	NC
Bank: ∑ pos coeff	0.001885	NC	0.003211	NC	0.00593	NC
Bank: ∑ neg coeff	-0.00223	NC	-0.00279	NC	-0.00437958	NC
Bank: ∑|coeff|	0.004115	NC	0.006001	NC	0.01030958	NC

Notes: Cell entries are the respective sums from Table B3. NC: Not converge

Table B4. Stock Market *Process-dynamics* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects (Garch)

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.036***	NC	-0.037***	NC	-0.038***	NC
Lag2	-0.011***		-0.010***		-0.011***	
Lag3	-0.016***		-0.016***		-0.016***	
ACE	0.479**		0.511*		0.220	
AET	0.384**		0.878***		1.388***	
AFL	0.078		0.207		-0.110	
ALL	0.741		0.787		0.659	
AON	1.002***		0.598		0.232	
BRK	0.585***		0.054		-0.030	
CB	-0.051		0.329		0.233	
CI	0.270		0.565+		0.796+	
CNA	-0.00938		-0.052		-0.217	
GNW	-0.148		0.157		0.373*	
HIG	-0.506**		-0.553*		0.214	
HUM	-0.951***		-0.720***		-0.798**	
LNC	-0.181		-0.428		0.821	
MFC	0.119		-0.042		-0.487**	
PFG	-0.179		-0.390*		-1.523**	
PGR	0.018		-0.068		-0.810**	
PRE	-0.498***		-1.217***		-1.364***	
PRU	0.805*		0.775+		0.740+	
RE	-0.460		-0.357		-0.663	
SLF	-1.487**		-1.429**		-1.400**	
TRV	-0.846***		-0.267		-0.309	
UNH	-0.589***		-0.853***		-0.874***	
UNM	-0.267+		-0.161		-0.267	
XL	-0.294		-0.297		-0.455*	
BAC	-1.008**		-0.876**		-0.959**	
BAP	-0.227***		-1.088***		0.293*	
BBT	-0.252**		-0.609***		-0.837**	
BK	0.378***		0.392**		-0.067	
BMO	0.156		0.087		0.443+	
BNS	0.429***		-1.093***		-1.119**	
BSBR	0.428		0.295		0.376	
C	0.753***		0.963***		-0.017	
CM	-0.618***		-0.046		0.119	
HBC	0.458***		0.105		-0.468***	
HDB	-0.534***		-0.180+		-0.183	
IBN	-0.070		-0.118		-0.111	
KEY	-0.426***		-0.608***		-0.682**	
MTB	0.437***		0.763***		1.121***	
PNC	-0.078		0.166		0.384*	
RF	-1.631***		-1.592***		-1.566***	
RY	-0.916		-1.137+		-1.051	
STD	-0.302		-0.223		-0.426+	
STI	-0.804***		-0.732**		-0.738**	

STT TD UBS USB WFC	-0.190** -0.432*** 0.172** -0.261** 1.308**		-0.631*** -0.062 0.105 -0.125 1.412***		-0.529*** -0.724+ -0.010 -0.360 1.403***3	
F-joint statistic	13.24 (<.0001)		19.39 (<.0001)		11.87 (<.0001)	
Arch1	0.0253***		0.0250***		0.0249***	
Garch1	0.9749***		0.9752***		0.9753***	

Notes: 61,069 observations. ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. Joint F-tests on all the coefficients in each column indicated significance at the <.0001 level, for all specifications. All specifications included firm specific intercepts and firm specific market returns ("firm FE*market returns", yielding the firm's beta from a CAPM perspective), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated as Garch(1,1) processes (on the error terms). We estimated our model using 5 alternative ways of measuring market returns---none of them made any difference for the results, so we present the results with only the VWRETD variable (VWRETD is the Value weighted return with dividends for all CRSP stocks).

Table B4a. Process-dynamics: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	4.481	NC	4.861	NC	5.676	NC
Ins: ∑ neg coeff	-6.46638	NC	-6.834	NC	-9.307	NC
Ins: ∑|coeff|	10.94738	NC	11.695	NC	14.983	NC
Bank: ∑ pos coeff	4.519	NC	4.288	NC	4.139	NC
Bank: ∑ neg coeff	-7.749	NC	-9.12	NC	-9.847	NC
Bank: ∑|coeff|	12.268	NC	13.408	NC	13.986	NC

Notes: Cell entries are the respective sums from Table B4. NC: Not converge

Table B.A3. Stock Market *Shifts* from Firm Shocks: No Day Fixed Effects vs Day Fixed Effects; 2011-2016 (Garch)

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.00021+	NC	-0.00009	NC	0.00060	NC
AET	0.00005		0.00010		0.00034	
AFL	0.00001		-0.00029		0.00008	
ALL	-0.00013		-0.00005		-0.00226***	
AON	0.00024+		0.00009		-0.00024	
BRK	-0.00011		-0.00016		0.00065**	
CB	-0.00001		-0.00034+		-0.00023	
CI	-0.00039***		-0.00060***		-0.00103***	
CNA	-0.00057		-0.00053		-0.00031	
GNW	-0.00028***		-0.00033***		-0.00038**	
HIG	0.00019		0.00029		-0.00002	
HUM	-2.16E-6		0.00007		0.000074	
LNC	0.000020		0.00030		-0.00011	
MFC	0.000037		-0.00013		-0.00061	
PFG	-0.00006		0.00007		-0.00002	
PGR	-0.00005		7.736E-6		-0.00005	
PRE	-0.00015*		-0.00009		-0.00054***	
PRU	-0.00027**		-0.00039**		-0.00047*	
RE	-0.00013		-0.00006		-0.00014	
SLF	0.00027**		0.00009		-0.00015	
TRV	0.00025*		0.00017		0.00011	
UNH	0.000030		-0.00014		-0.00024	
UNM	8.109E-6		0.00011		-0.00045*	
XL	-0.00016+		-4.12E-6		-0.00008	
BAC	0.000083		0.00023**		-0.00045	
BAP	0.000085		0.00040***		0.000058	
BBT	0.00023**		0.00041***		-0.00005	
BK	-0.00017*		-0.00015		0.00066***	
BMO	-0.00025***		-0.00015		0.00046**	
BNS	0.000091		0.00015		0.00101**	
BSBR	0.000069		0.00010+		-0.00007	
C	-0.00012+		-0.00011		-0.00026	
CM	-0.00004		-0.00080***		-0.00080***	
HBC	0.00028***		0.00038***		0.00030**	
HDB	0.00011+		-0.00008		-0.00043*	
IBN	-0.00016***		-0.00012+		0.00043***	
KEY	0.000086		0.00004		-0.00004	
MTB	0.000081		-0.00005		0.00044**	
PNC	0.000086		0.00007		-0.00030	
RF	-0.00031***		-0.00019		-0.00037	
RY	0.00040***		0.00004		-0.00037	
STD	-0.00030***		-0.00010		0.00105***	
STI	-0.00049***		-0.00044***		0.00088***	
STT	0.00042***		0.00065***		0.00105***	
TD	-0.00059***		-0.00043***		-0.00074***	
UBS	-8.32E-6		7.9997E-6		-0.00003	

USB	0.00047***		-8.296E-6		0.00066+	
WFC	0.00012		0.00050***		0.00026	
Joint F-statistic	5.10 (<.0001)		4.48 (<.0001)		143.54 (<.0001)	

Notes: ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. All specifications included firm specific intercepts and firm specific market returns (firm FE*market returns, yielding the firm's beta in a CAPM model), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated as Garch(1,1) processes (on the error terms).

Table B.A3a. Network Shifts: Aggregated Coefficients, No Day Fixed Effects vs Day Fixed Effects

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	0.0011051	NC	0.00129774	NC	0.001854	NC
Ins: ∑ neg coeff	-0.002522	NC	-0.0032041	NC	-0.00733	NC
Ins: ∑|coeff|	0.0036273	NC	0.00450186	NC	0.009184	NC
Bank: ∑ pos coeff	0.002611	NC	0.002978	NC	0.007258	NC
Bank: ∑ neg coeff	-0.002438	NC	-0.0026283	NC	-0.00391	NC
Bank: ∑|coeff|	0.0050493	NC	0.0056063	NC	0.011168	NC

Notes: Cell entries are the respective sums from Table B.A3. NC: Not converge

Table B.A4. Stock Market *Process-dynamics* from Financial Shocks:; 2011-2016

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.00898***	NC	-0.0106***	NC	-0.0108***	NC
Lag2	-0.00029		0.00050		-0.00117	
Lag3	-0.00814***		-0.00873***		-0.0114***	
ACE	0.886+		0.500		0.269	
AET	0.238		-0.848+		-0.517	
AFL	1.479_		0.739		1.753+	
ALL	4.104*		4.071*		3.892*	
AON	-0.299		-0.521		0.140	
BRK	-0.846+		0.342		-0.276	
CB	-2.138**		-1.119		-0.163	
CI	0.090		0.025		-1.372	
CNA	1.734		1.689		0.043	
GNW	-0.187		-0.336		0.051	
HIG	1.095**		-0.229		-0.079	
HUM	-0.284		-0.347		-0.744	
LNC	-1.721+		-2.039+		-1.452	
MFC	-1.215**		-1.261+		-2.685+	
PFG	-0.537+		-1.585		-0.728	
PGR	-0.706		-0.523		-0.273	
PRE	-0.301		-0.155		0.672	
PRU	-0.193		-0.029		-0.740	
RE	3.758*		3.825*		4.069***	
SLF	0.478		-0.112		-1.122	
TRV	0.979		1.772+		0.888	
UNH	0.418*		0.268		-1.692***	
UNM	0.311		1.139		1.869	
XL	1.359		1.530		0.482	
BAC	-0.617		-0.687		-0.642	
BAP	-0.279		0.221		-0.562	
BBT	1.285***		0.161		1.463**	
BK	0.037		0.803**		3.025***	
BMO	-0.174		1.434***		-3.267***	
BNS	-0.019		-2.174***		9.291***	
BSBR	-0.499		-0.886+		-1.232**	
C	0.987***		-0.557+		0.356	
CM	1.275***		2.426***		3.527***	
HBC	-0.165		-0.672**		0.314+	
HDB	-0.677***		-0.786**		0.235	
IBN	-0.148		-0.525		-0.662+	
KEY	-0.127		0.505		-0.640	
MTB	0.939***		-0.071		-1.034+	
PNC	-1.208***		-0.968***		-1.019	
RF	1.958**		2.118**		1.756***	
RY	-3.184+		-3.488+		-3.202+	
STD	-2.293***		-2.814***		-2.992***	
STI	3.054***		2.807**		1.955*	
STT	-0.936***		-2.436***		-3.158***	

TD UBS USB WFC	0.780** -0.058 -1.620*** 2.170		2.856*** 0.156 0.894* 2.569		1.670** -0.214 0.790 1.166	
F-joint statistic	4.36 (<.0001)		6.36 (<.0001)		9.36 (<.0001)	
Arch0	5.67E-6***		5.72E-6***		2.59E-6***	
Arch1	0.0750***		0.0737***		0.0442***	
Garch1	0.8935***		0.8947***		0.9415***	

Notes: 73,630 observations. ***=significant at 1% level, **=significant at 5% level, *=significant at 10% level, +=significant at 20% level. All specifications included firm specific intercepts and firm specific market returns ("firm FE*market returns", yielding the firm's beta from a CAPM perspective), and firm specific market shocks on other firms (whose coefficients are included in the next table). All specifications were estimated as Garch(1,1) processes (on the error terms).We estimated our model using 5 alternative ways of measuring market returns---none of them made any difference for the results, so we present the results with only the VWRETD variable (VWRETD is the Value weighted return with dividends for all CRSP stocks).

Table B.A4a. Network Shifts: Aggregated Coefficients, With and Without Controls for Trends (Day FE)

	2 Std. Dev. Shocks		3 Std. Dev. Shocks		4 Std. Dev. Shocks	
	No Day FE	Day FE	No Day FE	Day FE	No Day FE	Day FE
Ins: ∑ pos coeff	16.929	NC	15.90	NC	14.128	NC
Ins: ∑ neg coeff	-8.427	NC	-9.104	NC	-11.843	NC
Ins: ∑|coeff|	25.356	NC	25.004	NC	25.971	NC
Bank: ∑ pos coeff	12.485	NC	16.95	NC	25.548	NC
Bank: ∑ neg coeff	-12.004	NC	-16.064	NC	-18.624	NC
Bank: ∑|coeff|	24.489	NC	33.014	NC	44.172	NC

Notes: Cell entries are the respective sums from Table B.A4. NC: Not converge