Systemic Network Risk in a Generalized Event Study (GES) Model

Richard J. Butler
Brigham Young University and University of Arizona
richard_butler@byu.edu

Craig Merrill
Brigham Young University
craig_merrill@byu.edu

Gene Lai
Washington State University
genelai@wsu.edu

Abstract: We merge the event studies framework with network effects framework, viewing our framework as a rough analogue to error correction models (for cointegrated time series). We call our model the Generalized Event Study (GES) framework which adds to standard event studies an autoregressive process in the returns regression, and then measures—as network events—large standard deviation (SD) shocks in the daily returns of the individual banks and insurers. This study focuses on interconnected financial activity in a network equilibrium instead of cointegrated regressors moving together over time. We estimate the model on 2006-2010 market data for the 25 largest publicly-traded insurers and 25 largest publicly-traded banks. The impact of SD shocks on daily returns is estimated both as shifts in the intercept, and as a rescaling of the autoregressive process, which adjustments indicate system stability. We label these later, adjustment speeds as the 'process-dynamics' of the returns. We find stability in the network overall. Bank return-shocks have a larger impact on the generation of potential network instability than insurer return-shocks, which differential only increases when restricting the estimates to systemic risk (rather than overall risk, which includes both common temporal-shock risk and systemic risk). We also find systemic risk is much more important during our sample period than common temporal-shock risk (hereafter, simply temporal risk).

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I. Introduction

This paper models how heterogeneous, but interconnected financial firms move towards network equilibrium. We use the 25 largest publicly-traded insurers and the 25 largest publicly-traded banks both to illustrate our model and to examine equilibrium shifts during the financial crisis of 2007-2009. Our model, and the application here, provides a useful framework for analyzing systemic risk.

There are different definitions of systemic risk. 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. Inasmuch as our model estimates empirical pathways through which stability is maintained, our model addresses this type of systemic risk. Our sample lies at the heart of systemic risk concerns, as many equate systemic risk to behavior of banks, while others equate systemic risk to insurers.

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. We would like to provide additional insight about the role of the insurance industry in systemic risk.

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. Billio et al. (2012), in an excellent review of the emerging literature, identify three measures recently developed in the finance literature to estimate the linkages among financial institutions. Billio's 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 network 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, the importance of their Granger-casualty tests.

Like Billio et al. (2012), this study focuses on the linkages between the banking industry and the insurance industry. We expand the event-study framework to networks in developing our generalized event study framework (GES), identifying causal relationships with fixed effects and a reasonable exclusion restriction. Hence, the GES is a multidimensional alternative to the measures of network linkages given above. Instead of examining the impact of specific 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, which adjustments indicate system stability. We label these later autoregressive adjustments due to financial 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 four findings are readily summarized. 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 insurance shocks. However, 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 (rather than overall risk, which includes both common temporal risk and systemic risk). Finally, we also find systemic risk is much more important during our sample periods (2006-2010, and also for 2011-2016) than common temporal risk.

Our study differs from the literature in several aspects. First, our framework can be viewed as a rough analogue to error correction models (for cointegrated time series), but this empirical study focuses on networks of interconnected financial activity in a network equilibrium instead of cointegrated regressors moving together over time. Second, while Billio et al. examine the impact of returns of one financial institution (e.g., banking) on other financial institutions (e.g., insurance companies, hedge funds and broker/dealers), our paper investigates the impact of shocks (volatility) of returns of banks/insurers on other banks/insurers. Volatility of returns are important because volatility is the number one concern of investors other than returns.

II. General 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):

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

In this study, 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 t-statistics 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 value relative to the last 4 weeks (other variable lengths for the standard deviation model: 10 days, or 30 days, had no impact on the results and so 20 was chosen as a sensible period in which to establish a baseline trend), 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).

SD3—same for 3-standard deviation jumps.

SD4—same 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. This assumes that the market reveals information on each firm's outlier-returns to every other firm in the network, and all firms have a sense of what is 'unusual' to each firm, and what is not. This is both a sensible measure of what is 'usual' in a financial network with 'perfect' information of past network outcomes, and it 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 relatively random. (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 equilibrium daily returns in one of two ways--either via overall network one-time adjustment to returns ($\sum_k \alpha_{k \neq i} SD_k$), and/or as changes in the autoregressive process-dynamics ($\sum_k \pi_{k \neq i} SD_k (\sum_{j=1}^{J} \theta_j r_{i,t-j})$) – as given in equation 2 below:

$$2)\ r_{i,t} = \gamma_{0,i} + \gamma_{1,i} R_t + \sum_{j=1}^{J} \theta_j r_{i,t-j} + \sum_k \alpha_{k \neq i} SD_{k,t-1} + \sum_k \pi_{k \neq i} SD_{k,t-1} (\sum_{j=1}^{J} \theta_j r_{i,t-j}) + \mu_{i,t}$$

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 jumps (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 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 in network equilibrium, 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 regular 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 equilibrium 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 equilibrium relative to a static-baseline shock, there will be an approximately equal number of complement and substitute responses to shifts 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" equilibrium.

The extensive margin of complementarity in Hypothesis 1a is a good measure of tendency to the baseline static-equilibrium 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-equilibrium:

Hypothesis 1b, intensive margin: For short-term equilibrium 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 equilibrium, 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.[1] Our empirical speed of adjustment results of three lagged days squares 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," consistent with the empirical results of Damodaran (1993), Patell and Wolfson (1984), and Hasbrouck and Lo (1987).

Hence, the term next to far right hand term in Equation 2 ($\sum_k \pi_{k\neq i} SD_{k,t-1}(\sum_{j=1}^{J} \theta_j r_{i,t-j})$) represents how shocks affect the stability of dynamic process—that is, how quickly, if at all, the network returns towards its original equilibrium 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 equilibrium, given a shock for firm k. Otherwise, the degree of shifting towards equilibrium

[1] 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.

depends on the value of the SD shock. If $\pi > 0$, then the return to the equilibrium 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 equilibrium doubles as follows:

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

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

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

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 equilibrium is slowed down.

Going further, if $\pi < -(\frac{1}{SD})$, then the return-to-mean process becomes destabilizing relative to the initial equilibrium 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 equilibrium 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 equilibrium. Rather, they are moving towards a new equilibrium 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 equilibrium 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 equilibrium 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 equilibrium.

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 equilibrium 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.

Systemic Risk Combined with Temporal Risk vs. Systemic Risk without Temporal Risk

So far, we have said nothing about whether these adjustment mechanisms are for systemic risk or for temporal risk (some denote temporal risk as "systematic risk"). They can be both. To help differentiate the two types of risk, we employ an exclusion restriction: that a SD jump for firm *k* potentially affects all other firms (other firms are surprised by the SD shock the next day), but does not have a feedback effect on firm *k* itself (firm *k* knows that it had a SD yesterday, and is not surprised by its existence today).

We examine results without day fixed effects (these results will reflect both systemic with temporal risk), and results with day fixed effects eliminating temporal risk and leaving systemic risk only. Comparing the coefficients of the two alternative models allows us to discern something about the relative importance of each type of risk, given our model-specific definitions.

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

Hypothesis 3. We hypothesize that systemic risk remains, even after controlling for daily FEs (i.e., controlling for temporal or systematic risk).

III. Descriptive Statistics

The returns and shocks in Table 1 summarize, in board terms, trends in the data. The small average returns in 2006 and 2007 (just a daily return on insurance stock values of .0004; significantly higher for banks during these years), declined in 2008 for both banks and insurers and then rebounded in 2009 and 2010. The spread in the returns was greatest for these firms in 2008, mirroring more general market responses.

Standard Deviation (SD) Shocks

Table 2 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, while insurers shocks are (in the sense of spread) highest for 2006 relative to latter years (note the standard deviations of shocks are highest for either financial group in the first three years of our sample).

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.[2] Likewise, when 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.

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

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). Indeed, 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 systematically 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. Results of Generalized Event Study Framework: Estimated Network Shifts and Process-dynamics

Estimation

Equation 2 is nonlinear in its parameters, given the second term from the right, so 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 the second term from right-hand side 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 estimated initially employ a Garch model, and the autoregressive process θ_j in the fourth term from the right hand side 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 fourth term from the right hand side for θ_j, were fixed as values for θ_j in the second term from the right hand side, 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 models Garch models employing either STATA or SAS software). So the estimated Garch models (appendix Tables B3 and B4) could not differentiate systematic from temporal risk for our model in Equation 2. Hence Tables 3 and 4 where estimated with standard errors clustered by day—specifications employed along with Garch models to estimate financial 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 will be 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 equilibrium, 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).

The sums of coefficients in Table 3a, with addition across individual firm responses both by coefficient sign and financial institution type, suggest total network shift effects that are c*ollectively* (for our sample of 50 firms) only a magnitude larger than the average returns for *individual* daily returns (i.e., compare the accumulated values in Table 3a, about .01 for SD2 and SD3 shocks, with the means in Table 1, .001 for banks in 2006 and 2010). 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). 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), our static-baseline equilibrium model (Hypothesis 1a), the absolute value of positive shifts should roughly balance the absolute value of negative shifts. Each firm is equally likely to present a standard deviation shift in any period. These "intercept" shifts due to shocks are measured as the coefficients included in the third term to the right of the equal sign 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), 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 the same equalities for SD3 and SD4 shifts as well. This supports Hypothesis 1a, the static-baseline equilibrium, when *temporal risk is not separated from systemic risk*, as is the case in the No Day FEs results.

Results with the day FEs in the model removes the temporal risk component, leaving only the systemic risk component of network shifts. This helps distinguish results between banks and insurance in terms of systemic risk without temporal 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 temporal 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 temporal 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 equilibrium adjustments (.0128) are only slightly higher than insurance 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).

Hence, Table 3 estimates, and the resulting derivations in 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 banking and insurer sectors as well (Tables 3 and 3a). This supports hypothesis 1a. (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 that includes systemic with temporal risk) with the day fixed-effect results (on the right hand side that controls for temporal risk, so only records the systemic risk response). Overall, they describe a financial network that returns to equilibrium 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, indicates a network generally returning to equilibrium, after controlling for basic CAPM response of returns following the common market average. So after allowing for this market-average response, 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, SD2 coefficients are very similar to SD3 process shock coefficients which in turn are very similar to SD4 process shocks. Second, regression to the mean (via the autoregressive structure) is stronger holding temporal risk constant: for the SD2 shifts, -.0389, -.0137, and -.0333 yields a stronger regression to the mean than -.0213, .0021, and -.0316. Hence, it cannot be temporal 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 $\pi < -(\frac{1}{SD})$. Note that there are many other firms, in both sectors, estimated to have large negative process dynamic effects but are not statistically significant.

Hence, a summary of the network dynamic process effects tabulates 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 summed the intensive margin of the results in Table 3. If all of the positive insurance 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 equilibrium 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 insurance 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 temporal 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 temporal 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 temporal) 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 temporal risk. Moreover, we find that systemic risk is much more important than temporal 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 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 IBES. 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. Moreover, the day fixed effects regression also controls for temporal changes in regulatory pressures common to all firms in our network.

Table 5 reports the results containing 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 temporal risk (via day FEs).

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). 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

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 appendix Table A2: 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, a period of relative financial stability after the financial storms of 2006-2010, we re-estimate our clustered standard error models for the later period with the results given in Tables 6 and 7 (Garch models without day FEs in appendix Tables B6 and B7). 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 equilibrium, 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 temporal 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 6 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 equilibrium tendencies somewhat. Like the 2006-2010 sample, the 2011-2016 static-baseline equilibrium 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 6a 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 in absolute value than the sum of all negative coefficient, 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≈ .0043 + .0032) such that that overall effect is close to zero. This is partial, weak support for Hypothesis 4a.

Comparing Table 6a 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 temporal risk in network shifts is at least as important in Table 6a as they were in Table 3a, but the relation is reversed. Insurers, for all types of shocks, the results show that systemic risk without controlling for temporal risk is now larger than systemic risk controlling for temporal (temporal risk in 2011-2016, apparently offsets part of the systemic risk). For insurers, for example, .0043 (systemic risk cumulative network response controlling for temporal risk) > .0036 (temporal and systemic cumulative network response). This supports hypothesis 4b. Moreover, holding temporal 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 7a (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 2011 (tables 3a vs. 6a), *process dynamics* continues to be important (the sums in 7a are larger than the sums in Table 4a). Table 7a are effects are larger in part because of the mechanical effect of a diminished autoregressive process, so that larger coefficients in 7a 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 financial activity in a network equilibrium. We estimate the model on 2006-2010 market data for the 25 largest publicly-traded insurers and 25 largest publicly-traded banks. Specifically, our paper develops new methodological tools that offer insight into the explicit nature of systemic network risk in the first investigation of the impact of shocks (volatility) of returns of banks on insurance companies and vice versa. Volatility of returns are important because volatility is the number one concern of investor other than returns.

We summarize our findings below. First, 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. 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 insurance shocks for the turmoil of 2006-2010, but the pattern is not so clear cut for calm that followed. But through both periods, and across all specifications, we find systemic risk is much more important during these periods than common temporal-shock risk.

Results from the 2011 to 2016 varied somewhat from the 2006-2010 results: the network shifts still suggest a static-baseline equilibrium 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 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. Temporal 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, 2005; 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, which also control for *current* temporal risk as well. Hence, the identification of systemic risk and the control for lead shocks both accomplished by the daily FEs specification. Interestingly, daily FEs (and hence, controlling for temporal 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 insurance companies, 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.

References

Ball R. and S. P. Kothari, 1991, Security Returns around Earnings Announcements, The accounting review, 66, 4, PP. 718 -738.

Baluch, Faisal, Stanley Mutenga, and Chris Parsons, 2011, “Insurance, Systemic Risk, and the Financial Crisis,” The Geneva Papers 36: 126-163.

Bell, Marian and Benno Keller, 2009, Insurance and Stability: The Reform of Insurance Regulation (Zurich, Switzerland: Zurich Financial Services Group).

Bilio, M, M. Getmansky, A.W. Lo, L. Pelizzon (2012), Market Institutions, Financial Market Risks and Financial Crisis, Journal of Financial Economics, Volume 104, Issue 3, June 2012, Pages 535–559

Chen, H., J.D. Cummins, K.S. Viswanathan, M.A. Weiss (2014), Systemic Risk and the Interconnectedness Between Banks and Insurers: An Econometric Analysis, Journal of Risk and Insurance, Volume 81, Issue 3 September 2014, pp. 623–652.

Cummins, J D, C.M. Lewis, R. Wei (2006), The market value impact of operational loss events for US banks and insurers, Journal of Money and Banking, Volume 30, Issue 10, October 2006, Pages 2605–2634.

Cummins, J. David and Mary A. Weiss, 2014, “Systemic Risk and Regulation of the U.S. Insurance Industry,” in John H. Biggs and Matthew Richardson,eds., Modernizing Insurance Regulation (New York: John Wiley).

Damodaran, A., 1993, “A Simple Model of Price Adjustment Coefficients”, Journal of Finance, v 48, no. 1, pp. 387-400.

Gottardo, Pietro, 2011, “Speed of Adjustment and Infraday/Intraday Volatility in the Italian Stock and Futures Market”, Modern Economy, v 2, pp. 735-742.

Grace, Martin F., 2010, “The Insurance Industry and Systemic Risk: Evidence and Discussion,” working paper, Georgia State University, Atlanta, GA.

Group of Thirty, 2006. Reinsurance and International Financial Markets (Washington, D.C.).

Harrington, Scott E., 2009, “The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation,” The Journal of Risk and Insurance 76 (4): 785-819.

Hasbrouck, J. and T. Ho, 1987, “Order Arrival, Quote Behavior, and the Return-Generating Process,” Journal of Finance, v 42, no. 4, pp. 1035-1049.

Hamilton, James D. (1994). "Difference Equations". Time Series Analysis. Princeton University Press.

Lo, Andrew W. (2004) "The adaptive markets hypothesis." The Journal of Portfolio Management 30.5 :15-29.

Lo, Andrew W. (2005). "Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis."

Lütkepohl, Helmut (2008). "Impulse response function". The New Palgrave Dictionary of Economics (2nd ed.).

Merrill, Craig B., Taylor D. Nadauld, and Philip E. Strahan, 2014, “Final Demand for Structured Finance Securities,” working paper, Brigham Young University, Provo, Utah, USA.

Patell, J. M. and M. A. Wolfson, 1984, "The Intraday Speed of Price Adjustment of Stock Prices to Earnings and Dividend Announcements," Journal of Financial Economics, v. 13, no. 2, pp 223-252.

Swiss Re, 2001, Reinsurance – A Systemic Risk? Sigma No. 5/2003 (Zurich, Switzerland).

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 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.
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

	SD2 shocks				SD3 Shocks				SD4 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 Financial Shocks: Systemic vs Temporal risk (Clusterd SEs)

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand 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 leve., using l.

Table 3a. 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	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 Financial Shocks: Systemic vs Temporal risk

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand 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, 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	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 Equilibrium 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	0.0369**	0.0472***	0.0392**	0.0465***	0.0423***	0.0491***
Volume	0.0176**	0.0145*	0.0171**	0.0139*	0.0175**	0.0141*
Analysts	-0.0001	-0.0000	-0.0001	-0.0000	-0.0001	-0.0000
Value*Process Dynamics	-0.9485+	-0.4030+	-2.7870**	-1.3074***	-3.0247	-1.3099*
Volume*Process Dynamics	0.0317	0.0338	-0.3603	-0.1585	-1.3001*	-0.7047***
Analysts*Process 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 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).

Table 6. Stock Market *Shifts* from Firm Financial Shocks: Systemic vs Temporal risk; 2011-2016, Clustered SEs

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand 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 2011-2017 daily returns, N=73,630 observations).

Table 6a. Network Shifts: Aggregated Coefficients, With and Without Controls for Trends (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	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 6.

Table 7. Stock Market *Process-dynamics*: Systemic vs Temporal risk; 2011-2016 using clustered SEs

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand 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 7a. Process-dynamics: Aggregated Coefficients, With and Without Controls for Trends (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 7.

Appendix A: Standard Deviation Jumps in 2011-2016

Table A2: 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.
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 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.
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

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

Table B3. Stock Market *Shifts* from Firm Financial Shocks: Systemic vs Temporal risk (Garch)

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand Dev Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.00038*		-0.00054*		-0.00021	
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, 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	0.003459		0.003442		0.00408	
Ins: ∑ neg coeff	-0.00361		-0.00404		-0.00803	
Ins: ∑|coeff|	0.007069		0.007482		0.01211	
Bank: ∑ pos coeff	0.001885		0.003211		0.00593	
Bank: ∑ neg coeff	-0.00223		-0.00279		-0.00437958	
Bank: ∑|coeff|	0.004115		0.006001		0.01030958	

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

Table B4. Stock Market *Process-dynamics* from Firm Financial Shocks: Systemic vs Temporal risk (Garch)

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand Dev Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.036***		-0.037***		-0.038***	
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	-0.190**		-0.631***		-0.529***	
TD	-0.432***		-0.062		-0.724+	
UBS	0.172**		0.105		-0.010	
USB	-0.261**		-0.125		-0.360	
WFC	1.308**		1.412***		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, 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	4.481		4.861		5.676	
Ins: ∑ neg coeff	-6.46638		-6.834		-9.307	
Ins: ∑|coeff|	10.94738		11.695		14.983	
Bank: ∑ pos coeff	4.519		4.288		4.139	
Bank: ∑ neg coeff	-7.749		-9.12		-9.847	
Bank: ∑|coeff|	12.268		13.408		13.986	

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

Table B6. Stock Market *Shifts* from Firm Financial Shocks: Systemic vs Temporal risk; 2011-2016 (GArch)

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand Dev Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
ACE	-0.00021+		-0.00009		0.00060	
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 B6a. 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	0.0011051		0.00129774		0.001854	
Ins: ∑ neg coeff	-0.002522		-0.0032041		-0.00733	
Ins: ∑|coeff|	0.0036273		0.00450186		0.009184	
Bank: ∑ pos coeff	0.002611		0.002978		0.007258	
Bank: ∑ neg coeff	-0.002438		-0.0026283		-0.00391	
Bank: ∑|coeff|	0.0050493		0.0056063		0.011168	

Notes: Cell entries are the respective sums from Table B6.

Table B7. Stock Market *Process-dynamics* from Firm Financial Shocks: Systemic vs Temporal risk; 2011-2016

	2 Stand Dev Shocks		3 Stand Dev Shocks		4 Stand Dev Shocks	
	No day FE	Day FE	No day FE	Day FE	No day FE	Day FE
Lag1	-0.00898***		-0.0106***		-0.0108***	
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	0.780**		2.856***		1.670**	
UBS	-0.058		0.156		-0.214	
USB	-1.620***		0.894*		0.790	
WFC	2.170		2.569		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 B7a. 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		15.90		14.128	
Ins: ∑ neg coeff	-8.427		-9.104		-11.843	
Ins: ∑|coeff|	25.356		25.004		25.971	
Bank: ∑ pos coeff	12.485		16.95		25.548	
Bank: ∑ neg coeff	-12.004		-16.064		-18.624	
Bank: ∑|coeff|	24.489		33.014		44.172	

Notes: Cell entries are the respective sums from Table B7.