Tackling the Volatility Paradox: Spillover Persistence and Systemic Risk *

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This version: June 3, 2024.

Abstract

Financial losses can have persistent effects on the financial system. This paper proposes an empirical measure for the duration of these effects, Spillover Persistence. I document that Spillover Persistence is strongly correlated with financial conditions; during banking crises, Spillover Persistence is higher, whereas in the run-up phase of stock market bubbles it is lower. Lower Spillover Persistence also associates with a more fragile system, e.g., a higher probability of future crises, consistent with the volatility paradox. The results emphasize the dynamics of loss spillovers as an important dimension of systemic risk and financial constraints as a key determinant of persistence.

Keywords: Systemic Risk, Fragility, Financial Crises, Asset Price Bubbles, Fire Sales.

*This paper supersedes what used to be an initial idea first formulated with Helmut Gründl in the previously circulating drafts "Systemic Risk: Time-Lags and Persistence" and "How persistent are equity shock spillovers?". I thank Helmut for many fruitful conversations at these early stages. I also thank Oliver Boguth, Lauren Cohen, Jean-Edouard Colliard, Hans Degryse, Johanna Eckert, Rob Engle, Till Förstemann, Mila Getmansky Sherman, Paolo Giudici, Robin Greenwood, Michael Hasler, Tobias Herbst, Ralph Koijen, Michael Kötter, Wolfgang Kürsten, Matt Linn, Mei Li, Andrea Modena, Johanna Mühlnickel, Felix Noth, Martin Oehmke, Lasse H. Pedersen, Loriana Pelizzon, Diane Pierret, Peter Raupach, Oliver Rehbein, Simon Rother, Farzad Saidi, Christian Schlag, Isabel Schnabel, Sascha Steffen, Quentin Vandeweyer, Laura Veldkamp, Ge Wu, Haoxiang Zhu, and participants at the 2021 Eastern Finance Association meeting, 6th IWH FIN-FIRE Workshop, 7th Bonn Research Workshop in Financial Economics, 2017 AFA meeting, 2016 ICIR-SAFE Systemic Risk Workshop, 2016 DGF meeting, 2016 ARIA meeting, 2016 Huebner Doctoral Colloquium, and at seminars at University of Bonn, Deutsche Bundesbank, Goethe-University Frankfurt, Isenberg School of Management, MIT Sloan, University of Guelph, University of Jena, and St. John's University for helpful comments. I thank Markus Brunnermeier, Simon Rother, and Isabel Schnabel for sharing their data on asset price bubbles. I gratefully acknowledge financial support from the International Center for Insurance Regulation (ICIR) at Goethe-University Frankfurt, from the research cluster ECONtribute, funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1 – 390838866, and from the German Insurance Science Association (DVfVW). The views expressed in this paper are the author's and do not necessarily reflect those of the European Central Bank or the Eurosystem. Send correspondence to: Christian Kubitza, European Central Bank, Directorate General Research, Sonnemannstr. 20, 60314 Frankfurt (Main), Germany; +49 69 13444199.

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Abstract

Financial losses can have persistent effects on the financial system. This paper proposes an empirical measure for the duration of these effects, Spillover Persistence. I document that Spillover Persistence is strongly correlated with financial conditions; during banking crises, Spillover Persistence is higher, whereas in the run-up phase of stock market bubbles it is lower. Lower Spillover Persistence also associates with a more fragile system, e.g., a higher probability of future crises, consistent with the volatility paradox. The results emphasize the dynamics of loss spillovers as an important dimension of systemic risk and financial constraints as a key determinant of persistence.

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1 Introduction

Modern macro-finance models consider the presence of financial frictions. In such models, adverse shocks tighten agents' balance sheet constraints and, therefore, make them less willing or able to hold assets, e.g., resulting in fire sales. This depresses asset prices further, amplifying the initial shocks. Because it takes time for agents' balance sheets to recover from large shocks, such shocks have persistent effects. Conversely, in environments with loose financial constraints, agents are better capable of absorbing shocks, which mitigates amplification effects. At the same time, loose constraints motivate agents to take more risk, e.g., by increasing leverage, and, therefore, the financial system becomes more fragile, i.e., the probability of future crises increases.

Motivated by these dynamics, I propose a novel empirical measure for the persistent effects of large losses within the financial system, called *Spillover Persistence*. Spillover Persistence is the duration over which risk in the financial system remains elevated following a financial institution's initial loss. The measure is, thus, related to the recovery period of balance sheets after large losses. Underscoring this linkage to macro-finance models, I document that fluctuations in Spillover Persistence reflect the amplification and fragility dynamics described above, focusing on three key questions: (1) Does Spillover Persistence capture variation in financial constraints and the resulting amplification effects? (2) Is Spillover Persistence related to fragility of the financial system? (3) Does Spillover Persistence reflect new information relative to traditional measures of systemic risk?

The existing literature has emphasized the persistent effects of financial crises. For example, He and Krishnamurthy (2013) document that bond market spreads took about six months to halve from their 2007-08-financial-crisis–peak levels to pre-crisis levels. This paper examines the persistent effects of losses at a more granular level. To that end, I compute Spillover Persistence at the firm-by-year level. Exploiting this rich variation, I shed light on its determinants and relationship with amplification and fragility dynamics.

Spillover Persistence is defined as the systemic-risk–weighted average time-lag between initial losses of an individual financial institution and subsequent losses of the financial system. Systemic risk measures, such as ΔCoVaR (Adrian and Brunnermeier, 2016) and Marginal Expected Shortfall (MES; Acharya et al., 2017), are typically based on equity return losses and, thus, are readily available for every listed firm and with a long time series.[1] For a given systemic risk measure M^I_τ, Spillover Persistence is computed in two steps. First, M^I_τ is used to measure the tail correlation between a financial institution's initial losses and subsequent losses of the financial system at different time-lags τ. Second, Spillover Persistence is the systemic-risk–weighted average time-lag τ, similarly to the Macaulay duration:

$$\text{Spillover Persistence} = \frac{\int_{\tau=1}^{\tau^{\max}} \tau \, M^I_\tau \; d\tau}{\int_{\tau=1}^{\tau^{\max}} M^I_\tau \; d\tau}. \tag{1}$$

Therefore, Spillover Persistence measures persistence in the financial system's response to an institution's initial losses: it is larger when an institution's losses are followed by elevated risk in the system over a longer time period.

Various systemic risk measures M^I_τ can be used to compute Spillover Persistence in

[1] A possible concern is that Spillover Persistence picks up stock market illiquidity instead of loss spillover dynamics. I address this concern by excluding firms with illiquid stocks (e.g., small firms) and documenting that Spillover Persistence does not positively correlate with measures for stock market illiquidity. I also remove predictable variation from equity returns and show that all baseline results continue to hold.

Equation (1). Traditional systemic risk measures mechanically respond to changes in stock market volatility (Adrian and Brunnermeier, 2016; Acharya et al., 2017; Benoit et al., 2017). On the one hand, amplification dynamics are closely linked to volatility: weaker amplification effects correspond with lower volatility, yet simultaneously engender the build-up of fragility–a phenomenon known as the *volatility paradox* (Brunnermeier and Sannikov, 2014). On the other hand, fluctuations in volatility also mirror macroeconomic characteristics other than financial conditions, such as economic uncertainty (Baker et al., 2016) and industry growth (Engle et al., 2013). This interplay complicates the disentanglement of amplification dynamics within the financial system. It is, thus, desirable that a measure for Spillover Persistence does *not* mechanically respond to volatility. Therefore, I introduce a new systemic risk measure, the Excess Conditional Shortfall Probability (ΔCoSP), which does neither mechanically respond to a financial institution's nor the system's volatility:

$$\Delta \mathrm{CoSP}_{\tau}^{I} = \mathbb{P}\left(-r_{t+\tau}^{S} \geq VaR^{S}(q) \mid -r_{t}^{I} \geq VaR^{I}(q)\right) - q. \tag{2}$$

$\Delta \mathrm{CoSP}_{\tau}^{I}$ is the probability that losses of the system exceed their Value-at-Risk ($VaR^{S}(q)$) τ days after large losses of institution I, compared to an average day. This measure is closely related to ΔCoVaR, with the main difference that it is defined as the *probability* of large losses instead of their Value-at-Risk, and, hence, does not *mechanically* increase with volatility. As a result, Spillover Persistence based on ΔCoSP exhibits a much lower correlation with stock market volatility (13%) than if it is based on ΔCoVaR (33%) or MES (44%).

I compute Spillover Persistence based on $\Delta \mathrm{CoSP}_{\tau}^{I}$ for an international sample of more than 1,000 financial institutions, covering commercial banks, broker-dealers, insurers, and real estate firms from more than 25 countries from 1985 to 2017. The average Spillover Persistence is one month, which means that large losses of an average institution are followed by an increase in the system's risk for about one month. Spillover Persistence substantially differs from existing systemic risk measures. For example, its correlation with ΔCoVaR is small (less than 10%) and variation in ΔCoVaR explains only 1% of the variation in Spillover Persistence. Thus, Spillover Persistence captures a novel dimension of systemic risk.

In the first part of the main empirical analysis, I provide evidence that Spillover Persistence positively correlates with tighter financial conditions. A 1 standard deviation increase in the Chicago Fed's National Financial Conditions Index (NFCI) is associated with an increase in Spillover Persistence by 0.28 standard deviations. Spillover Persistence is also larger during banking crises, namely approximately 2 days in the U.S. (and 4.6 days in the full sample of countries), and it significantly increases with larger bond credit spreads and lower credit growth.

An important amplification mechanism is the forced selling of assets ("fire sales"), which depresses asset prices and, thereby, constrains other agents (Shleifer and Vishny, 1992; Brunnermeier and Pedersen, 2009). Thus, fire sales tighten financial conditions and, therefore, might raise Spillover Persistence. To examine this hypothesis, I exploit hurricane Katrina, which made landfall in August 2005, as an exogenous shock to the liquidity of U.S. insurers exposed to the hurricane. Exposed insurers were forced to sell large volumes of their asset holdings to pay hurricane-related insurance claims. Consistent with the hypothesis, Spillover Persistence is significantly larger after the hurricane for exposed relative to unexposed insurers. This result emphasizes the role of tight financial conditions, propagated to the financial system through fire sales, as a determinant of Spillover Persistence.

Financial conditions are typically loose during the boom phase of asset price bubbles (Borio and Lowe, 2002; Brunnermeier and Oehmke, 2013; Brunnermeier et al., 2020). I test whether Spillover Persistence captures such loose financial conditions by focusing on a large set of stock market bubbles. The results show that Spillover Persistence is significantly lower during boom episodes. During an average bubble boom, Spillover Persistence increases and is larger around the bubble's burst than during the early run-up phase, emphasizing the important role of financial conditions.

In the second part of the main empirical analysis, I investigate whether fragility in the financial system builds up in times with low Spillover Persistence, reflecting loose financial conditions. In macro-finance models, leverage is a key driver of fragility. The volatility paradox (Brunnermeier and Sannikov, 2014) predicts that leverage builds up in tranquil times, when financial conditions are loose. To test whether Spillover Persistence reflects this relationship between financial conditions and leverage, I regress an institution's leverage ratio on its one-year–lagged Spillover Persistence. The results show that a 1 standard deviation decline in Spillover Persistence is associated with a 0.03 standard deviation increase in the leverage of financial institutions. This effect is particularly pronounced for institutions that ex ante face tighter financial constraints, such as banks with a larger share of intangible assets and higher (ex-ante) leverage.

Fragility is typically associated with a larger probability of future crises. To examine the relation between Spillover Persistence and crises, I leverage Laeven and Valencia (2018)'s database of banking crises. Consistent with lower Spillover Persistence reflecting higher fragility, I document that a one standard deviation decline in Spillover Persistence increases the likelihood of a subsequent banking crisis by 4 percentage points (ppt). Compared to the average crisis likelihood of 19.5% in the sample, this effect is sizable. It is robust to alternative definitions of banking crises. Spillover Persistence also negatively correlates with the severity of crises. These results strongly support the hypothesis that low Spillover Persistence captures loose financial conditions that nurture fragility in the financial system.

The empirical findings hold in a variety of alternative empirical specifications. In particular, they are robust to including a large set of macroeconomic control variables and absorbing time-invariant differences across firms and aggregate shocks in macroeconomic conditions. Moreover, the results are unaffected by controlling for traditional systemic risk measures. Thus, Spillover Persistence captures new information about systemic risk.

The determinants of Spillover Persistence are very similar across different systemic risk measures used as inputs to compute Spillover Persistence, emphasizing the robust relationship with financial conditions. However, the ability of Spillover Persistence to capture fragility disappears once it is based on ΔCoVaR or MES. This finding points to the importance of disentangling amplification and volatility dynamics to capture build-ups of fragility.

Recent macro-finance models highlight the link between systemic risk and financial frictions (e.g., Adrian and Boyarchenko, 2012; He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014). In these models, losses have persistent effects because balance sheets take time to recover after shocks. Motivated by this prediction, this paper introduces a novel measure that empirically captures the duration of the effects of loss spillovers at the firm-by-year level and sheds light on its determinants.

The volatility paradox suggests that fragility builds up when financial conditions are loose. Consistent with this prediction, prior studies document that periods with loose financial conditions precede periods with low GDP growth and financial crises (e.g., Schularick and Taylor, 2012; Jordà et al., 2015; Krishnamurthy and Muir, 2020; Adrian et al., 2018, 2019).[2] These studies primarily rely on financial market prices and quantities and balance sheet characteristics to capture fluctuations in funding constraints (e.g., bond spreads) and, thus, focus on specific channels through which these affect financial institutions. Complementing these studies, Spillover Persistence takes a "global" perspective, encompassing various mechanisms without taking a stand on the causes of systemic risk. Its ability to capture amplification and fragility dynamics is robust to controlling for numerous firm and macroeconomic characteristics that have been found to predict crises.

In contrast to macroeconomic indicators, Spillover Persistence is measured at the firm level. Thus, it captures variation across firms, adding to existing work on measuring firm-level systemic risk (Billio et al., 2012; Adrian and Brunnermeier, 2016; Acharya et al., 2017).[3] Whereas traditional systemic risk measures capture the *contemporaneous* effects of loss spillovers (e.g., the financial system's risk on days on which JP Morgan faces large losses), this paper analyzes the *persistent* effects of loss spillovers (e.g., the financial system's risk on days *after* JP Morgan faces large losses). I document that these two perspectives on systemic risk differ. Spillover Persistence captures variation in financial conditions and fragility in the financial system even after controlling for traditional systemic risk measures, suggesting that it reflects a novel and informative dimension of systemic risk.

The volatility paradox has been highlighted as a weak spot of traditional systemic risk

[2] The related literature on leverage cycles documents that bank leverage negatively correlates with a bank's individual risk (Adrian and Shin, 2014). Complementing this literature, I focus on the financial system's risk instead of firms' individual risk.

[3] Global measures of systemic risk (such as ΔCoVaR and MES) are the most central metrics in the systemic risk literature (Benoit et al., 2017). Other measures focus on specific mechanisms that potentially create systemic risk, such as fire sales (Greenwood et al., 2015; Duarte and Eisenbach, 2021), portfolio similarity (Cai et al., 2018; Girardi et al., 2021), and liquidity risk (Bai et al., 2018).

measures, impairing their ability to detect fragility *before* amplification effects arise as these measures mechanically respond to volatility fluctuations.[4] Volatility is not necessarily a reliable empirical indicator of fragility. For example, Danielsson et al. (2018) document that banking crises are on average preceded by a high level of volatility as well as by large deviations of volatility from its trend. Whereas below-trend deviations are a particularly significant predictor, their findings also suggest that volatility fluctuations do not only pick up variation in financial conditions but also in other crises-related factors. Because optimal policy tightens to fight a build-up of fragility but loosens to mitigate amplification effects (Adrian and Boyarchenko, 2012; Brunnermeier and Sannikov, 2014; Phelan, 2016; Farhi and Werning, 2021), it is important for policymakers to identify and distinguish buildups of fragility from amplification effects. Tackling this challenge, I propose a modified version of ΔCoVaR, called ΔCoSP, which removes ΔCoVaR's mechanical correlation with volatility. Indeed, Spillover Persistence based on ΔCoSP significantly declines with the buildup of fragility at the onset of stock market booms and increases with amplification effects arising at their burst. Moreover, the main empirical results are robust to controlling for volatility, which highlights the importance of understanding the persistence in risk spillovers.

[4] For example, ΔCoVaR is proportional to the volatility of the financial system (Adrian and Brunnermeier, 2016, p.1413) and MES is proportional to a firm's beta multiplied by its individual risk (Benoit et al., 2017, p.137). Brunnermeier and Oehmke (2013, p.66) note that "[...] because systemic risk usually builds up in the background during the low-volatility environment of the run-up phase, regulations based on risk measures that rely mostly on contemporaneous volatility are not useful. They may even exacerbate the credit cycle. Hence, the volatility paradox rules out using contemporaneous risk measures and calls for slow-moving measures that predict the vulnerability of the system to future adverse shocks." Billio et al. (2012, p.537) stress that "[...] measures based on probabilities invariably depend on market volatility, and during periods of prosperity and growth, volatility is typically lower than in periods of distress. This implies lower estimates of systemic risk until after a volatility spike occurs, which reduces the usefulness of such a measure as an early warning indicator."

2 Hypotheses

The macro-finance literature considers financial frictions as a key determinant of financial instability and business cycle fluctuations. Due to financial frictions, shocks to agents' net worth make them less willing or able to hold assets, which further depresses prices, amplifying the initial shock. Amplification effects are already present in seminal models in this literature (e.g., Kiyotaki and Moore, 1997; Bernanke et al., 1999). Modern macro-finance models, which solve for the complete equilibrium dynamics, stress the non-linear nature of amplification effects, which are small in tranquil times but substantial during crises (e.g., in Brunnermeier and Sannikov, 2014). Three key predictions emerge from these models. First, weaker balance sheets are associated with stronger amplification of initial shocks and, thus, higher risk in the financial system.[5] Second, net worth takes time to recover after large shocks because these impair agents' borrowing capacity. In other words, large shocks persistently weaken agents' balance sheets and, therefore, persistently affect the system's risk. Finally, the "volatility paradox" in Brunnermeier and Sannikov (2014) says that loose financial conditions motivate agents to take more risk and increase their leverage. This makes the financial system more fragile, increasing the probability of future crises.

In this paper, I provide empirical evidence for the persistent effects of large losses on risk in the financial system, reflected in a new measure called *Spillover Persistence*. Spillover Persistence is the duration over which risk in the financial system remains elevated following a

[5] For example, in He and Krishnamurthy (2013), the higher the financial intermediary's leverage, the more do risk premia rise when intermediary capital declines. In Brunnermeier and Sannikov (2014), amplification of exogenous fundamental shocks is stronger when agents have more leverage, and in Di Tella (2017), "weaker balance sheets amplify the direct effect of higher idiosyncratic risk" (Di Tella, 2017, p.2064).

financial institution's initial loss. Whereas existing studies do not explicitly consider Spillover Persistence, it is conceptually related (while not equivalent) to the time it takes agents' balance sheets to recover from initial losses in macro-finance models: the longer it takes balance sheets to recover, the more persistent are the effects of initial losses.

Slow balance sheet recovery in macro-finance models results from agents' financial constraints. Motivated by this mechanism, I hypothesize that financial conditions are an important determinant of Spillover Persistence: the tighter financial conditions are, the longer it takes to restore net worth and, thus, the longer is the system's risk elevated following large shocks.[6] To test this relationship, I use financial-market–based indicators for financial conditions and variation in financial conditions related to banking crises, asset fire sales, and stock market price bubbles:

Hypothesis 1 (Determinants of Spillover Persistence)**.** *Spillover Persistence is*

i. higher when financial market conditions are tighter,

ii. higher during banking crises,

iii. higher following asset fire sales,

iv. and lower during the run-up phase of stock market price bubbles.

Based on Hypothesis 1 (that Spillover Persistence captures the severity of financial conditions) and the volatility paradox (that loose financial conditions nurture fragility in the financial system), I hypothesize that lower Spillover Persistence is associated with a more

[6]The relationship between amplification (driven by financial constraints) and persistence in macro-finance models is not unambiguous. In Brunnermeier and Sannikov (2016), risk premiums sharply increase during crises and, therefore, agents recapitalize relatively quickly even after large shocks; however, this is at odds with the long duration of crises in the data (Gopalakrishna, 2023). In an extension proposed by Gopalakrishna (2023), (specialized) agents become less productive and exit more often during crises, which prolongs the system's time to recover.

fragile financial system:

Hypothesis 2 (Spillover Persistence and Fragility)**.** *Lower Spillover Persistence is associated with*

i. more risk-taking by financial institutions

ii. and a higher probability of future banking crises.

In the following sections, I propose an empirical framework to measure Spillover Persistence and test Hypotheses 1 and 2.

3 Empirical Framework and Data

3.1 Spillover Persistence

I define Spillover Persistence as the time horizon over which risk in the financial system is elevated following an institution's initial losses, building on the literature on systemic risk measures to construct it. For a given time-lag $\tau \geq 0$, M_τ^I denotes a systemic risk measure that reflects the (tail-)dependence between initial losses $-r_t^I$ of an institution I and future losses $-r_{t+\tau}^S$ of financial system. Spillover Persistence is the systemic-risk–weighted average time-lag, similarly to the Macauly duration:

Definition 1. *Spillover Persistence based on a systemic risk measure M_τ^I is given by*

$$\bar{\tau} = \frac{\int_{\tau=1}^{\tau^{\max}} \tau \, M_\tau^I \, d\tau}{\int_{\tau=1}^{\tau^{\max}} M_\tau^I \, d\tau}, \tag{3}$$

where $\tau^{\max}$ is the maximum time-lag.

The prior literature has formulated desirable properties of systemic risk measures (e.g., Brunnermeier and Oehmke, 2013; Adrian and Brunnermeier, 2016). Two additional properties are particularly useful in the context of Spillover Persistence. First, to interpret $\bar{\tau}$ as an average systemic-risk–weighted time horizon, M_τ^I must be weakly positive, $M_\tau^I \geq 0$. Whereas most systemic risk measures can theoretically have both positive and negative values, they are typically positive, reflecting positive tail dependence of losses (see Table 1).

Second, the volatility paradox predicts that fragility builds up in times with loose financial conditions, typically characterized by low volatility. However, fluctuations in volatility also mirror macroeconomic characteristics other than financial conditions, such as economic uncertainty (Baker et al., 2016) and industry growth (Engle et al., 2013). This interplay complicates the disentanglement of amplification dynamics within the financial system, and both unusually large and small levels of volatility may indicate high fragility (Danielsson et al., 2018).[7] Thus, in order to not conflate amplification and fragility with volatility dynamics, it is desirable that $\bar{\tau}$ does not mechanically respond to fluctuations in volatility. For example, this property is satisfied if M_τ^I is not mechanically linked to volatility. However, traditional systemic risk measures, such as ΔCoVaR and MES, by design increase with higher volatility of the system or the financial institution (Adrian and Brunnermeier, 2016; Benoit et al., 2017). Therefore, $\bar{\tau}$ can violate this second property if it is based on traditional measures. For this reason, in the next section, I propose a modified systemic risk measure which is not mechanically linked to volatility.

[7] In my sample, a higher level of stock market volatility is associated with a significantly *higher* likelihood of a crisis in the subsequent year.

3.2 Excess Conditional Shortfall Probability

In the following, I propose a new systemic risk measure that, on one hand, closely follows the design of existing measures but, on the other hand, does *not* mechanically respond to changes in volatility. I define by $VaR^I(q)$ the $(1-q)\times 100\%$ percentile of the unconditional distribution of institution i's equity return loss $-r_t^I$,

$$\mathbb{P}(-r_t^I \geq VaR^I(q)) = q, \tag{4}$$

where r_t^I is the change in the log market value of an institution's equity between $t-1$ and t, t denotes time (in days), and $\mathbb{P}$ is a (time-)unconditional probability measure. Typically, $q \in (0,1)$ is small and $VaR^I(q)$ is a large positive number, as it reflects the smallest return loss that is not exceeded with probability $(1-q)\times 100\%$. Analogously, by replacing the institution's return r_t^I with the system's return r_t^S, $VaR^S(q)$ is the system's risk.[8]

The system's Conditional Shortfall Probability (CoSP) is the conditional probability that the system's unconditional Value-at-Risk is exceeded:

Definition 2. *For $\tau > 0$ and $q \in (0,1)$, $\Delta CoSP_\tau^I$ is the probability of large losses of the system τ days after large losses of institution I compared to an average day,*

$$\Delta CoSP_\tau^I = \mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q) \mid -r_t^I \geq VaR^I(q)\right) - q. \tag{5}$$

ΔCoSP exhibits several properties that are important in the context of measuring Spillover

[8] The system's return is the return of an index of all institutions in the financial system, excluding the currently considered institution I (as described in Appendix B.1).

Persistence. First, by definition of $VaR^S(q)$, if the returns r_t^S are issued from a stationary process, it is $\mathbb{P}(-r_{t+\tau}^S \geq VaR^S(q)) = q$. Therefore, if the institution's and system's losses are independently distributed, then $\Delta\text{CoSP}_\tau^I = \mathbb{P}(-r_{t+\tau}^S \geq VaR^S(q)) - q = 0$. Instead, if $\Delta\text{CoSP}_\tau^I > 0$, then, compared to an average day, the probability of large losses in the system is $\Delta\text{CoSP}_\tau^I \times 100$ ppt (percentage points) larger following losses of institution I.

Second, analogously to ΔCoVaR, ΔCoSP is derived from the conditional distribution of the system as it conditions on large losses of the financial institution. Therefore, ΔCoVaR and ΔCoSP share a similar interpretation: both reflect the tail dependence of return losses. The main difference is that, instead of being based on the (conditional) quantile function, ΔCoSP is based on its inverse, namely the cumulative distribution function: using Bayes' theorem, ΔCoSP can be rewritten as follows:

$$\Delta\text{CoSP}_\tau^I = \frac{1}{q}\mathbb{P}\left(\left(-r_{t+\tau}^S \geq VaR^S(q)\right) \cap \left(-r_t^I \geq VaR^I(q)\right)\right) - q. \tag{6}$$

In other words, ΔCoSP fixes the quantile and compares the probability of breaching it, whereas ΔCoVaR fixes the probability and compares the quantile that attains it.[9] As a consequence, ΔCoSP does not measure risk in monetary units, in contrast to traditional (systemic) risk measures, reducing its responsiveness to fluctuations in volatility.[10]

[9] I illustrate the differences and similarities of ΔCoSP and ΔCoVaR in Appendix Figure IA.2. Note that ΔCoVaR conditions on the event $\{-r_t^I = VaR^I(q)\}$, whereas ΔCoSP conditions on $\{-r_t^I \geq VaR^I(q)\}$. The reason for this difference is that Adrian and Brunnermeier (2016) estimate ΔCoVaR using quantile regressions (which assume a linear relationship with r_t^I), whereas a non-parametric estimator for ΔCoSP is readily available when conditioning on $\{-r_t^I \geq VaR^I(q)\}$.

[10] A common characteristic of traditional (systemic) risk measures is positive homogeneity (Chen et al., 2013): namely, that for losses X and all scalars $\alpha \geq 0$ it is $\rho(\alpha X) = \alpha\rho(X)$. Then, when losses are given as $X = \sigma\varepsilon$ with $\sigma > 0$ and ε being a random variable with unit variance, the risk measure is proportional to volatility: $\rho(\sigma\varepsilon) = \sigma\rho(\varepsilon)$. In contrast, ΔCoSP does not satisfy positive homogeneity, decoupling it from volatility fluctuations.

Third, because the unconditional probability of exceeding the Value-at-Risk is by definition fixed to q, changes in neither the institution's nor the system's unconditional volatility mechanically affect ΔCoSP.[11] Therefore, ΔCoSP isolates variation in tail dependence from variation in volatility, consistent with the second desirable property in Section 3.1.

Fourth, ΔCoSP^I_τ is related to measures of Granger causality (such as those proposed by Billio et al., 2012). The core idea of Granger causality is that the system's losses at time $t+\tau$, $\tau > 0$, cannot directly cause losses of institution I at time t.[12] However, it is worth stressing that, similar to existing systemic risk measures, ΔCoSP does not *causally* identify loss spillovers. Instead, it is a statistical measure for tail correlation. Thus, it may also capture institutions' exposure to common shocks, which is an important component of financial (in-)stability (Adrian and Brunnermeier, 2016; Brunnermeier et al., 2020).[13]

Finally, by definition, ΔCoSP can be negative. Figure 1 provides an example. Whereas $\Delta\text{CoSP}^I_\tau < 0$ for several time-lags τ in Figure 1 (a), clearly these instances result from estimation errors rather than from systematically negative ΔCoSP. In Appendix B.2, I provide detailed evidence that ΔCoSP is indeed typically (weakly) positive: an individual institution's losses are *positively* correlated with losses in the financial system.

[11] Assume that $r^I_t = \sigma_I \varepsilon_I$ and $r^S_{t+\tau} = \sigma_S \varepsilon_S$ with $\sigma_I, \sigma_S > 0$, joint distribution $(\varepsilon_I, \varepsilon_S) \sim F$, and marginal distributions $\varepsilon_I \sim F_I$ and $\varepsilon_S \sim F_S$ with unit variance, respectively. Then, the Value-at-Risk is equal to $VaR^I(q) = -\sigma_I F_I^{-1}(q)$ and $VaR^S(q) = -\sigma_S F_S^{-1}(q)$, respectively, and it is $\Delta\text{CoSP}^I_\tau = \frac{1}{q} F\left(F_I^{-1}(q), F_S^{-1}(q)\right) - q$, which is independent of the level of the firm's and system's volatility σ_I and σ_S.

[12] If stock markets were not sufficiently liquid, the system's stock return at time $t+\tau$ could reflect old information that have caused the institution's losses at time t. In Section 6, I show that CoSP measures are not driven by stock market illiquidity.

[13] Several robustness analyses suggest that the baseline results are not primarily driven by exposure to aggregate shocks (see Section 6).

3.3 Estimation

Denote by $D_t^I = \mathbb{1}_{\left\{-r_t^I \geq VaR^I(q)\right\}}$ and $D_t^S = \mathbb{1}_{\left\{-r_t^S \geq VaR^S(q)\right\}}$ binary random variables for large losses of financial institution I and the system S, respectively. A standard, non-parametric estimator for ΔCoSP is then given by (see Appendix B.2 for details):

$$\widehat{\Delta\text{CoSP}}(\tau) = \frac{1}{q(n-\tau)} \sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I(q),\, -r_{t+\tau}^S \geq \widehat{VaR}^S(q)\right\}} - q, \tag{7}$$

where n is the number of observations and the Value-at-Risk estimator is the nq^x-th (or $([nq^x]+1)$-th) order statistic of r^x if nq^x is an integer (if it is not).

Intuitively, the correlation between an institution's initial losses and future losses in the system may diminish over time and, thus, ΔCoSP_τ^I decreases with an increasing time-lag. Consistent with this conjecture, ΔCoSP_τ^I is exponentially decreasing in the example of Figure 1 (a), whereas its shape is similar but its decline less steep in Figure 1 (b).

Motivated by these observations, I estimate Spillover Persistence by, first, fitting ΔCoSP_τ^I to an exponential function of τ, $\Delta\text{CoSP}_\tau^I = \alpha^I e^{\tau\beta^I}$.[14] The parameters α^I and β^I are varying in the cross-section of institutions and across time (I omit the superscripts in the following). I disregard observations if the fitted value for α is negative and, thus, the weights to compute Spillover Persistence are non-negative for remaining observations, consistent with the first desirable property formulated above. In the example of Figure 1, the estimated parametric model closely matches the non-parametric estimate. More generally, in Appendix B.2, I provide comprehensive evidence that the parametric estimation approach mitigates the impact

[14] Directly using $\widehat{\Delta\text{CoSP}}(\tau)$ to weight time-lags in Equation (3) leads to substantial estimation error as I document in Appendix B.2.

of estimation errors on Spillover Persistence and does not create a systematic bias.

For each institution and estimation windows, I first calculate the average level of systemic risk across time-lags, using the fitted parameters $\hat{\alpha}$ and $\hat{\beta}$:

$$\bar{\psi} = \frac{1}{\tau^{\max} - 1} \int_{1}^{\tau^{\max}} \hat{a} e^{\hat{b}\tau} d\tau = \frac{\hat{a}}{\hat{b}(\tau^{\max} - 1)} \left[e^{\hat{b}\tau^{\max}} - e^{\hat{b}} \right]. \tag{8}$$

I refer to $\bar{\psi}$ as Average ΔCoSP. Then, Spillover Persistence is defined as the systemic-risk–weighted average time-lag:

$$\begin{aligned} \text{Spillover Persistence} &= \frac{1}{\bar{\psi}(\tau^{\max} - 1)} \int_{1}^{\tau^{\max}} \tau \hat{a} e^{\hat{b}\tau} d\tau \qquad (9) \\ &= \frac{\hat{a}}{\hat{b}^2 \bar{\psi}(\tau^{\max} - 1)} \left[(\hat{b}\tau^{\max} - 1) e^{\hat{b}\tau^{\max}} - (\hat{b} - 1) e^{\hat{b}} \right]. \qquad (10) \end{aligned}$$

Importantly, this approach to compute Spillover Persistence applies to other systemic risk measures, as well. To examine the role of the underlying systemic risk measure in calculating Spillover Persistence, I compute two alternative versions of Spillover Persistence based on systemic risk measures other than ΔCoSP. For each of the measures, I first evaluate the measure for different time-lags between the institution's and system's return losses, second, fit the measure to the same parametric function as ΔCoSP, $\alpha e^{\beta\tau}$, and, then, use Equations (8) and (10) to compute Spillover Persistence. The main comparison is with Adrian and Brunnermeier (2016)'s ΔCoVaR because it is most closely related to ΔCoSP:

$$\Delta\text{CoVaR} = CoVaR_{-r^I = VaR^I(q)} - CoVaR_{-r^I = VaR^I(0.5)}, \tag{11}$$

where $\mathbb{P}(-r^S \geq CoVaR_E \mid E) = q$ for event E, and ΔCoVaR is estimated using quantile regressions of weekly equity market returns.[15] As a robustness check, I also consider Acharya et al. (2017)'s Marginal Expected Shortfall (MES), which is defined as

$$MES = \mathbb{E}[-r^I \mid -r^S \geq VaR^S(q)]. \tag{12}$$

Following Acharya et al. (2017), I estimate MES for each year as institution I's average return during days with the $q \times 100\%$ largest losses of the system.

3.4 Data

The estimation of systemic risk measures is based on daily equity market returns. I retrieve from Thomson Reuters Datastream data on all financial institutions in the Datastream universe that are either currently listed or dead but with an available primary major equity quote (as of February 2019). The sample starts on January 1, 1985, and ends on December 31, 2017, including three recessions (1990-1991, 2001, and 2007-2009) and several crises (1987, 1994, 1997, 1998, 2000, 2008, 2011), and it covers a large number of financial institutions across multiple countries.

For each institution, I obtain data on the unpadded and unadjusted price of common equity in local currency, the number of outstanding shares, and market capitalization in USD. I drop institutions with less than one year of price data and African and South American institutions.[16] Following Adrian and Brunnermeier (2016), I focus on the following financial

[15] Macroeconomic state variables used as explanatory variables in quantile regressions are reported in Appendix Table IA.2. In the main analyses, I use the annual average of weekly ΔCoVaR.

[16] To omit a potential bias from public offerings or share repurchases, I drop days on which the number of an institution's outstanding shares changed by more than 0.5% compared to the previous day. To ensure

sectors: banks (i.e., commercial banks or depository institutions; BAN), broker-dealers (i.e., credit firms, investment banks, or security and commodity brokers; BRO), insurance companies (INS), and real estate firms (i.e., real estate property operators, developers, agents, or managers; RE).[17]

Each institution is assigned (1) to one country and (2) to one of the following regions based on its headquarter location: Europe, Asia (excluding Japan), North America, Japan, and Australia. By accounting for institutions' locations, I acknowledge geographical variation in the macro-economic environment (such as interest rate levels).

Losses in the financial system are defined as daily return losses of a market-value–weighted index of financial institutions in the system. Following Brunnermeier et al. (2020), for each currently considered institution I, I define the relevant system as the set of other financial institutions in the same geographical region. For instance, the financial system for JP Morgan contains all North American financial institutions except for JP Morgan.[18]

I use backward-looking rolling estimation windows with a size of 5 years to estimate ΔCoSP.[19] To alleviate estimation errors, I exclude institutions from a given estimation window if there are less than 700 non-missing and non-zero observations of daily returns.[20] The reference level to compute systemic risk measures is $q = 5\%$, which is similar to other

that securities are sufficiently liquid, I also drop days on which an institution's market capitalization does not exceed USD 100,000. Moreover, I exclude all days on which at least 95% of the institutions in the sample do not report a price.

[17] I classify an institution as bank if its SIC is between 6000 and 6199 or equal to 6712, as broker-dealer if its SIC is between 6200 and 6299, as insurer if its SIC is between 6300 and 6399, and as real estate institution if its SIC is between 6500 and 6599.

[18] Details are described in Appendix B.1.

[19] A relatively long estimation window is needed to ensure that economically significant losses occur within the time window and that systemic risk measures exhibit a reasonably small estimation error.

[20] I also exclude from each time series of equity returns (a) periods with more than 5 subsequently missing returns and (b) 1500-day periods with more than 180 missing returns.

studies.[21] The maximum considered time lag is $\tau^{\max} = 50$ days. I winsorize systemic risk measures at the 1th and 99th percentiles.

Finally, I enrich the sample with firm characteristics obtained from Thomson Reuters Worldscope, namely firm size (log of total assets), leverage (total assets to the market value of equity), and equity valuation (market-to-book value), and additional bank and broker-dealer characteristics obtained from Moody's Analytics BankFocus, namely the volume of deposits, impaired loans, intangible assets, credit default swap notional (all relative to total assets), and a bank's liquidity ratio (liquid assets over deposits and short-term funding). Data on stock market bubbles is from Brunnermeier et al. (2020). Moreover, I include a wide range of macroeconomic characteristics, such as inflation, GDP, investment and credit growth, banking crises, equity market volatility, interest rates, and fixed income spreads. An overview of variable definitions and data sources as well as summary statistics for institution and macroeconomic characteristics are in Appendix A.

3.5 Summary Statistics

The baseline sample includes 1,094 financial institutions from 56 countries and ranges from 1989 to 2017.[22] Most firms are (commercial) banks, followed by real estate firms, broker-dealers, and insurers.[23] The total market value of firms in the baseline sample is 9.77

[21] The choice of q is subject to a trade-off between capturing more severe losses (smaller q) and relying on more observations and, thus, reducing the estimation error (larger q). For example, Adrian and Brunnermeier (2016) use 1% and 5%, Brunnermeier et al. (2020) use 2%, and Acharya et al. (2017) use 5% as reference levels.

[22] Here and in the following, *year* refers to the last year in a 5-year estimation window for systemic risk measures. 42.4% of firm-year observations are for institutions located in Europe, 30.2% in North America, 18.5% in Asia, 5% in Japan, and 3.9% in Australia.

[23] More specifically, 43% of firm-year observations are for banks, 24% for real estate firms, 20% for broker-dealers, and 13% for insurers.

trillion USD in December 2017, which corresponds to 86% of the market value of financial firms worldwide. The subsample of U.S. firms captures 75% of publicly listed U.S. financial institutions.[24] Thus, the sample is representative for the vast majority of publicly listed financial institutions.

Table 1 provides summary statistics for the main variables (see Appendix Table IA.3 for the remaining variables). Following a financial institution's losses, the probability of losses in the system is elevated by 3ppt on average, reflected by Average ΔCoSP, for an average time horizon of 17.81, reflected by Spillover Persistence. As Figure 2 (a) illustrates, Average ΔCoSP peaks during the 2007-08 financial crisis, the Asian financial crisis in the late 1990s, and the Japanese banking crisis at the beginning of the 1990s. Figure 2 (b) depicts the evolution of Spillover Persistence, which, on average, resembles that of Average ΔCoSP. The correlation between these measures is 65%, pooled across institutions and time (see Appendix Table IA.4). To disentangle variation in Spillover Persistence from that in the level of systemic risk, I control for Average ΔCoSP in regressions with Spillover Persistence as explanatory variable. The correlation of Spillover Persistence with contemporaneous systemic risk measures is substantially lower, namely 9% with ΔCoVaR and 14% with MES. Therefore, most of the variation in Spillover Persistence is orthogonal to the variation in contemporaneous systemic risk measures.

Spillover Persistence dynamics are sensitive to the choice of its underlying systemic risk measure. Although the summary statistics for Spillover Persistence are similar across dif-

[24]The total market value of U.S. firms in the sample is 3.82 trillion USD in December 2017. To measure the total market value of the financial sector, I use the STOXX Global 3000 FINANCIALS index and STOXX USA 900 FINANCIALS index (both retrieved from Thomson Reuters Datastream), which on December 29, 2017, record a total market value of 11.36 trillion USD and 5.06 trillion USD, respectively. The FTSE WORLD FINANCIALS and FTSE USA FINANCIALS index are at similar (but slightly lower) levels.

ferent systemic risk measures, the dynamics are different. In fact, the correlation between Spillover Persistence based on ΔCoSP is only 30% with that based on ΔCoVaR and 37% with that based on MES (see Appendix Table IA.4 and Figure IA.4). One reason for these differences may be the volatility-dependence of ΔCoVaR and MES. In fact, Spillover Persistence correlates substantially more with stock market volatility when it is based on ΔCoVaR (33%) and MES (43%) than when it is based on ΔCoSP (14%) (see Appendix Figure IA.5).

4 Determinants of Spillover Persistence

4.1 Financial Conditions

Hypothesis 1 states that Spillover Persistence is positively correlated with tighter financial conditions. To test this hypothesis, in Panel (A) in Table 2, I first use the Chicago Fed's National Financial Conditions Index (NFCI), which reflects financial conditions in U.S. financial markets. A higher level of the NFCI indicates tighter conditions. Consistent with the hypothesis, for U.S. financial institutions, I find that Spillover Persistence significantly and positively correlates with the NFCI. A 1 standard deviation increase in the NFCI is associated with a 0.28 standard deviations increase in Spillover Persistence. Thus, tight financial market conditions are an important driver of high Spillover Persistence.

In column (2), I additionally consider other macroeconomic characteristics that reflect U.S. financial conditions as explanatory variables, such as a banking crisis indicator (from Laeven and Valencia, 2018), credit growth, and bond spreads. Crises are particularly strongly correlated with Spillover Persistence. During crises, Spillover Persistence is 2.14 days larger than in normal times, which corresponds to approximately 30% of its standard deviation. Other indicators for tighter financial conditions are also significantly correlated with larger Spillover Persistence, such as lower credit growth and a higher growth in the short-term treasury rate, term spread, and credit spread.

These relationships qualitatively also hold in the full, international sample (column 3). Whereas some coefficients become insignificant (though with the same sign as in the U.S. sample), the coefficients on crises and interest rate growth remain significantly positive. The coefficient on crises is larger in the international sample and implies that, on average, crises are associated with 4.6 days larger Spillover Persistence. Overall, these results are consistent with the hypothesis that tighter financial conditions are associated with larger Spillover Persistence.

In column (4), I consider Spillover Persistence based on ΔCoVaR instead of ΔCoSP. In both cases, banking crises are associated with a significantly larger Spillover Persistence. However, the signs on the coefficients of other measures for financial conditions flip, suggesting that *looser* financial conditions relate to larger Spillover Persistence. More specifically, Spillover Persistence based on ΔCoVaR is positively correlated with larger credit growth and with smaller interest rate, term spread, and credit spread growth. These mixed results for ΔCoVaR are consistent with the significant differences in Spillover Persistence across systemic risk measures and emphasize the importance to measure Spillover Persistence using a systemic risk measure that does not mechanically respond to volatility.

4.2 Fire Sales

To zoom in on the role of amplification effects, I consider asset fire sales. Pecuniary externalities resulting from fire sales are an important driver of amplification effects in macroeconomic models as they interact with agents' financial constraints. To examine this mechanism empirically, I exploit hurricane Katrina as an exogenous shock to property & casualty (P&C) insurers that were active in the hurricane-exposed region.

Hurricane Katrina made first landfall on August 25, 2005, and has been one of the costliest Atlantic hurricanes on record. It predominantly affected the U.S. states Alabama, Louisiana, and Mississippi and triggered 41.1 billion USD in insurance claims being filed.[25] The volume of claims corresponds to more than twice the total premiums collected in 2004 by P&C insurers in these states. To fund these large insurance payments, P&C insurers engaged in substantial fire sales (Manconi et al., 2016; Girardi et al., 2021).

I estimate the effect of Katrina on the Spillover Persistence of U.S. P&C insurers that were exposed to the hurricane relative to other insurers. Exposed insurers are defined as those with the 25% largest share of premiums written in the states affected by the hurricane, while other U.S. insurers are in the control group (details are reported in Appendix A.2.3).

To isolate the impact of Katrina, I estimate Spillover Persistence daily based on 18-months backward-looking rolling windows (and, due to the shorter estimation window, with a 20-day maximum time lag). In the baseline specification, I regress Spillover Persistence of insurer i on day t ($\bar{\tau}_{i,t}$) on the interaction of the exposure-to-Katrina indicator (Exposed_i) and a post dummy that is equal to one for August 25, 2005, and after, and zero otherwise,

[25] Total claims are reported at
`https://www.iii.org/article/infographic-hurricane-katrina-10-years-later`.

controlling for time-invariant heterogeneity at the insurer level (u_i):

$$\bar{\tau}_{i,t} = \alpha \text{Exposed}_i \times \text{post}_t + \beta \text{post}_t + u_i + \varepsilon_{i,t}. \tag{13}$$

α estimates the change in Spillover Persistence between the pre- and post-Katrina period for hurricane-exposed insurers relative to unexposed insurers. I expect that $\alpha > 0$, consistent with the hypothesis that fire sales by exposed insurers contribute to an increase in Spillover Persistence. The model is estimated from August 8 to September 16, 2005, and, thereby, excludes the effect of the potentially confounding hurricane Rita on September 18, 2005. Due to the small number of U.S. insurers, I use unclustered (heteroskedasticity-robust) standard errors.

Panel (B) in Table 2 reports the estimated coefficients. The difference-in-difference estimate in column (4) is significantly different from zero (the t-statistic is 4.45) and implies that Hurricane Katrina raised Spillover Persistence by roughly 0.3 days for Katrina-exposed insurers relative to other insurers. The effect is also economically significant, as it corresponds to 13% of the standard deviation of Spillover Persistence in the sample.

The result is robust to additionally including time fixed effects (column 5). It also holds when increasing the estimation window length or including Canadian insurers in the control group or when Spillover Persistence is based on ΔCoVaR or MES (see Appendix Table IA.5). Overall, the results strongly support Hypothesis 1 that tighter financial conditions, resulting from fire sales, raise Spillover Persistence.

4.3 Asset Price Bubbles

Whereas crises often occur upon the burst of asset price bubbles, bubble booms emerge when financial conditions are loose (Borio and Lowe, 2002; Brunnermeier and Oehmke, 2013; Brunnermeier et al., 2020). Building on this characterization of bubbles, in this section, I use stock market booms as a proxy for loose financial conditions. Hypothesis 1 then implies that stock market booms are associated with low Spillover Persistence, particularly at the onset of booms.

By cutting each stock market bubble in two halves at its global price peak, I distinguish between boom and bust phases of a bubble. Bubble characteristics include the current length of a boom or bust. Additionally, I define the first month of a bubble's bust phase as its *burst* and create a variable that measures the current distance to a bubble's burst (Appendix A.2.4 provides more details on the bubbles sample). The summary statistics in Table 1 show that 12% of observations (pooled across firms and years) are labeled as stock market booms and 5% as bust periods.

First, I regress Spillover Persistence $\bar{\tau}_{i,t}$ of firm i in country c in year t on the vector of boom and bust indicators ($I_{c,t}^{Bubble}$), controlling for the current boom and bust length ($L_{c,t}^{Bubble}$), macroeconomic characteristics ($M_{c,t}$), and time-invariant cross-sectional heterogeneity (u_i),

$$\bar{\tau}_{i,t} = \alpha I_{c,t}^{Bubble} + \beta L_{c,t}^{Bubble} + \gamma M_{c,t} + u_i + \varepsilon_{i,t}. \tag{14}$$

Column (1) in Table 3 reports the estimated coefficients (standard errors are clustered at firm and country-year levels, accounting for autocorrelation at the firm level). They show that Spillover Persistence is significantly smaller during stock market booms than in other years (the t-statistic is 3.05).[26] The economic significance is large: during booms, Spillover Persistence is 5 days smaller (68% of its standard deviation). In column (2), I additionally include year fixed effects, which absorb aggregate fluctuations, and detailed control variables that reflect market and financial institutions' characteristics. Adding these controls addresses concerns that institutions may contribute to the creation of bubbles, e.g., by providing excessive credit.[27] Moreover, I control for ΔCoVaR. Despite this battery of additional control variables, the coefficient on the boom indicator remains significantly negative with a sizable magnitude (-1.8 days). This result suggests that bubble boom periods are associated with substantially lower Spillover Persistence even beyond what can be explained by market and firm characteristics.

In the baseline specifications, I control for the boom and bust length in order to alleviate the concern that the results are driven by potential correlation between bubbles and early years in Spillover Persistence's estimation window (which is from $t-4$ to t). The results are also robust to regressing Spillover Persistence on bubble indicators from the first year of the estimation window (which is $t-4$), as I show in column (3).

Second, I explore the dynamics of Spillover Persistence during boom episodes by estimating the following specification:

$$\bar{\tau}_{i,t} = \alpha_0 \text{Burst Distance}_{c,t} \times I_{c,t}^{Boom} + \alpha_1 I_{c,t}^{Bubble} + \beta L_{c,t}^{Bubble} + \gamma M_{c,t} + u_i + \varepsilon_{i,t}, \tag{15}$$

[26] Booms can but must not necessarily result in financial crises (Jordà et al., 2015), which is a potential explanation for why Spillover Persistence during bust periods is not significantly larger than during non-bubble times.

[27] Schularick and Taylor (2012) and Jordà et al. (2015) argue that excessive credit and financial leverage fuel the systemic nature of asset price bubbles and financial crises.

where Burst Distance$_{c,t}$ is the current distance to a bubble's burst. This model tests for a trend of Spillover Persistence during the boom phase of bubbles. If $\alpha_0 < 0$, then Spillover Persistence increases during booms, i.e., with shorter distance to the burst.

Column (4) reports the estimated coefficients within the subsample of bubble episodes. The point estimate for α_0 is significantly negative, which implies that Spillover Persistence significantly declines with a larger distance to a bubble's burst, i.e., increases over time during booms. The effect remains highly significant in the baseline specification (column 5) as well as when including additional control variables for market and financial institutions' characteristics and ΔCoVaR (column 6). Additionally, in column (6), I control for the number of boom and bust years in the CoSP estimation window. This alleviates concerns that Spillover Persistence dynamics are due to variation in the number of boom or bust years that enter the estimation window. The findings show that Spillover Persistence is particularly low during the onset of stock market booms, consistent with the particularly loose financial conditions during such episodes.

In Appendix Table IA.6, I estimate the regressions from Table 3 with Spillover Persistence based on ΔCoVaR (instead of ΔCoSP) as dependent variable. The results are consistent with the baseline results, both in magnitude as well as statistical significance, emphasizing their robustness.

5 Spillover Persistence and Fragility

In this section, I empirically test Hypothesis 2 that lower Spillover Persistence is associated with a more fragile financial system.

5.1 Leverage and Risk-Taking

In canonical macro-finance models (e.g., Brunnermeier and Sannikov, 2014), fragility is driven by high leverage, which builds up in times of loose financial conditions. Using leverage as a measure for fragility, I regress a financial institution i's one-year–ahead leverage (total assets over the market value of equity) on its Spillover Persistence $\bar{\tau}_{i,t}$ in year t:

$$\text{Leverage}_{i,t+1} = \alpha\bar{\tau}_{i,t} + \beta\bar{\psi}_{i,t} + \gamma F_{i,t-1} + \eta M_{c,t} + u_i + \varepsilon_{i,t+1}, \tag{16}$$

controlling for Average ΔCoSP ($\bar{\psi}_{i,t}$), time-invariant differences across firms (u_i), lagged firm characteristics ($F_{i,t-1}$) and macroeconomic characteristics ($M_{c,t}$) in firm i's country c. In the most granular specifications, I also include year fixed effects, which absorb aggregate fluctuations in the economic environment. Standard errors are clustered at the firm and country-year levels, which accounts for autocorrelation at the firm level and for correlation of residuals across firms within country-years.

In column (1) in Table 4, I find that leverage significantly increases when Spillover Persistence declines (the t-statistic is 2.4). A one-standard deviation decline in Spillover Persistence relates to an increase in leverage by 3% of its standard deviation. The result also holds within the subsample of banks and brokers with a similar magnitude (column 2).

If, as hypothesized, leverage increases because lower Spillover Persistence reflects looser financial conditions, it seems reasonable that financial institutions with a weaker balance sheet are more responsive: these would benefit relatively more from looser financial conditions. Consistent with this hypothesis, in column (3), I find that the (negative) correlation between Spillover Persistence and leverage is significantly stronger when banks have more intangible assets or higher leverage ex ante.

In columns (4) and (5), I replace leverage with credit default swap (CDS) exposure (CDS notional relative to total assets) as the dependent variable. Derivatives may be used to take risks, particularly highly leveraged positions, and, thus, derivatives exposure may also negatively correlate with Spillover Persistence. Indeed, in column (4), I find that the correlation is negative for the average bank, however, not significantly different zero (but with a relatively large t-statistic of -1.25). Nonetheless, column (5) shows that the correlation is significantly negative (t-statistic: -2) for banks with average characteristics. The coefficients on the interactions with bank characteristics have the same signs as with leverage as dependent variable. A higher share of impaired loans is significantly associated with a stronger (negative) correlation between Spillover Persistence and CDS exposure, consistent with weaker balance sheets fueling the impact of loose financial conditions.

Nonetheless, the results on CDS exposure are slightly more mixed than those with leverage as dependent variable, e.g., banks that are larger and more liquid exhibit a stronger correlation between Spillover Persistence and CDS exposure. One likely reason is that CDS contracts can also be used to hedge rather than take (credit) risks. Nonetheless, the firm-level results overall provide strong support for Hypothesis 2.

5.2 Predicting Crises

Higher fragility increases the likelihood and severity of future crises (e.g., Brunnermeier and Sannikov, 2014). Therefore, Hypothesis 2 can be tested with the following linear probability model, which regresses an indicator for one-year–ahead banking crises on the Spillover Persistence of firms i in country c in year t:

$$\text{Crisis}_{c,t+1} = \alpha\bar{\tau}_{i,t} + \beta\bar{\psi}_{i,t} + \gamma F_{i,t-1} + \eta M_{c,t} + u_i + v_t + \varepsilon_{i,t+1}, \tag{17}$$

controlling for Average ΔCoSP ($\bar{\psi}_{i,t}$), time-invariant differences across firms (u_i), aggregate shocks (v_t), lagged firm characteristics ($F_{i,t-1}$) and macroeconomic characteristics ($M_{c,t}$) in firm i's country c. If lower Spillover Persistence is associated with a more fragile financial system, then $\alpha < 0$.

In column (6) in Table 4, I report the estimated coefficients when only controlling for $\bar{\psi}_{i,t}$ and including firm fixed effects. The estimate for α is significantly negative, implying that lower Spillover Persistence is associated with a larger probability of one-year–ahead banking crises. The magnitude implies that banking crises are by about 0.1 standard deviations (4 ppt) more likely following a one standard deviation reduction in Spillover Persistence, which highlights the economic significance of Spillover Persistence for fragility.

The relation between Spillover Persistence and future crises is robust to including the full set of controls (column 7). Importantly, by including time fixed effects, the result implies that decreases in Spillover Persistence in one country are associated with a higher crisis probability in this country *relative* to other countries, holding aggregate factors fixed. Lower Spillover Persistence also associates with a higher crisis probability two years ahead (column 8). This suggests that the relation between Spillover Persistence and future crises is not driven by spurious correlation but, instead, reflects structural changes in the financial system. Overall, the results provide strong evidence for Hypothesis 2, namely that lower

Spillover Persistence is associated with a more fragile financial system.

Additionally, in Appendix Table IA.7, I present evidence that lower Spillover Persistence is also associated with a higher likelihood of crises occurring three years in the future, of crises that become systemic, and with a larger crisis-induced output loss. Interestingly, although a larger ΔCoVaR is associated with a higher likelihood of future crises when only including firm fixed effects, this relationship becomes negative when controlling for Spillover Persistence. In contrast, the coefficient on Spillover Persistence in Equation (17) remains largely unchanged after controlling for ΔCoVaR. This suggests that Spillover Persistence captures a dimension of fragility that is not captured by ΔCoVaR.

Finally, I find that Spillover Persistence based on ΔCoVaR or MES (instead of ΔCoSP) does *not* significantly correlate with future crises. This finding points to the importance of using a systemic risk measure that does not mechanically respond to volatility in order to capture fragility in the financial system: as the volatility paradox predicts that fragility builds up during times of low volatility, volatility-driven measures may not be able to distinguish between high and low fragility during such tranquil episodes.

6 Robustness Analysis

It is beyond the scope of this paper to provide a causal identification of loss spillovers. Instead, aggregate shocks can potentially result in losses for both an individual institution I on day t and the system on day $t + \tau$, especially when the stock market is relatively illiquid. Adrian and Brunnermeier (2016) and Brunnermeier et al. (2020) argue that it is an advantage of systemic risk measures to pick up exposure to aggregate shocks because these may be an important source of systemic risk. Nonetheless, I provide empirical evidence that Spillover Persistence is not trivially explained by stock market illiquidity and that the results are not primarily driven by aggregate shocks.

First, aggregate shocks that uniformly affect institutions are absorbed by including time fixed effects in the regressions. Second, illiquidity of the securities whose prices are used to estimate systemic risk might bias Spillover Persistence, e.g., when information is priced with delay. To address this concern, I examine the correlation between stock market illiquidity and Spillover Persistence and Average ΔCoSP, using a firm's turnover by volume as a measure for stock market liquidity as well as Amihud (2002)'s measure for stock market illiquidity. The results show that neither Spillover Persistence nor Average ΔCoSP are larger when stocks are less liquid (see Appendix D.2).

Third, and more generally, it is possible that omitted variables lead to persistent losses, e.g., losses in the financial system on days t and $t+\tau$. The presence of such omitted variables can lead to autocorrelation in the system's equity return and, therefore, may raise the level of Spillover Persistence. Alleviating this concern, I document that Spillover Persistence does not significantly increase with a stronger auto-serial correlation of the system's equity return (see Appendix D.2).

Finally, omitted variables might differently affect individual institutions and the system. I address this concern by estimating ΔCoSP based on the system's return *innovations*, defined as innovations in an autoregressive model of the system's equity return. Thereby, I strip out predictable variation from the system's return, e.g., caused by omitted variables.[28]

[28]This approach is called "prewhitening" and common in the forecasting literature (Giglio et al., 2016; Dean and Dunsmuir, 2016).

Based on the resulting time series of AR(1)-innovations, I re-estimate ΔCoSP and Spillover Persistence. I find that all main results are robust to using this alternative construction of Spillover Persistence (see Appendix Tables IA.8 to IA.10).

7 Conclusion

Spillover Persistence is a novel characteristic of systemic risk, which reflects the dynamics of losses in the financial system. It captures the time over which losses "cascade" through the financial system: the longer-lasting the effect of a firm's losses on the financial system, the larger is Spillover Persistence. Motivated by the predictions of modern macro-finance models, this paper documents that Spillover Persistence captures the dynamics of amplification effects and fragility in the financial system.

Building on a large multi-country sample from 1989 to 2017, I document that Spillover Persistence positively correlates with tighter financial conditions. For example, it is significantly larger during banking crises but significantly lower during the onset of stock market booms. Consistent with the volatility paradox, the financial system is more fragile during times of low Spillover Persistence, i.e., financial institutions take more risks and future crises are more likely. These results suggest that Spillover Persistence captures key dynamics of the financial cycle.

Because Spillover Persistence *negatively* correlates with fragility but *positively* with amplification effects, it can be used to distinguish between fragility and amplification regimes. This distinction is important for policymakers to implement countercyclical regulation and extends existing systemic risk measures.

This paper bridges recent advances in macro-finance theory and in the empirical literature on risks in the financial system. Thereby, it reveals a novel and relevant dimension of systemic risk and presents new stylized facts. These can potentially serve as guideposts for future – empirical and theoretical – research of systemic risk, and may prove useful for regulators to construct early-warning signals for fragility and to guide and implement policy.

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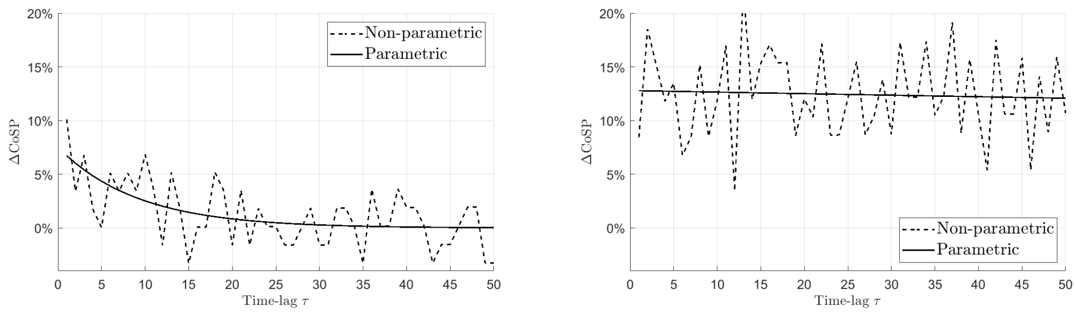
Figures and Tables

Figure 1. Illustration of ΔCoSP Dynamics.

The figures depict the non-parametric and parametric estimates for ΔCoSP for JP Morgan for (a) 2018 and (b) 2009.



(a) 2018. (b) 2009.

Figure 2. Time Series of AverageΔCoSP and Spillover Persistence.

The figures depict the annual cross-sectional mean and 25th and 75th percentiles of Average ΔCoSP and Spillover Persistence (based on CoSP). Both measures are estimated based on daily equity return losses in 5-year backward-looking rolling windows. The year displayed on the x-axis corresponds to the last year of the respective estimation window.

(a) Average ΔCoSP. (b) Spillover Persistence (based on CoSP).

Table 1. Summary Statistics.

This table depicts summary statistics for key variables in the empirical analysis. In the baseline sample, observations are at the firm-year level, Average ΔCoSP and Spillover Persistence are estimated based on daily equity return losses in 5-years backward-looking rolling windows with end-years 1989 to 2018, ΔCoVaR is the annual average of the weekly ΔCoVaR, which is estimated based on weekly equity return losses using quantile regressions, and MES is based on daily equity return losses for a given year. In the fire sales sample, observations are at the firm-day level, Spillover Persistence is estimated in 18-months backward-looking rolling windows with end-dates August 18 to September 5, 2005, for all U.S. insurers. The bubbles sample only includes countries with available data on bubbles. Leverage in the fragility sample is from Worldscope and in the Ban & Bro sample is from BankFocus. The Ban & Bro sample is constrained to firms from BankFocus. Variable descriptions and data sources are provided in Table IA.1. Summary statistics for remaining variables are provided in Appendix Table IA.3.

	N	Mean	Median	SD	p5	p95
Baseline sample						
Spillover Persistence (ΔCoSP, in days)	12,368	17.31	20.12	7.32	1.44	25.10
Average ΔCoSP (in ppt)	12,368	0.03	0.03	0.03	0.00	0.09
Spillover Persistence (ΔCoVaR, in days)	10,033	15.13	18.48	8.62	1.23	25.14
Spillover Persistence (MES, $\bar{\tau}$, in days)	9,779	13.71	17.45	9.52	1.22	25.40
ΔCoVaR (in ppt)	9,923	3.02	2.96	1.64	0.52	5.92
MES (in ppt)	11,713	2.20	1.80	1.80	0.10	5.89
Crisis (binary)	10,106	0.15	0.00	0.35	0.00	1.00
NFCI (U.S. only)	2,798	-0.37	-0.46	0.46	-0.77	0.80
Fire sales sample						
Spillover Persistence (ΔCoSP, in days)	286	4.89	4.79	2.26	1.16	8.62
(Hurricane-Katrina) Exposed	286	0.18	0.00	0.39	0.00	1.00
Bubbles sample						
Boom	6,896	0.12	0.00	0.32	0.00	1.00
Bust	6,896	0.05	0.00	0.22	0.00	0.00
Boom $\times$ Burst Distance	6,896	0.28	0.00	0.91	0.00	2.33
Fragility sample						
Leverage$_{t+1}$	8,380	11.59	6.08	16.12	0.83	40.16
100 $\times$ Crisis$_{t+1}$	6,755	19.50	0.00	39.62	0.00	100.00
Ban & Bro sample						
Leverage$_{t+1}$	1,676	14.39	9.39	14.37	2.95	42.61
CDS$_{t+1}$	693	0.19	0.00	0.58	0.00	1.27

Table 2. Spillover Persistence and Financial Conditions.
Each column presents estimated coefficients from a specification of the form:

$$\bar{\tau}_{i,t} = \Gamma' C_{i,t} + \varepsilon_{i,t},$$

where $\bar{\tau}_{i,t}$ is the Spillover Persistence of firm f in year t and $C_{i,t}$ is a vector of explanatory variables and fixed effects. Panel A: Columns (1) to (4) report OLS regressions of Spillover Persistence at the firm-year level based on either ΔCoSP (coumns 1-3) or ΔCoVaR (column 4) on indicators for financial conditions. NFCI is the Chicago Fed's National Financial Conditions Index. The sample runs from 1989 to 2017, and in columns (1) and (2) only includes U.S. firms. Panel B: Columns (5) and (6) report difference-in-difference estimates for the effect of hurricane Katrina on the Spillover Persistence (based on ΔCoSP) of exposed U.S. property & casualty insurers relative to other U.S. insurers. The sample is at the firm-day level and runs from August 18 to September 5, 2005. post-Katrina equals 1 from August 25, 2005 onwards, and zero otherwise. Exposed equals 1 if an insurer's share of total P&C premiums in Alabama, Louisiana, and Mississippi from 2004Q3 to 2005Q2 relative to all insurance premiums is in the upper quartile across all U.S. insurers.
Variable definitions are provided in Table IA.1. t-statistics are shown in brackets and based on standard errors clustered at the firm level in columns (1) and (2) and at the firm and country-by-year levels in columns (3) to (4). Standard errors in columns (5) and (6) are heteroscedasticity-consistent. Standardized coefficients are the change in Spillover Persistence (in standard deviations) for a one standard deviation change in the explanatory variable. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	(A) Macro-financial conditions				(B) Fire sales	
Dependent variable:	Spillover Persistence					
Underlying measure:	ΔCoSP			ΔCoVaR	ΔCoSP	
Sample:	U.S.		Full		U.S. insurers	
NFCI	4.54***	3.73***				
	[18.81]	[12.00]				
Crisis		2.14***	4.64***	3.99***		
		[6.98]	[5.99]	[5.61]		
Credit growth		-0.79***	-0.02	0.11**		
		[-12.21]	[-0.28]	[2.00]		
3M yield change		1.15***	0.55*	-0.06		
		[10.82]	[1.78]	[-0.24]		
Term spread change		0.68***	0.30	-0.13		
		[7.10]	[1.12]	[-0.55]		
Credit spread change		0.76***	0.27	-0.13		
		[10.68]	[1.27]	[-0.84]		
post-Katrina × Exposed					0.30***	0.30***
					[4.45]	[4.11]
post-Katrina					-0.30***	
					[-4.45]	
Firm FE	Y	Y	Y	Y	Y	Y
Time FE						Y
No. of firms	207	207	935	619	22	22
No. of obs.	2,798	2,798	10,106	4,652	286	286
Adj. R^2	0.135	0.236	0.176	0.159	0.971	0.971
Adj. R^2 within	0.082	0.189	0.053	0.032	0.107	0.020
Standardized coefficients						
NFCI	.276	.227				

Table 3. Spillover Persistence and Stock Market Bubbles.

Each column reports OLS regressions of Spillover Persistence on stock market bubble indicators from a specification of the form:

$$\bar{\tau}_{i,t} = \alpha' X_{i,t} + \Gamma' C_{i,t} + \varepsilon_{i,t},$$

where $\bar{\tau}_{i,t}$ is Spillover Persistence (based on ΔCoSP), $X_{i,t}$ is a vector of bubble indicators, and $C_{i,t}$ is a vector of control variables and fixed effects for firm i at year t. Bubble indicators are equal to one if there is a bubble, boom, or bust for at least 6 months in the country-year associated with a given firm-year, respectively. The sample is at the firm-year level and runs from 1989 to 2015. Spillover Persistence is estimated in 5-year backward-looking rolling windows, where the last year in columns (1), (2) and (4) to (6) is t and in column (3) it is $t+4$. The sample in columns (4) to (6) exclude bubbles without bursts and only includes bubble episodes in column (4). Macro controls are inflation, log(interest rate), GDP growth, investment growth, and credit growth. Market controls are the short-term yield, credit spread, and term spread changes, TED spread, and stock market return and volatility. Firm characteristics are size, leverage, and market-to-book ratio, all lagged by one year. Boom & bust years are the number of boom and bust years in the 5-year estimation window of ΔCoSP. Variable definitions are provided in Table IA.1. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Spillover Persistence		Spillover Persistence$_{t+4}$	Spillover Persistence		
Sample:	Baseline			Within bubbles	Baseline	
Boom	-5.00***	-1.84**	-3.58***	3.11*	3.68**	0.36
	[-3.05]	[-2.54]	[-2.66]	[1.90]	[2.07]	[0.36]
Bust	-2.41	-0.32	-1.39		-0.43	1.14
	[-1.32]	[-0.37]	[-1.46]		[-0.32]	[1.33]
Boom × Burst Distance				-1.96***	-3.03***	-0.77*
				[-4.54]	[-5.42]	[-1.95]
ΔCoVaR		0.06				0.16
		[0.35]				[0.81]
Macro controls	Y	Y	Y	Y	Y	Y
Market controls		Y			Y	Y
Firm characteristics		Y			Y	Y
Boom & bust length	Y	Y		Y	Y	Y
Boom & bust years						Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE		Y				Y
No. of firms	664	664	464	231	573	573
No. of obs.	6,896	6,896	5,108	1,001	5,706	5,706
Adj. R^2	0.233	0.463	0.134	0.448	0.329	0.493
Adj. R^2 within	0.114	0.048	0.062	0.337	0.212	0.072
p-value for H0: Same coefficient on boom and bust	0.12	0.15	0.11			

Table 4. Spillover Persistence and Fragility in the Financial System.
Each column presents estimated coefficients from a specification of the form:

$$y_{i,t} = \alpha \bar{\tau}_{i,t} + \Gamma' C_{i,t} + \varepsilon_{i,t},$$

where $y_{i,t}$ is an outcome variable, $\bar{\tau}_{i,t}$ is Spillover Persistence, and $C_{i,t}$ is a vector of control variables and fixed effects for firm i at year t. Columns (1) to (5) report OLS regressions of firm characteristics on Spillover Persistence (based on ΔCoSP) at the firm-year level. The dependent variable in columns (1) to (3) is one-year–ahead leverage and in columns (4) and (5) one-year–ahead CDS notional scaled by total assets. The sample in column (1) runs from 1989 to 2017, in columns (2) and (3) from 1991 to 2017, and in columns (4) and (5) from 2005 to 2017. Columns (2) to (5) only include firms from BankFocus. All firm characteristics are standardized. Columns (6) to (8) report OLS regressions of one-year- and two-year–ahead banking crisis indicators on Spillover Persistence at the firm-year level based on a sample that runs from 1989 to 2016. Macro controls are inflation, log(interest rate), GDP growth, investment growth, and credit growth. Market controls are the short-term yield, credit spread, and term spread changes, TED spread, and stock market return and volatility. Firm characteristics are size, leverage, and market-to-book ratio, all lagged by one year. Bank characteristics are liquidity ratio, and demand deposits, impaired loans, and intangible assets as a share of total assets, all lagged by one year. Variable definitions are provided in Table IA.1. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. Standardized coefficients are the change in the dependent variable (in standard deviations) for a standard deviation change in Spillover Persistence. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Leverage$_{t+1}$			CDS$_{t+1}$		100× Crisis$_{t+1}$		100× Crisis$_{t+2}$
Sample:	Baseline	Ban & Bro				Baseline		
Spillover Persistence	-0.07**	-0.09*	-0.06	-0.00	-0.01**	-0.60*	-0.48***	-0.39***
	[-2.43]	[-1.76]	[-1.18]	[-1.25]	[-2.00]	[-1.77]	[-3.66]	[-3.02]
Spillover Persist. × Size			0.02		0.01**			
			[0.69]		[2.33]			
Spillover Persist. × Leverage			-0.17**		-0.00			
			[-2.52]		[-0.84]			
Spillover Persist. × Market-to-Book			-0.08***		-0.01***			
			[-2.68]		[-2.77]			
Spillover Persist. × Liquidity ratio			0.04		0.02*			
			[1.50]		[1.77]			
Spillover Persist. × Demand deposits			-0.05		-0.01			
			[-1.54]		[-1.63]			
Spillover Persist. × Impaired loans			-0.03		-0.03***			
			[-1.21]		[-2.71]			
Spillover Persist. × Intangible assets			-0.05***		-0.01			
			[-2.61]		[-1.51]			
Macro controls	Y	Y	Y	Y	Y		Y	Y
Market controls		Y	Y		Y		Y	Y
Firm characteristics	Y	Y	Y	Y	Y		Y	Y
Bank characteristics		Y	Y	Y	Y		Y	Y
Average ΔCoSP	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y		Y	Y
No. of firms	792	195	195	77	77	631	631	619
No. of obs.	8,380	1,676	1,676	688	688	6,755	6,755	6,403
Adj. R^2	0.723	0.852	0.854	0.809	0.825	0.162	0.744	0.748
Adj. R^2 within	0.187	0.179	0.192	0.071	0.150	0.136	0.308	0.272
Standardized coefficient:	-0.03	-0.04	-0.03	-0.04	-0.10	-0.11	-0.09	-0.07

Internet Appendix for

Tackling the Volatility Paradox: Spillover Persistence and Systemic Risk

A Data and Summary Statistics

A.1 Variable Definitions

Table IA.1: Variable Definitions and Data Sources.

Equity market data is at daily frequency, all other variables are at annual frequency. All systemic risk measures and firm and bank characteristics are winsorized at 1%/99%.

Variable	Definition
Equity Market Data	
Stock price	Daily unadjusted and unpadded price of common equity. *Source*: Thomson Reuters Datastream
Nr. of outstanding shares	Daily number of outstanding shares of common equity. *Source*: Thomson Reuters Datastream
Market value	Daily market value of equity in USD. *Source*: Thomson Reuters Datastream
(Systemic) Risk Measures	
ΔCoSP(τ)	Likelihood of losses of the system τ days after losses of the institution in excess of the reference level $q = 0.05$
Average ΔCoSP ($\bar{\psi}$)	Average level of ΔCoSP across time-lag
Spillover Persistence ($\bar{\tau}$)	Systemic-risk–weighted average time-lag
ΔCoVaR	Change in the system's Value-at-Risk conditional on a firm being under distress compared to its median state
MES	Firm's average equity return loss conditional on large system losses on the same day
Macroeconomic Characteristics	
NFCI	Federal Reserve Bank of Chicago's National Financial Conditions Index; annual average; standardized for the period from 1989 to 2018. *Source*: FRED
Inflation	Δlog(Consumer Price Index); annual rate, country-level. *Source*: BIS
GDP growth	Δlog(real GDP); annual rate, country-level. *Source*: OECD
Investment growth	Δlog(investment/GDP); annual rate, country-level. *Source*: OECD
Credit growth	Δlog(credit/GDP); annual rate, country-level. *Source*: BIS
Crisis	Indicator for the occurrence of banking crises. *Source*: Laeven and Valencia (2018)
Output loss	3-year cumulative deviation from GDP trend associated with banking crises. *Source*: Laeven and Valencia (2018)

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Table IA.1 – *Continued from previous page*

Variable	**Definition**
log(interest rate)	*log*(10-year government bond rate); annual average of weekly rate, continent-level. *Source*: see Table IA.2
3M yield change	Weekly change in 3-month government bond rates; annual average. *Source*: see Table IA.2
Term spread change	Weekly change in yield spread between 10-year and 3-month government bond rates; annual average. *Source*: see Table IA.2
TED spread	Spread between 3-month Libor (interbank) and 3-month government bond rates; average per year. *Source*: see Table IA.2
Credit spread change	Weekly change in the spread between Moody's Baa rated bonds and 10-year government bond rates; annual average. *Source*: see Table IA.2
Market return	Weekly market return of system-specific MSCI indices; annual average. *Source*: see Table IA.2
Equity volatility	22-day rolling window market return of system-specific MSCI indices; annual average. *Source*: see Table IA.2
Boom	Indicator for whether a country experiences a stock market boom. *Source:* Brunnermeier et al. (2020)
Bust	Indicator for whether a country experiences a stock market bust. *Source:* Brunnermeier et al. (2020)
Boom length	Current length of a country's stock market boom. *Source:* Brunnermeier et al. (2020)
Bust length	Current length of a country's stock market bust. *Source:* Brunnermeier et al. (2020)
Burst distance	Current distance to a country's stock market bubble's burst. *Source:* Own calculation based on data from Brunnermeier et al. (2020)
Firm Characteristics (*Source: Worldscope.*)	
Size	log(total assets)
Leverage	Total assets / market value of common equity
Market-to-book	Market value of equity / book value of equity
Bank Characteristics (Ban & Bro Sample) (*Source: BankFocus if not stated otherwise*)	
Size	log(total assets)
Leverage	Total assets / market value of equity *Source*: BankFocus (total assets) and Worldscope (market value)
Demand deposits	Customer deposits that can be withdrawn immediately without notice or penalty / total assets
Intangible assets	(Goodwill + other intangible assets) / total assets
Impaired loans	Impaired & non-performing exposure on customer and inter-bank loans before loan loss reserves / total assets

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Table IA.1 – *Continued from previous page*

Variable	**Definition**
Liquidity ratio	Liquid assets (cash and balances with central banks, net loans & advances to banks, reverse repos, securities borrowed & cash collateral, and financial assets: trading and at fair value through P&L less any mandatory reserve deposits with central banks) / deposits and short-term funding
CDS	Total credit default swap notional / total assets
Fire Sale Sample	
Exposed	Indicator whether insurer's total P&C premiums written in Alabama, Louisiana, and Mississippi (at insurance group level) from 2004Q3 to 2005Q2 are in the upper quartile of the distribution across US insurers. *Source:* own calculation based on insurers' quarterly Schedule T filings to the NAIC retrieved from S&P Global Market Intelligence
post-Katrina	Indicator for August 25, 2005, and afterwards

Table IA.2. Region-level macroeconomic state variables and data sources.

The table depicts the region-level macroeconomic variables, which also serve as state variables to estimate ΔCoVaR with quantile regressions, and compares them to the state variables used by Adrian and Brunnermeier (2016) for the U.S. The choice of state variables is motivated by that in Brunnermeier et al. (2020).

Used by	**Data used instead**					
AB2016	**North America**	**Europe**	**Japan**	**Australia**	**Asia (ex Japan)**	**Africa**
10Y treasury rate	US 10Y treasury rate (FRED)	German 10Y govt. bond rate (Datastream)	Japanese 10Y govt. bond rate (Datastream)	Australian 10Y govt. bond rate (Datastream)	Indian 10Y govt. bond rate (Datastream)	South African 10Y govt. bond rate (Datastream)
3M T-Bill rate	US 3M T-Bill rate (FRED)	German 3M govt. bond rate (Datastream)	Japanese 3M govt. bond rate (Datastream)	Australian 3M govt. bond rate (Datastream)	Indian 3M govt. bond rate (Datastream)	South African 3M govt. bond rate (Datastream)
3M Libor rate	3M Libor rate (FRED)	3M Fibor rate (Datastream)	3M Japanese Libor rate (FRED)	Australian 3M interbank rate (Datastream)	Indian 91-day T-bill rate (Datastream)	South African 3M interbank rate (Datastream)
Moody's Baa rated bonds	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)
S&P500	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)	MSCI Asia (excl Japan) (Datastream)	MSCI Africa (Datastream)
CRSP equity market index	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)	MSCI Asia (excl Japan) (Datastream)	MSCI Africa (Datastream)

A.2 Variable Construction

A.2.1 Macroeconomic Characteristics. In many analyses, I control for macroeconomic variables that capture key differences in economic environments, namely inflation, GDP growth, credit growth, investment growth, and an indicator for banking crises (all at country-level), and the logarithm of the annual average of the 10-year government bond rate (at region level).[1]

Additionally, I use granular variables on funding conditions and financial markets (motivated by their use by Adrian and Brunnermeier, 2016), namely annual averages of the weekly changes in 3-month government bond rate, weekly changes in the slope of the yield curve (10-year and 3-month government bond rate spread), the TED spread (3-month interbank and government bond rate spread), weekly changes in credit spreads (between Moody's Baa-rated bonds and the 10-year government bond rate), and the weekly equity market return and volatility. I use different government bond rates, interbank market rates, and equity market indices for different geographical regions (Europe, North America, Asia, Japan, and Australia). I retrieve all available data on a daily basis, interpolate missing data by using cubic spline interpolation, and winsorize each variable at 1% and 99%. The data sources are St. Louis FRED database and Thomson Reuters Datastream. A detailed description of variable definitions and data sources is given in Tables IA.1 and IA.2.

A.2.2 Firm Characteristics. I consider several firm-level variables that have been shown to be relevant for systemic risk, namely firm size (the logarithm of total assets), the ratio of

[1] The annual average of the 10-year government bond rate is strictly positive throughout the whole sample after merging with systemic risk measures. I use its logarithm following Brunnermeier et al. (2020). The results are robust to using the actual level of the interest rate level instead of its logarithm.

market to book value, and leverage (the ratio of total assets to the market value of equity). Annual data for these variables are from Thomson Reuters Worldscope.

Additionally, I zoom in on granular characteristics of banks and broker-dealers. For this purpose, I retrieve detailed bank-level data from 1990 to 2016 for all banks featured in both Moody's Analytics BankFocus and the sample of systemic risk measures. I consider bank-level variables that provide granular information on banks' liquidity profile, namely the relative size of intangible assets, demand deposits, time deposits, loans, and impaired (and non-performing) loans (all scaled by total assets), and banks' liquidity ratio defined by liquid assets over deposits and short-term funding.[2] For additional analyses on bank risk-taking, I also retrieve data on banks' CDS exposure, which is the CDS notional as a share of total assets. To ensure consistency in accounting, I use total assets from BankFocus as a scaling factor for all bank-related variables and also re-calculate size and leverage for banks using BankFocus in all regressions for the sample of BankFocus firms.

A.2.3 Exposure to Hurricane Katrina. For each US insurer, I calculate the share of total P&C insurance premiums written (at the group level) in Alabama, Louisiana, and Mississippi relative to total premiums written in the year prior to Katrina (i.e., in quarters 2004Q3 to 2005Q2). US insurers in the upper quartile of the cross-sectional distribution of premium shares are defined as exposed to Katrina, remaining US insurers are in the control group.[3]

[2] Detailed variable definitions are given in Table IA.1. If available, I use banks' consolidated balance sheet, and the unconsolidated balance sheet otherwise.

[3] Since life insurers were relatively unaffected by the hurricane, it is reasonable to include them in the control group. Although many lives were lost during Katrina, most of them were uninsured (see Towers Watson, "Hurricane Katrina: Analysis of the Impact on the Insurance Industry" available at `https://biotech.law.lsu.edu/blog/impact-of-hurricane-katrina-on-the-insurance-industry-towers-watson.pdf`).

US insurance companies report premiums for direct insurance business (excluding reinsurance business) at the state-level in Schedule T of their quarterly statutory filings. I retrieve this data from S&P Global Market Intelligence. To detect reporting errors, I compare the sum of premiums across states reported on Schedule T with that reported in the insurer's overview filings and exclude insurer-quarters if there is a discrepancy larger than 50 thd USD and 50% of the average total direct premiums reported across the filing pages. I then calculate (1) the sum of total P&C premiums written in Louisiana, Mississippi, and Alabama and (2) the sum of total direct premiums written from 2004Q3 to 2005Q2 at the insurance group - state level.

To merge premiums to equity market data, I retrieve insurer groups' stock tickers and CUSIP identifiers from S&P Global Market Intelligence and match these to CUSIPs and stock tickers, and manually check the resulting matching. In the sample of all (51) matched insurance groups, I flag insurers as exposed to hurricane Katrina if they are headquartered in the US and the ratio of premiums written in exposed states is in the upper quartile of the cross-sectional distribution, and all other insurers as unexposed. By accounting for headquarter location, I assign two non-US insurers to the control group which would otherwise be treated (AXA and Beazley). The reason is that US premiums written are only a small fraction of the premiums written by these insurers.[4]

A.2.4 Bubbles. Bubble indicators are based on the well-established Backward Sup Augmented Dickey-Fuller (BSADF) approach by Phillips et al. (2015a,b) and Phillips and Shi

[4]In 2005, less than 7% of AXA's P&C gross premiums were written in the US (see Annual Report 2005). In 2009, 10% of Beazley's gross premiums were written in the US (*Source: S&P Global Market Intelligence*).

(2018), applied to the main stock price indices in 17 countries from 1987 to 2015.[5] Bubble characteristics include the current length of a boom or bust. Bubble indicators are merged to the baseline sample of systemic risk measures and firm characteristics at the firm-year level.[6] The "bubbles sample" covers 33 bubbles, 17 countries, and 693 financial firms from 1989 to 2015.[7]

[5]The BSADF approach uses multiple Augmented Dickey-Fuller tests to identify non-stationary behavior in asset prices. For methodological details I refer to Brunnermeier et al. (2020), who kindly shared their sample of bubble indicators with me.

[6]I label a firm-year as stock market boom or bust observation if the respective bubble phase is present in at least 6 months of the firm's headquarter country in that year.

[7]The sample includes Australia, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United States.

A.3 Additional Summary Statistics

Table IA.3. Additional summary statistics.

Boom & bust length & years summary statistics are provided conditional on bubble occurrence. Variable descriptions and data sources are provided in Table IA.1.

Fragility sample						
Size_{t-1}	8,380	2.62	2.62	2.30	-1.10	6.52
Leverage_{t-1}	8,380	11.34	6.00	15.60	0.79	40.12
$\text{Market-to-Book}_{t-1}$	8,380	1.70	1.28	1.48	0.47	4.26
Ban & Bro sample						
Size_{t-1}	1,676	3.93	3.76	1.73	1.15	7.14
Leverage_{t-1}	1,676	14.57	9.73	14.70	2.95	42.37
$\text{Market-to-Book}_{t-1}$	1,676	1.46	1.27	0.90	0.44	3.04
$\text{Liquidity ratio}_{t-1}$	1,676	0.45	0.30	0.64	0.05	1.04
$\text{Demand deposits}_{t-1}$	1,676	0.20	0.17	0.15	0.02	0.47
$\text{Impaired loans}_{t-1}$	1,676	0.02	0.01	0.02	0.00	0.05
$\text{Intangible assets}_{t-1}$	1,676	0.02	0.01	0.03	0.00	0.07
Macro controls						
Inflation	8,380	2.04	1.98	1.54	-0.22	4.67
GDP growth	8,380	4.10	4.21	2.79	-1.65	8.31
Investment growth	8,380	-0.38	0.39	4.07	-6.97	4.22
Credit growth	8,380	1.22	1.07	3.69	-4.55	7.26
log(Interest rate)	8,380	0.97	1.29	0.98	-1.26	2.06
Market controls						
3M yield change	8,380	-0.52	-0.07	2.10	-3.95	2.50
Term spread change	8,380	0.06	-0.26	2.30	-2.88	2.93
TED spread	8,380	37.44	30.85	31.83	0.12	101.73
Credit spread change	8,380	0.09	-0.08	1.89	-3.17	3.31
Stock Market Return	8,380	0.13	0.20	0.39	-0.66	0.61
Stock Market Volatility	8,380	1.05	0.97	0.45	0.49	2.08
Bubbles sample						
Boom length	1,162	2.14	1.67	1.68	0.00	4.92
Bust length	1,162	0.34	0.00	0.57	0.00	1.33
$\text{Boom years}_{(t-4):t}$	1,162	2.73	3.00	1.34	1.00	5.00
$\text{Bust years}_{(t-4):t}$	1,162	0.41	0.00	0.70	0.00	2.00

B Empirical Methodology and Estimation Details

B.1 Firm's and System's Return

A firm's and system's equity return are mechanically correlated if the system's index included the firm. This might bias systemic risk measures. I alleviate this concern by excluding firm I from the associated system S for each pair (I, S) as described in the following.

Denote by MC_t^I the market capitalization of firm I at time t in USD. By P_t^I I denote a firm I's unpadded and unadjusted price of common equity in local currency, and by N_t^I the number of shares of the firm's common equity. A system is given by a subset $S \subseteq \{1, ..., N\}$, where N is the number of all firms in the sample. Then, the index for system S excluding firm $I \in \{1, ..., N\}$ is given as the weighted average of remaining firms' returns:

$$INDEX_t^{S|I} = INDEX_{t-1}^{S|I} \sum_{s \in S \setminus \{I\}} \frac{MC_{t-1}^s}{\sum_{j \in S \setminus \{I\}} MC_{t-1}^j} \frac{P_t^s N_t^s}{P_{t-1}^s N_{t-1}^s}. \tag{IA.1}$$

The system's log equity return is

$$r_t^S = r_t^{S|I} = \log \left(\frac{INDEX_t^{S|I}}{INDEX_{t-1}^{S|I}} \right) \tag{IA.2}$$

and the firm's log equity return is

$$r_t^I = \log \left(\frac{P_t^I N_t^I}{P_{t-1}^I N_{t-1}^I} \right). \tag{IA.3}$$

B.2 Estimation Details

Denote by $D_t^I = \mathbb{1}_{\left\{-r_t^I \geq VaR^I(q)\right\}}$ and $D_t^S = \mathbb{1}_{\left\{-r_t^S \geq VaR^S(q)\right\}}$ binary random variables for large losses of financial institution I and the system S, respectively, where the stationary distribution of $(r_t^x)_t$ satisfies $\mathbb{P}(-r_t^x \geq VaR^x(q)) = q$ for $x \in \{S, i\}$. Assume that $(D_t^I, D_t^S)_t$ is a stationary time series with the time-invariant means $\mathbb{P}(D_t^I = 1) = \mathbb{P}(D_t^S = 1) = q$ and variances $\mathbb{E}[(D_t^I - q)^2] = \mathbb{E}[(D_t^S - q)^2] = q(1-q)$. Then, ΔCoSP equals

$$\Delta\psi(\tau) = (1-q) \cdot r_{CC}(\tau), \tag{IA.4}$$

where $r_{CC}(\tau)$ is the (time-invariant and normalized) cross-correlation function of $(D_t^I, D_t^S)_t$, defined as

$$r_{CC}(\tau) = \frac{\mathbb{E}\left[(D_t^I - q)(D_{t+\tau}^S - q)\right]}{q(1-q)}. \tag{IA.5}$$

Using a standard non-parametric estimator for $r_{CC}(\tau)$, a non-parametric estimator for ΔCoSP is given by

$$\Delta\widehat{\text{CoSP}}(\tau) = \frac{1}{q(n-\tau)} \sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I(q),\, -r_{t+\tau}^S \geq \widehat{VaR}^S(q)\right\}} - q, \tag{IA.6}$$

where the Value-at-Risk estimator is the nq^x-th (or $[nq^x]+1$)-th) order statistic of r^x if nq^x is an integer (if it is not). Note that $\Delta\widehat{\text{CoSP}}(\tau) + q$ equals the OLS estimator for ψ in the linear model

$$\mathbb{1}_{\left\{-r_{t+\tau}^S \geq \widehat{VaR}^S(q)\right\}} = \psi \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I(q)\right\}} + \varepsilon_t$$

if $q(n-\tau)$ is an integer (and, otherwise, asymptotically).[8]

To compute Spillover Persistence, I assume that ΔCoSP is exponentially declining with a larger time-lag, $\Delta\text{CoSP}(\tau) = ae^{\beta\tau}$ with $\alpha > 0$ and $\beta < 0$. This assumption is motivated by the dynamics of the non-parametric estimate $\widehat{\Delta\text{CoSP}}(\tau)$. I estimate the parameters α and β by fitting $\widehat{\Delta\text{CoSP}}(\tau)$ to $ae^{\beta\tau}$ individually for each institution and estimation window using Matlab's trust-region-reflective algorithm. I disregard observations with $\alpha \leq 0$ or $\beta \geq 0$ because, in such cases, there is either no systemic risk present or the dynamics of ΔCoSP are implausible (as they would imply that tail-returns are more correlated when they are further apart).

Figure 1 depicts the non-parametric and parametric estimates of ΔCoSP for an exemplary institution. In Figure 1 (a), from a relatively tranquil market period, ΔCoSP is clearly exponentially declining. Instead, in Figure 1 (b), from crisis times, ΔCoSP is almost constant. In both cases, the parametric estimate fits the dynamics of the non-parametric estimate very well.

An important concern is that the parametric estimation of ΔCoSP induces a systematic bias. I assess that concern in Figure IA.1. I start by examining the difference between the non-parametric and parametric estimates pooled across all time-lags and firms. Figure IA.1 (a) shows that the average difference is essentially zero and its distribution symmetric around zero in all years. This result strongly suggests that there is no systematic bias resulting from the parametric estimation of ΔCoSP. The absolute value of the 10th and 90th percentile of

[8] The OLS estimator is $\frac{\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I,\, -r_{t+\tau}^S \geq \widehat{VaR}^S\right\}}}{\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I\right\}}}$ and for integer $q(n-\tau)$ it equals $\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I\right\}} = q(n-\tau)$, in which case the OLS estimator coincides with $\widehat{\Delta\text{CoSP}}(\tau) + q$.

differences is approximately $\pm 5\%$. The symmetry in the distribution is consistent with the absence of a systematic bias, whereas the levels suggest that estimation errors are contained.

The most likely cause for a potential bias in the parametric estimation is the presence of negative values of ΔCoSP. First, it is important to note that the parametric form $\alpha e^{\beta\tau}$ allows for systematically negative ΔCoSP (in this case, it is $\alpha < 0$). More generally, ΔCoSP may be negative for two reasons: because of estimation errors or because its true value is negative. Exemplary evidence is provided by Figure 1 (a), in which $\Delta\widehat{\text{CoSP}}$ drops below zero only in some instances, which are clearly estimation errors around its average dynamics.

To examine the occurrence of negative values of $\Delta\widehat{\text{CoSP}}$, Figure IA.1 (b) plots the share of all firm-by-year observations with at least x negative time-lags. Whereas in almost 90% of observations, there is at least one time-lag with a negative value of $\Delta\widehat{\text{CoSP}}$, in only 10% of observations, half (25) of the time-lags are associated with negative values. There are considerably less instances of three consecutive time-lags with negative $\Delta\widehat{\text{CoSP}}$. In only 5% of firm-year pairs, at least one fifth of the time-lags τ exhibit a negative value of $\Delta\widehat{\text{CoSP}}$ and are followed by lags $j \in \{\tau + 1, \tau + 2\}$ with $\Delta\widehat{\text{CoSP}}(j) < 0$. Thus, time-lags with negative values of $\Delta\widehat{\text{CoSP}}$ are typically *not* followed by lags with negative values of $\Delta\widehat{\text{CoSP}}$ but, instead, occur in isolation. These results are consistent with negative values of $\Delta\widehat{\text{CoSP}}$ resulting from estimation errors rather than from systematically negative ΔCoSP.

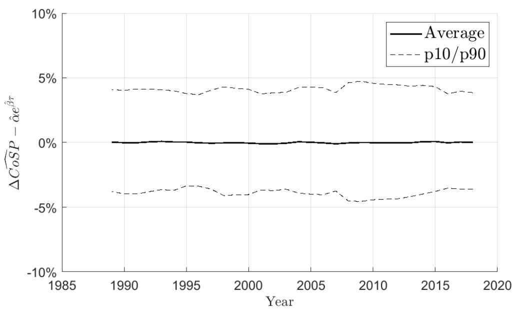
I disregard observations when the fitted parameters of $\alpha e^{\beta\tau}$ are such that $\alpha \leq 0$ or $\beta \geq 0$ or when Average ΔCoSP is below 10^{-5}. Figure IA.1 (c) shows that these criteria disregard less than 25% of observations and, in the second half of the sample, less than 15% of observations. This provides further support that the parametric estimation approach is appropriate.

Finally, in Figure IA.1 (d), I compare the baseline (parametric) measure for Spillover Persistence with an alternative (non-parametric) version that weights time-lags with $\Delta\widehat{\text{CoSP}}$, allowing for negative weights $\Delta\widehat{\text{CoSP}} < 0$. The figure shows substantial deviation between these two measures when Spillover Persistence is small. The large dispersion of the non-parametric estimate in these cases suggest a significant impact of estimation errors. Moreover, the non-parametric Spillover Persistence frequently drops below zero, inconsistent with its interpretation as average time-lag.

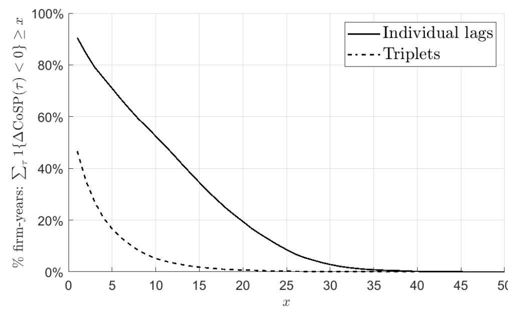
Taken together, these observations suggest that the parametric estimation procedure for ΔCoSP does not create a systematic bias and is appropriate especially in the context of estimating Spillover Persistence.

Figure IA.1. Estimation Details.

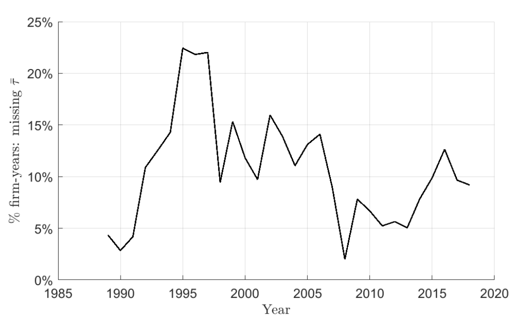
Figure (a) plots the average and 10/90th percentiles of the pooled distribution of the difference between the non-parametric and parametric estimate for $\Delta\text{CoSP}(\tau)$ across firms and time-lags τ. Figure (b) plots the share of firm-by-year observations with at least x individually negative time-lags (solid line), i.e., $\Delta\widehat{\text{CoSP}}(\tau) < 0$ for at least x time-lags τ, and with at least x consecutively negative time-lags (dashed line), i.e., $\Delta\widehat{\text{CoSP}}(\tau) < 0$ and $\Delta\widehat{\text{CoSP}}(\tau+1) < 0$ and $\Delta\widehat{\text{CoSP}}(\tau+2) < 0$ for at least x time-lags τ. Figure (c) plots the share of firms with a non-parametric estimate for ΔCoSP but not for Spillover Persistence. Figure (d) is a scatter plot of all observations for Spillover Persistence fitted to $\alpha e^{\beta\tau}$ against that based on the non-parametric estimate $\Delta\widehat{\text{CoSP}}$ (allowing that $\Delta\widehat{\text{CoSP}} < 0$).



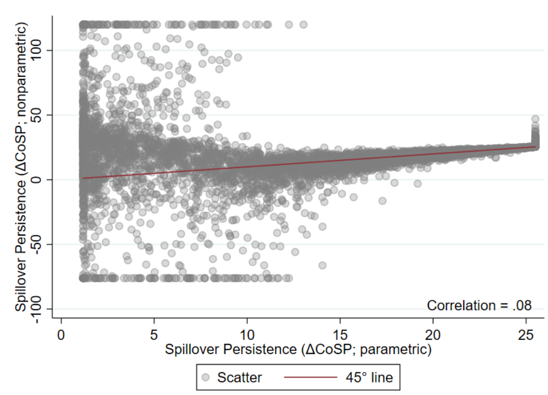
(a) Residuals from Exponential Fit.



(b) Observations with Negative $\Delta\text{CoSP}(\tau)$.



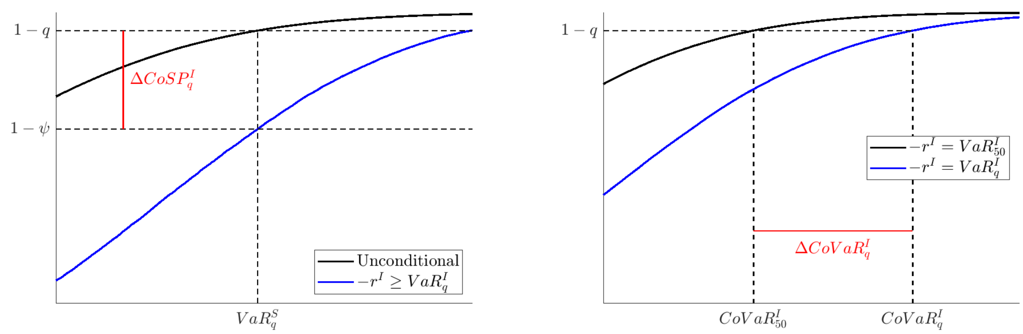
(c) Observations without Exponential Fit.



(d) Spillover Persistence: baseline vs. non-parametric.

C Additional Figures and Tables

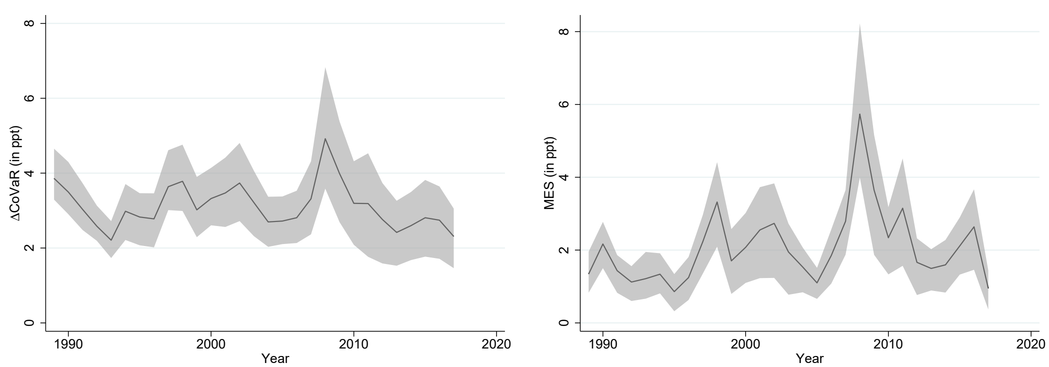
Figure IA.2. Conceptual Illustration of ΔCoSP in Comparison with ΔCoVaR.
The figures depict (conditional) cumulative distribution functions (cdfs) of the system's return losses ($-r^S$) and the quantiles and probabilities that correspond to (a) ΔCoSP and (b) ΔCoVaR. In Figure (a), the upper (black) solid line is the unconditional cdf and the lower (blue) is the cdf conditional on the institution's return losses exceeding their Value-at-Risk ($-r^I \geq VaR^I_q$). CoSP equals one minus the value of the conditional cdf at the system's Value-at-Risk. ΔCoSP is the difference between the two cdfs at the system's Value-at-Risk. In Figure (b), the upper (black) solid line is the cdf conditional on the institution's return losses being at their median and the lower (blue) is the cdf conditional on the institution's return losses being at their distressed Value-at-Risk. CoVaR is the respective quantile at $1 - q$. ΔCoVaR is the difference between the two quantiles corresponding to $1 - q$.



(a) ΔCoSP.

(b) ΔCoVaR.

Figure IA.3. Contemporaneous Systemic Risk Measures: Evolution over Time.
The figures depict the annual mean and 25th and 75th percentiles of ΔCoVaR and MES across firms.



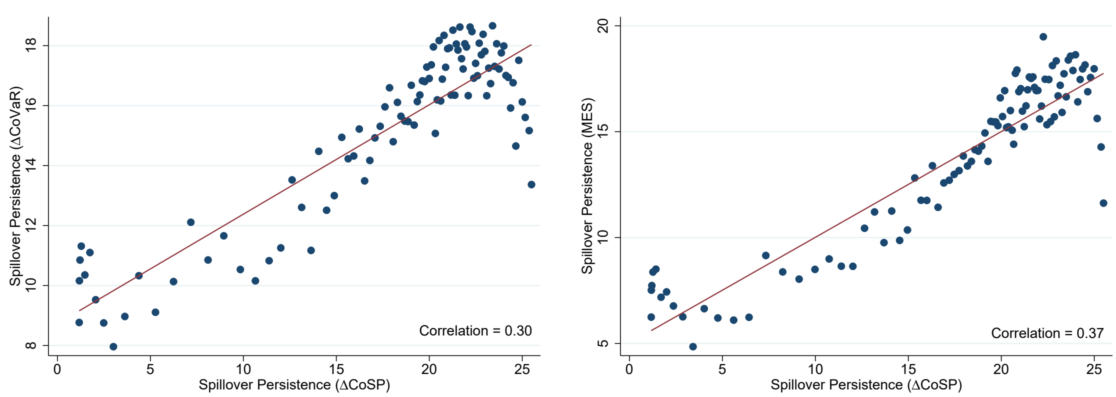
(a) ΔCoVaR.

(b) MES.

Table IA.4. Correlation of Spillover Persistence with Other Measures.
This table reports the correlation of Spillover Persistence based on ΔCoSP with other systemic risk measures and Spillover Persistence based on other systemic risk measures as well as the corresponding adjusted R^2.

Measure	(1) Average ΔCoSP	(2) ΔCoVaR	(3) MES	(4) Spillover Persistence (ΔCoVaR)	(5) Spillover Persistence (MES)
Correlation	0.65	0.09	0.14	0.30	0.37
Adj. R^2	0.42	0.01	0.02	0.09	0.14

Figure IA.4. Comparison of Spillover Persistence across Different Systemic Risk Measures.
These figures plot Spillover Persistence based on ΔCoSP (x-axis) against that based on (a) ΔCoVaR and (b) MES (y-axis) as binscatter plots based on firm-by-year–level observations.

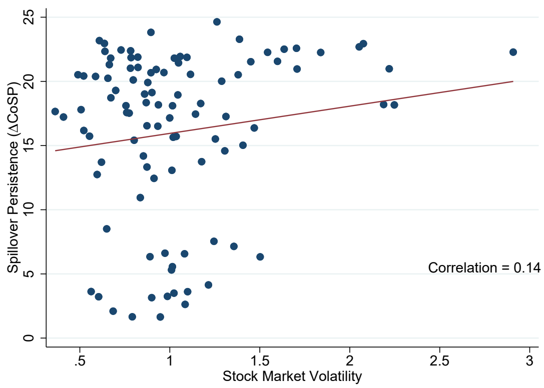


(a) ΔCoSP and ΔCoVaR.

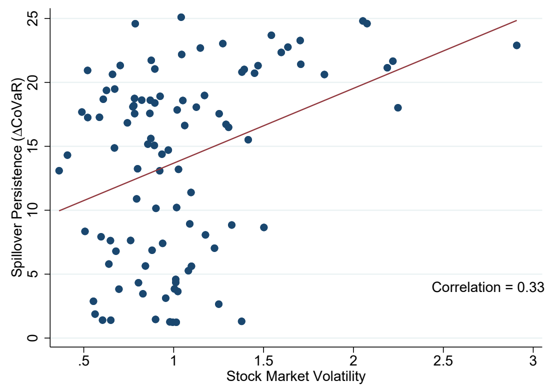
(b) ΔCoSP and MES.

Figure IA.5. Correlation of Spillover Persistence with Stock Market Volatility.

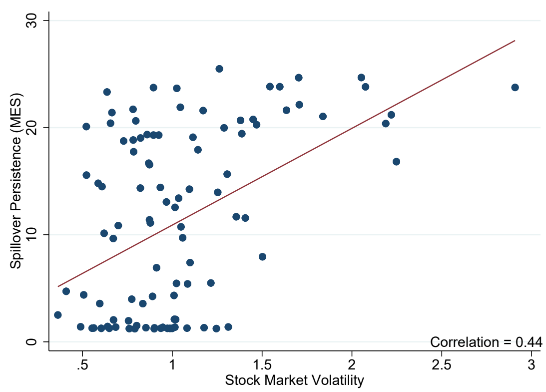
These figures plot the annual average of the 22-day trailing standard deviation of the system's equity returns (x-axis) against Spillover Persistence for the system's median institution (y-axis) based on (a) ΔCoSP, (b) ΔCoVaR, (c) MES as binscatter plots based on system-by-year–level observations.



(a) Based on ΔCoSP.



(b) Based on ΔCoVaR.



(c) Based on MES.

D Sensitivity Analyses

D.1 Robustness

Table IA.5. Robustness: Fire Sales.

Each column presents difference-in-difference estimates for the effect of hurricane Katrina on the Spillover Persistence (based on ΔCoSP) of exposed US property & casualty insurers relative to other U.S. insurers:

$$\bar{\psi}_{i,t} = \text{post-Katrina}_t \times \text{Exposed}_i + u_i + \varepsilon_{i,t},$$

where u_i are firm fixed effects. post-Katrina equals 1 from August 25, 2005 onwards, and zero otherwise. Exposed equals 1 if an insurer's share of total P&C premiums in Alabama, Louisiana, and Mississippi from 2004Q3 to 2005Q2 relative to all insurance premiums is in the upper quartile across all U.S. insurers. The sample is at the firm-day level. In columns (1) and (2) it runs from August 11 to September 12, 2005, and in columns (3) and (4) from August 18 to September 5, 2005. In columns (1) and (2), Spillover Persistence is based on ΔCoSP, in column (3) based on ΔCoVaR, and in column (4) based on MES. t-statistics are shown in brackets and based on standard errors that are heteroscedasticity-consistent. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence			
Underlying measure:	ΔCoSP		ΔCoVaR	MES
Sample:	U.S. insurers	U.S. & CA insurers	U.S. insurers	
Window length:	Long		Baseline	
post-Katrina × Exposed	0.41***	0.57***	0.49**	0.89***
	[3.17]	[4.44]	[2.50]	[4.61]
Firm FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
No. of firms	22	27	22	22
No. of obs.	506	621	495	475
Adj. R^2	0.895	0.895	0.792	0.855
Adj. R^2 within	0.009	0.014	0.006	0.038

Table IA.6. Spillover Persistence based on ΔCoVaR and Stock Market Bubbles.
This table presents OLS estimates analogously to those in Table 3 with the difference that Spillover Persistence is based on ΔCoVaR. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Spillover Persistence (ΔCoVaR)		Spillover Persistence$_{t+4}$	Spillover Persistence		
Sample:	Baseline			Within bubbles	Baseline	
Boom	-5.16***	-1.73**	-1.45	4.03**	1.18	-0.72
	[-3.79]	[-2.02]	[-1.55]	[2.21]	[0.80]	[-0.46]
Bust	-1.67	1.70	-1.04		-0.03	1.17
	[-0.94]	[1.41]	[-0.79]		[-0.02]	[0.84]
Boom × Burst Distance				-2.88***	-2.67***	-0.60
				[-5.43]	[-5.62]	[-1.19]
ΔCoVaR		0.76***				0.97***
		[2.91]				[3.31]
Macro controls	Y	Y	Y	Y	Y	Y
Market controls		Y			Y	Y
Firm characteristics		Y			Y	Y
Boom & bust length	Y	Y		Y	Y	Y
Boom & bust years						Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE		Y				Y
No. of firms	612	612	441	182	526	526
No. of obs.	5,536	5,536	4,301	730	4,575	4,575
Adj. R^2	0.172	0.271	0.182	0.347	0.227	0.282
Adj. R^2 within	0.046	0.045	0.088	0.205	0.105	0.053
p-value for H0: Same coefficient on boom and bust	0.04	0.01	0.77			

Table IA.7. Robustness: Spillover Persistence and Crises.

Each column reports OLS regressions of banking crises indicators on systemic risk measures at the firm-year level:

$$y_{i,t} = \alpha X_{i,t} + \Gamma' C_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ is either Spillover Persistence or ΔCoVaR and $C_{i,t}$ is a vector of control variables and fixed effects. Output loss is the % loss in GDP associated with banking crises, following Laeven and Valencia (2018). All crisis indicators are multiplied by 100 for readability. Variable definitions are analogous to those in Table 4. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	$100\times$ $1\{\text{Crisis}_{t+1}\}$		$100\times$ $1\{\text{Crisis}_{t+3}\}$	$100\times$ $1\{\text{Crisis}_{t+1}\}$		$100\times$ $1\{\text{Systemic Crisis}_{t+1}\}$	Output loss_{t+1}
ΔCoVaR	17.52***	-3.28***					
	[5.63]	[-3.13]					
Spillover Persistence (ΔCoSP)		-0.49***	-0.23**			-0.37***	-0.16***
		[-3.76]	[-2.24]			[-3.30]	[-3.96]
Spillover Persistence (ΔCoVaR				0.28			
				[1.19]			
Spillover Persistence (MES)					0.11		
					[0.56]		
Macro controls		Y	Y	Y	Y	Y	Y
Market controls		Y	Y	Y	Y	Y	Y
Firm characteristics		Y	Y	Y	Y	Y	Y
Bank characteristics		Y	Y	Y	Y	Y	Y
Average ΔCoSP/ΔCoVaR/MES		Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y	Y	Y
No. of firms	631	631	598	576	584	618	631
No. of obs.	6,755	6,755	5,959	5,487	5,340	6,646	6,755
Adj. R^2	0.160	0.745	0.755	0.073	0.100	0.624	0.703
Adj. R^2 within	0.133	0.313	0.246	0.023	0.039	0.317	0.367

Table IA.8. Robustness with Prewhitened CoSP: Spillover Persistence and Financial Conditions.

This table presents OLS estimates using prewhitened CoSP analogously to those in Table 2. t-statistics are shown in brackets and based on standard errors clustered at the firm level in columns (1) and (2) and at the firm and country-by-year levels in column (3). Standard errors in columns (4) and (5) are heteroscedasticity-consistent. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)
	(A) Macro-financial conditions			(B) Fire sales	
Dependent variable:	Spillover Persistence (prewhitened)				
Sample:	US		Full	US insurers	
NFCI	4.62***	4.41***			
	[19.40]	[14.85]			
Crisis		1.36***	4.26***		
		[4.92]	[5.62]		
Credit growth		-0.69***	-0.05		
		[-10.91]	[-0.84]		
3M yield change		1.12***	0.57**		
		[11.21]	[1.99]		
Term spread change		0.60***	0.31		
		[7.08]	[1.28]		
Credit spread change		0.71***	0.29		
		[11.11]	[1.55]		
post-Katrina × Exposed				0.16***	0.16**
				[2.79]	[2.43]
post-Katrina				-0.16***	
				[-2.79]	
Firm FE	Y	Y	Y	Y	Y
Time FE					Y
Standardized coefficients					
NFCI	.297	.284			
No. of firms	206	206	931	22	22
No. of obs.	2,711	2,711	9,821	286	286
Adj. R^2	0.138	0.229	0.167	0.980	0.981
Adj. R^2 within	0.094	0.189	0.052	0.045	0.007

Table IA.9. Robustness with Prewhitened CoSP: Spillover Persistence and Stock Market Bubbles.

This table presents OLS estimates using prewhitened CoSP analogously to those in Table 3. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Spillover Persistence (prewtd)		Spillover Persistence$_{t+4}$ (prewtd)	Spillover Persistence (prewtd)		
Sample:	Baseline			Within bubbles	Baseline	
Boom	-5.00***	-1.84**	-3.58***	3.11*	3.68**	0.36
	[-3.05]	[-2.54]	[-2.66]	[1.90]	[2.07]	[0.36]
Bust	-2.41	-0.32	-1.39		-0.43	1.14
	[-1.32]	[-0.37]	[-1.46]		[-0.32]	[1.33]
Boom × Burst Distance				-1.96***	-3.03***	-0.77*
				[-4.54]	[-5.42]	[-1.95]
ΔCoVaR		0.06				0.16
		[0.35]				[0.81]
Macro controls	Y	Y	Y	Y	Y	Y
Market controls		Y			Y	Y
Firm characteristics		Y			Y	Y
Boom & bust length	Y	Y		Y	Y	Y
Boom & bust years						Y
Firm FE	Y	Y	Y	Y	Y	Y
Time FE		Y				Y
No. of firms	664	664	464	231	573	573
No. of obs.	6,896	6,896	5,108	1,001	5,706	5,706
Adj. R^2	0.233	0.463	0.134	0.448	0.329	0.493
Adj. R^2 within	0.114	0.048	0.062	0.337	0.212	0.072
p-value for H0: Same coefficient on boom and bust	0.12	0.15	0.11			

Table IA.10. Robustness with Prewhitened CoSP: Spillover Persistence and Fragility in the Financial System.

This table presents OLS estimates using prewhitened CoSP analogously to those in Table 4. t-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. Standardized coefficients are the change in the dependent variable for a standard deviation change in Spillover Persistence. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Leverage_{t+1}			CDS_{t+1}		$100 \times 1\{\text{Crisis}_{t+1}\}$		
Sample:	Baseline	Ban & Bro				Baseline		
Spillover Persistence (prewtd)	-0.06**	-0.08	-0.02	-0.00	-0.01**	-0.69**	-0.37***	-0.37***
	[-2.05]	[-1.65]	[-0.41]	[-1.00]	[-2.24]	[-2.15]	[-3.25]	[-3.34]
Spillover Persist. × Size			0.06**		0.01**			
			[2.11]		[2.10]			
Spillover Persist. × Leverage			-0.15**		-0.01			
			[-2.50]		[-1.12]			
Spillover Persist. × Market-to-Book			-0.08**		-0.02***			
			[-2.40]		[-2.99]			
Spillover Persist. × Liquidity ratio			0.04		0.02			
			[1.13]		[1.66]			
Spillover Persist. × Demand deposits			-0.04		-0.01			
			[-1.46]		[-1.50]			
Spillover Persist. × Time deposits			0.02		-0.00			
			[0.83]		[-0.56]			
Spillover Persist. × Impaired loans			-0.09***		-0.03***			
			[-2.91]		[-2.90]			
Spillover Persist. × Intangible assets			-0.06**		-0.01			
			[-2.25]		[-1.41]			
ΔCoVaR								-3.16***
								[-3.08]
Macro controls	Y	Y	Y	Y	Y		Y	Y
Market controls		Y	Y		Y		Y	Y
Firm characteristics	Y	Y	Y	Y	Y		Y	Y
Bank characteristics		Y	Y	Y	Y		Y	Y
Average ΔCoSP	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y		Y	Y
No. of firms	788	189	189	76	76	624	624	624
No. of obs.	8,149	1,588	1,588	669	669	6,566	6,566	6,566
Adj. R^2	0.721	0.857	0.860	0.815	0.830	0.165	0.743	0.745
Adj. R^2 within	0.185	0.167	0.190	0.097	0.174	0.138	0.306	0.310
Standardized coefficient:	-0.02	-0.04	-0.01	-0.03	-0.10	-0.11	-0.06	-0.06

D.2 Liquidity and Autocorrelation of Stock Returns

Daily turnover by value (VA) and volume (VO) are from Thomson Reuters Datastream at the security-day-level. $VO_{i,t}$ is the median daily turnover by volume (in thd USD) for firm i's common equity in time period t. The Amihud measure is defined by (see Amihud, 2002)

$$ILLIQ_{i,t} = \frac{1}{n_t} \sum_{\tau=1}^{n_t} \frac{|r_{i,t,\tau}|}{VA_{i,t,\tau}}, \tag{IA.7}$$

where n_t is the number of observations in time period t, $r_{i,t,\tau}$ is the daily return and $VA_{i,t,\tau}$ the turnover by value in thd USD on day τ in time period t for firm i's common equity. To calculate the turnover by volume of the system, I use the average daily turnover volume across firms in the system. The Amihud measure for the system is based on the system's value-weighted return and average daily turnover by value. Finally, I winsorize all variables at the 1% and 99% levels.

To examine the relation between Spillover Persistence and the auto-serial correlation of stock prices, I estimate the autocorrelation function of the system's return for each estimation window. Then, I regress CoSP measures on the average autocorrelation coefficient across lags of 1 to 10 days. Table IA.12 reports the estimates. There is neither a significantly positive correlation between the level of autocorrelation and Spillover Persistence nor Average ΔCoSP.

Table IA.11. Spillover Persistence and Stock Market Liquidity.

This table reports estimates from OLS panel regressions of Spillover Persistence based on ΔCoSP in columns (1) to (4) and of Average ΔCoSP in columns (5) to (8) at the firm-year level. The explanatory variables are a financial institution's and the system's stock market turnover in columns (1), (2), (5), and (6), and the financial institution's and system's Amihud measure for illiquidity in columns (3), (4), (7), and (8). *t*-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Spillover Persistence				Average ΔCoSP			
log(Firm turnover)	0.29	-0.08			0.01***	0.00***		
	[1.07]	[-0.41]			[4.30]	[4.00]		
log(System turnover)	2.48***	1.27***			0.01***	0.00**		
	[8.38]	[2.93]			[8.66]	[2.22]		
Firm ILLIQ			-0.00	-0.00			-0.00***	-0.00**
			[-1.61]	[-0.81]			[-2.77]	[-2.09]
System ILLIQ			-3.60	-2.33			-0.04**	-0.02
			[-0.82]	[-0.68]			[-2.05]	[-1.41]
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE		Y		Y		Y		Y
No. of firms	932	932	726	726	932	932	726	726
No. of obs.	10,052	10,052	5,952	5,952	10,052	10,052	5,952	5,952
Adj. R^2	0.212	0.412	0.139	0.383	0.319	0.715	0.181	0.684
Adj. R^2 within	0.095	0.005	0.003	0.001	0.200	0.020	0.013	0.004

Table IA.12. Spillover Persistence and Stock Return Autocorrelation.

This table reports estimates from OLS panel regressions of Spillover Persistence based on ΔCoSP in columns (1) and (2) and of Average ΔCoSP in columns (3) and (4) at the firm-year level. The explanatory variable is the average (across 1 to 10-day lags) autocorrelation of the system's stock returns. *t*-statistics are shown in brackets and based on standard errors clustered at the firm and country-by-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence		Average ΔCoSP	
$ACF_{1:10}$	-151.48***	-33.30	-1.13***	-0.17
	[-4.97]	[-0.71]	[-7.41]	[-1.13]
Firm FE	Y	Y	Y	Y
Time FE		Y		Y
No. of firms	935	935	935	935
No. of obs.	10,106	10,106	10,106	10,106
Adj. R^2	0.179	0.404	0.307	0.709
Adj. R^2 within	0.057	0.001	0.187	0.002

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