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Tackling the Volatility Paradox: Spillover Persistence and Systemic Risk

Christian Kubitza
European Central Bank
christian.kubitza@ecb.europa.eu

Abstract

Financial losses can have persistent effects on the financial system. This article 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, for example, 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.

I. 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, for example, 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,

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agents are better able to absorb shocks, which mitigates amplification effects. At the same time, loose constraints motivate agents to take more risk, for example, by increasing leverage, which, in turn, makes the financial system 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 3 key questions: i) Does Spillover Persistence capture variation in financial constraints and the resulting amplification effects? ii) Is Spillover Persistence related to fragility of the financial system? iii) 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 6 months to halve from their 2007–2008 financial crisis peak levels to pre-crisis levels. This article 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, Pedersen, Philippon, and Richardson (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_τ^I, Spillover Persistence is computed in 2 steps. First, M_τ^I 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, similar to the Macaulay duration:

$$\overline{\tau} = \frac{\int_{\tau=1}^{\tau^{\max}} \tau M_\tau^I d\tau}{\int_{\tau=1}^{\tau^{\max}} M_\tau^I d\tau}. \tag{1}$$

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.

[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.

Various systemic risk measures M_τ^I can be used to compute Spillover Persistence in equation (1). Traditional systemic risk measures mechanically respond to changes in stock market volatility (Adrian and Brunnermeier (2016), Acharya et al. (2017), Benoit, Colliard, Hurlin, and Perignon (2017)). On the one hand, amplification dynamics are closely linked to volatility: Weaker amplification effects correspond with lower volatility, yet simultaneously contribute to 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, Bloom, and David (2016)) and industry growth (Engle, Ghysels, and Sohn (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:

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

ΔCoSP_τ^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%) compared to when it is based on ΔCoVaR (33%) or MES (44%).

I compute Spillover Persistence based on ΔCoSP for an international sample of more than 1000 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 approximately 1 month, which means that large losses of an average institution are followed by an increase in the system's risk for about 1 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 4.5 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

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(Shleifer and Vishny (1992), Brunnermeier and Pedersen (2009)). Thus, fire sales tighten financial conditions and, therefore, might raise Spillover Persistence. To test this hypothesis, I exploit Hurricane Katrina, which made landfall in Aug. 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 insurers 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, Rother, and Schnabel (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. For example, the volatility paradox in 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 1-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 face tighter financial constraints ex ante, such as banks with a larger share of intangible assets and higher leverage.

Fragility is typically associated with a higher probability of future crises. To examine the relation between Spillover Persistence and crises, I use Laeven and Valencia's (2020) database of banking crises. Consistent with lower Spillover Persistence reflecting higher fragility, I document that a 1-standard-deviation decline in Spillover Persistence increases the likelihood of a subsequent banking crisis by 3.3 percentage points (ppt). Compared to the average crisis likelihood of 19.4% 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

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controlling for traditional systemic risk measures. Thus, Spillover Persistence captures new information about systemic risk.

The determinants of Spillover Persistence are similar when different systemic risk measures are 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), He and Krishnamurthy (2013), and 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 article introduces a novel measure that empirically captures the duration of the effects of loss spillovers at the firm 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, Schularick, and Taylor (2015), Adrian, Boyarchenko, and Giannone (2019), Krishnamurthy and Muir (2020), and Adrian, Grinberg, Liang, Malik, and Yu (2022)).[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 shock propagation channels. 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, Getmansky, Lo, and Pelizzon (2012), Adrian and Brunnermeier (2016), and 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 article 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

[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, Landier, and Thesmar (2015), Duarte and Eisenbach (2021)), portfolio similarity (Cai, Eidam, Saunders, and Steffen (2018), Girardi, Hanley, Nikolova, Pelizzon, and Getmansky Sherman (2021)), and liquidity risk (Bai, Krishnamurthy, and Weymuller (2018)).

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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 measures, impairing their ability to detect fragility *before* amplification effects arise because these measures mechanically respond to volatility fluctuations.[4] Volatility is not necessarily a reliable empirical indicator of fragility. For example, Danielsson, Valenzuela, and Zer (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 crisis-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 build-ups 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 build-up 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.

II. 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, Gertler, and Gilchrist (1999)). Modern macro-finance models, which solve for the complete equilibrium dynamics, stress the nonlinear 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

[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."

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

Based on Hypothesis 1 (that Spillover Persistence reflects 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 fragile financial system:

[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)).

[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.

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

i. more risk-taking by financial institutions, and
ii. 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.

III. Empirical Framework and Data

A. 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. 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 the financial system. Spillover Persistence is the systemic-risk–weighted average time lag, similar to the Macaulay duration:

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

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

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 $\overline{\tau}$ 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]

[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.

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TABLE 1

Summary Statistics

Table 1 depicts summary statistics for the main 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-year 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-month backward-looking rolling windows with end-dates Aug. 18 to Sept. 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 that 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 Supplementary Material Table IA.1. Summary statistics for the remaining variables are provided in Supplementary Material Table IA.3.

	N	Mean	Median	Std.Dev.	p5	p95
Baseline Sample						
SPILLOVER_PERSISTENCE (ΔCoSP, in days)	11,860	17.64	20.23	7.01	1.93	25.11
AVERAGE_ΔCoSP (in ppt)	11,860	0.03	0.03	0.03	0.00	0.09
SPILLOVER_PERSISTENCE (ΔCoVaR, in days)	10,377	15.43	17.98	7.97	1.61	25.10
SPILLOVER_PERSISTENCE (MES, in days)	9796	14.43	17.44	8.89	1.23	25.40
ΔCoVaR (in ppt)	10,015	3.02	2.96	1.63	0.50	5.91
MES (in ppt)	11,836	2.19	1.79	1.80	0.10	5.86
CRISIS (binary)	10,234	0.14	0.00	0.35	0.00	1.00
NFCI (U.S. only)	2832	−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	6975	0.12	0.00	0.33	0.00	1.00
BUST	6975	0.05	0.00	0.22	0.00	1.00
BOOM × BURST_DISTANCE	6975	0.29	0.00	0.92	0.00	2.33
Fragility Sample						
LEVERAGE_{t+1}	8476	11.59	6.08	16.10	0.83	40.47
$100 \times \text{CRISIS}_{t+1}$	6833	19.38	0.00	39.53	0.00	100.00
Ban and Bro Sample						
LEVERAGE_{t+1}	1686	14.37	9.39	14.34	2.96	42.58
CDS_{t+1}	694	0.19	0.00	0.58	0.00	1.27

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, increase with volatility by design (Adrian and Brunnermeier (2016), Benoit et al. (2017)). Therefore, $\bar{\tau}$ can violate this second property when 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.

B. 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 $-r_t^I$,

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

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

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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 Excess Conditional Shortfall Probability (ΔCoSP) compares the conditional and unconditional probability that the system's unconditional Value-at-Risk is exceeded:

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

$$\Delta\text{CoSP}_\tau^I = \mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q) \middle| -r_t^I \geq VaR^I(q)\right) - q. \tag{5}$$

ΔCoSP exhibits several properties that are important in the context of measuring Spillover Persistence. First, by definition of $VaR^S(q)$, if the returns r_t^S are issued from a stationary process, it is $\mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q)\right) = q$. Therefore, if the institution's and system's losses are independently distributed, then $\Delta\text{CoSP}_\tau^I = \mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q)\right) - q = 0$. 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 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 probabilities of exceeding it, whereas ΔCoVaR fixes the probability and compares the quantiles that attain it.[9] As a consequence, ΔCoSP does not measure risk in monetary units, in contrast to traditional (systemic) risk measures, which reduces its responsiveness to fluctuations in volatility.

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.[10] Therefore, ΔCoSP isolates

[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 Supplementary Material Section B.1).

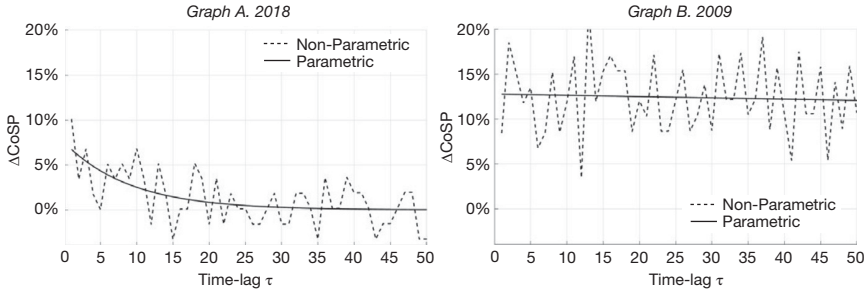
[9] I illustrate the differences and similarities of ΔCoSP and ΔCoVaR in Supplementary Material Figure IA.2. Note that ΔCoVaR conditions on the event $\left\{-r_t^I = VaR^I(q)\right\}$, whereas ΔCoSP conditions on $\left\{-r_t^I \geq VaR^I(q)\right\}$. The reason for this difference is that Adrian and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

[10] Assume that r_t^I and $r_{t+\tau}^S$ both belong to a location-scale family, such that $r_t^I = \mu_I + \sigma_I \varepsilon_I$ and $r_{t+\tau}^S = \mu_S + \sigma_S \varepsilon_S$ with $\sigma_I, \sigma_S > 0$. Denote the marginal distributions of ε_I and ε_S as F_I and F_S, respectively, both with unit variance. ε_I and ε_S (and, thus, r_t^I and $r_{t+\tau}^S$) may or may not be independently distributed. Then,

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FIGURE 1
Illustration of ΔCoSP Dynamics

Figure 1 depicts the nonparametric and parametric estimates for ΔCoSP for JP Morgan for 2018 (Graph A) and 2009 (Graph B).



variation in tail dependence from variation in volatility, consistent with the second desirable property in Section III.A.

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.[11] 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)).[12]

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 Graph A, clearly these instances result from estimation errors rather than from systematically negative ΔCoSP. In Supplementary Material Section 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.

using the definition of r^I_t and assuming the existence of the inverse cdf F_I^{-1}, the Value-at-Risk, defined by $\mathbb{P}(-(\mu_I+\sigma_I\varepsilon_I)\geq VaR^I)=q$, is equal to $VaR^I=-\mu_I-\sigma_I F_I^{-1}(q)$. Analogously, $VaR^S(q)=-\mu_S-\sigma_S F_S^{-1}(q)$. Using this and the definitions of r^I_t and $r^S_{t+\tau}$, it holds that

$$\begin{aligned}\Delta\text{CoSP}^I_\tau &= \mathbb{P}\left(-(\mu_S+\sigma_S\varepsilon_S)\geq -\mu_S-\sigma_S F_S^{-1}(q)\,|-(\mu_I+\sigma_I\varepsilon_I)\geq -\mu_I-\sigma_I F_I^{-1}(q)\right)-q\\ &= \mathbb{P}\left(-\sigma_S\varepsilon_S\geq -\sigma_S F_S^{-1}(q)\,|-\sigma_I\varepsilon_I\geq -\sigma_I F_I^{-1}(q)\right)-q\\ &= \mathbb{P}\left(\varepsilon_S<F_S^{-1}(q)\,|\varepsilon_I<F_I^{-1}(q)\right)-q,\end{aligned} \tag{7}$$

which depends on the joint distribution of $(\varepsilon_S,\varepsilon_I)$. Thus, holding the distribution of $(\varepsilon_S,\varepsilon_I)$ fixed, changes in the firm's or system's volatility, σ_I or σ_S, do not affect ΔCoSP^I_τ.

[11] 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 VI, I show that CoSP measures are not driven by stock market illiquidity.

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

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C. Estimation

A standard, nonparametric estimator for ΔCoSP is given by (see Supplementary Material Section B.2 for details):

$$\widehat{\Delta\text{CoSP}}_\tau = \frac{1}{q(n-\tau)} \sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^I \geq \widehat{VaR}^I(q), -r_{t+\tau}^S \geq \widehat{VaR}^S(q)\right\}} - q, \tag{8}$$

where n is the number of observations, and the Value-at-Risk estimator is the negative of the nq-th (or $([nq]+1)$-th) order statistic of returns if nq 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 Graph A, whereas its shape is similar but its decline less steep in Graph B.

Motivated by these observations, I estimate Spillover Persistence by, first, fitting ΔCoSP_τ^I to an exponential function of τ, $\Delta\text{CoSP}_\tau^I = \alpha^I e^{\tau\beta^I}$.[13] 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 nonnegative for the remaining observations, consistent with the first desirable property formulated above. In the example of Figure 1, the estimated parametric model closely matches the nonparametric estimate. More generally, in Supplementary Material Section B.2, I provide comprehensive evidence that the parametric estimation approach mitigates the impact of estimation errors on Spillover Persistence and does not create a systematic bias.

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

$$\overline{\psi} = \frac{1}{\tau^{\max}-1} \int_1^{\tau^{\max}} \widehat{\alpha} e^{\widehat{\beta}\tau} d\tau = \frac{\widehat{\alpha}}{\widehat{\beta}(\tau^{\max}-1)} \left[e^{\widehat{\beta}\tau^{\max}} - e^{\widehat{\beta}} \right]. \tag{9}$$

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

$$\text{SPILLOVER_PERSISTENCE} = \frac{1}{\overline{\psi}(\tau^{\max}-1)} \int_1^{\tau^{\max}} \tau \widehat{\alpha} e^{\widehat{\beta}\tau} d\tau \tag{10}$$

$$= \frac{\widehat{\alpha}}{\widehat{\beta}^2 \overline{\psi}(\tau^{\max}-1)} \left[\left(\widehat{\beta}\tau^{\max} - 1\right) e^{\widehat{\beta}\tau^{\max}} - \left(\widehat{\beta} - 1\right) e^{\widehat{\beta}} \right]. \tag{11}$$

Importantly, this approach applies to other systemic risk measures, as well. To examine the role of the underlying systemic risk measure in calculating Spillover

[13] Directly using $\widehat{\Delta\text{CoSP}}_\tau$ to weight time lags in equation (3) leads to substantial estimation error as I document in Supplementary Material Section B.2.

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Persistence, I compute two alternative versions of Spillover Persistence based on systemic risk measures other than ΔCoSP. For each measure, 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 (9) and (11) to compute Spillover Persistence. The main comparison is with Adrian and Brunnermeier's (2016) ΔCoVaR because it is most closely related to ΔCoSP:

$$\Delta\text{CoVaR} = CoVaR_{-r^I=VaR^I(q)} - CoVaR_{-r^I=VaR^I(0.5)}, \tag{12}$$

where $\mathbb{P}\left(-r^S \geq CoVaR_E | E\right) = q$ for event E, and ΔCoVaR is estimated using quantile regressions of weekly equity market returns.[14] As a robustness check, I also consider Acharya et al.'s (2017) Marginal Expected Shortfall (MES), which is defined as

$$\text{MES} = \mathbb{E}\left[-r^I | -r^S \geq VaR^S(q)\right]. \tag{13}$$

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.

D. 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 Feb. 2019). The sample starts on Jan. 1, 1985, and ends on Dec. 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 1 year of price data and African and South American institutions.[15] Following Adrian and Brunnermeier (2016), I focus on the following financial 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).[16]

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

[15]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 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.

[16]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.

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Each institution is assigned i) to one country and ii) to one of the following regions based on its headquarters' location: Europe, Asia (excluding Japan), North America, Japan, and Australia. By accounting for institutions' locations, I account for geographical variation in the macroeconomic 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.[17]

I use backward-looking rolling estimation windows with a size of 5 years to estimate ΔCoSP.[18] To alleviate estimation errors, I exclude institutions from a given estimation window if there are less than 700 nonmissing and nonzero observations of daily returns.[19] The reference level to compute systemic risk measures is $q = 5\%$, which is similar to other studies.[20] The maximum considered time lag is $\tau^{\max} = 50$ days. I winsorize systemic risk measures at the 1st 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), 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 are 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 Supplementary Material Section A.

E. Summary Statistics

The baseline sample includes 1067 financial institutions from 56 countries and ranges from 1989 to 2017.[21] Most firms are (commercial) banks, followed by real

[17]Details are described in Supplementary Material Section B.1.

[18]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.

[19]I also exclude from each time series of equity returns (a) periods with more than 5 subsequently missing returns and (b) 1,500-day periods with more than 180 missing returns.

[20]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.

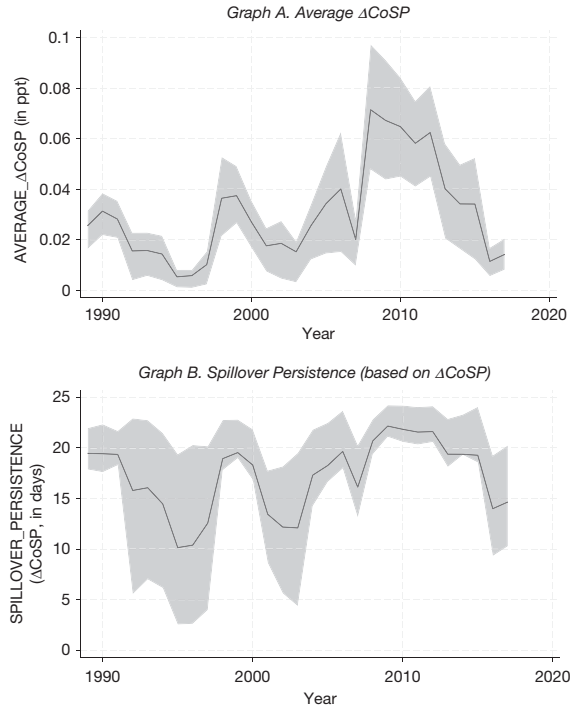
[21]Here and in the following, *year* refers to the last year in a 5-year estimation window for systemic risk measures. 41.9% of firm-year observations are for institutions located in Europe, 30.5% in North America, 18.3% in Asia, 5.3% in Japan, and 4% in Australia.

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FIGURE 2

Time Series of Average ΔCoSP and Spillover Persistence

Figure 2 depicts the annual cross-sectional mean and 25th and 75th percentiles of AVERAGE_ΔCoSP (Graph A) and SPILLOVER_PERSISTENCE (based on ΔCoSP, Graph B). 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.



estate firms, broker-dealers, and insurers.[22] The total market value of firms in the baseline sample is 9.61 trillion USD in Dec. 2017, which corresponds to 85% of the market value of financial firms worldwide. The subsample of U.S. firms captures 74% of publicly listed U.S. financial institutions.[23] Thus, the sample is representative for the vast majority of publicly listed financial institutions.

Table 1 provides summary statistics for the main variables (see Supplementary Material Table IA.3 for the remaining variables). Following a financial institution's losses, the probability of losses in the system is elevated by 3 ppt on average, reflected by AVERAGE_ΔCoSP, for an average time horizon of 17.64 days, reflected by SPILLOVER_PERSISTENCE. As Graph A of Figure 2 illustrates,

[22]More specifically, 43.3% of firm-year observations are for banks, 23.2% for real estate firms, 20.3% for broker-dealers, and 13.2% for insurers.

[23]The total market value of U.S. firms in the sample is 3.75 trillion USD in Dec. 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 Dec. 29, 2017, recorded 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.

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AVERAGE_ΔCoSP peaks during the 2007–2008 financial crisis, the Asian financial crisis in the late 1990s, and the Japanese banking crisis at the beginning of the 1990s. Graph B depicts the evolution of SPILLOVER_PERSISTENCE, which, on average, resembles that of AVERAGE_ΔCoSP. The correlation between these measures is 64%, pooled across institutions and time (see Supplementary Material 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 13% with MES. Therefore, most of the variation in SPILLOVER_PERSISTENCE is orthogonal to the variation in contemporaneous systemic risk measures.

Although the summary statistics for SPILLOVER_PERSISTENCE are similar across different underlying systemic risk measures, the dynamics of SPILLOVER_PERSISTENCE are very different. The correlation between SPILLOVER_PERSISTENCE based on ΔCoSP is only 30% with that based on ΔCoVaR and 38% with that based on MES (see Supplementary Material 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 (35%) and MES (41%) than when it is based on ΔCoSP (13%) (see Supplementary Material Figure IA.5).

IV. Determinants of Spillover Persistence

A. 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 financial 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 deviation 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 (2020)), 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.

TABLE 2

Spillover Persistence and Financial Conditions

Each column in Table 2 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 i in year t and $C_{i,t}$ is a vector of explanatory variables and fixed effects. Panel A, columns 1 to 4 report OLS estimates from regressions of SPILLOVER_PERSISTENCE at the firm-year level based on either ΔCoSP (columns 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 Aug. 18 to Sept. 5, 2005. POST-KATRINA equals 1 from Aug. 25, 2005 onward, and 0 otherwise. EXPOSED equals 1 if an insurer's share of total P&C premiums in Alabama, Louisiana, and Mississippi from 2004:Q3 to 2005:Q2 relative to all insurance premiums is in the upper quartile across all U.S. insurers.

Variable definitions are provided in Supplementary Material Table IA.1. *t*-statistics are shown in square 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 heteroskedasticity-robust. Standardized coefficients are the change in SPILLOVER_PERSISTENCE (in standard deviations) for a 1-standard-deviation change in the explanatory variable. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	Panel A.Macro-Financial Conditions				*Panel B. Fire Sales*	
	Dependent Variable: SPILLOVER_PERSISTENCE					
Underlying Measure:	ΔCoSP			ΔCoVaR	ΔCoSP	
Sample:	U.S.		Full		U.S. Insurers	
	1	2	3	4	5	6
NFCI	4.53***	3.71***				
	[19.71]	[12.97]				
CRISIS		2.14***	4.49***	3.72***		
		[7.66]	[6.01]	[5.89]		
CREDIT_GROWTH		−0.76***	−0.02	0.14***		
		[−11.86]	[−0.29]	[2.85]		
3M_YIELD_CHANGE		1.09***	0.50*	−0.18		
		[10.74]	[1.67]	[−0.80]		
TERM_SPREAD_CHANGE		0.65***	0.27	−0.26		
		[7.11]	[1.07]	[−1.23]		
CREDIT_SPREAD_CHANGE		0.72***	0.24	−0.20		
		[10.48]	[1.19]	[−1.24]		
POST – KATRINA × EXPOSED					0.30***	0.30***
					[4.45]	[4.11]
POST – KATRINA					−0.30***	
					[−4.45]	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE						Yes
No. of firms	209	209	938	654	22	22
No. of obs.	2832	2832	10,234	5063	286	286
Adj. R^2	0.140	0.238	0.177	0.162	0.971	0.971
Adj. R^2 within	0.084	0.188	0.052	0.037	0.107	0.020
Standardized coefficients						
NFCI	.279	.229				

These relationships qualitatively also hold in the full, international sample (column 3). Whereas some coefficients become insignificant (although 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 4.5 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

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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.

B. 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 its first landfall on Aug. 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.[24] 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, Massa, and Zhang (2016), Girardi et al. (2021)).

I estimate the effect of Katrina on 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 Supplementary Material Section A.2.3).

To isolate the impact of Katrina, I estimate SPILLOVER_PERSISTENCE daily based on 18-month 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 ($\overline{\tau}_{i,t}$) on the interaction of the exposure-to-Katrina indicator (Exposed_i) and a post dummy that is equal to 1 for Aug. 25, 2005, and after, and 0 otherwise, controlling for time-invariant heterogeneity at the insurer level (u_i):

$$\overline{\tau}_{i,t} = \alpha \text{EXPOSED}_i \times \text{POST}_t + \beta \text{POST}_t + u_i + \varepsilon_{i,t}. \tag{14}$$

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 coefficients are estimated based on data from Aug. 8 to Sept. 16, 2005, and, thereby, exclude the effect of the potentially confounding Hurricane Rita on Sept. 18, 2005. Due to the

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

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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 0 (t-stat = 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 Supplementary Material Table IA.5). Overall, the results strongly support Hypothesis 1 that tighter financial conditions, resulting from fire sales, raise Spillover Persistence.

C. 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 2 halves at its global price peak, I distinguish between the 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 (Supplementary Material Section 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 $\overline{\tau}_{i,t}$ 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):

$$\overline{\tau}_{i,t} = \alpha I_{c,t}^{Bubble} + \beta L_{c,t}^{Bubble} + \gamma M_{c,t} + u_i + \varepsilon_{i,t}. \tag{15}$$

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 (t-stat = 3.03).[25] The economic significance is large: During booms, SPILLOVER_PERSISTENCE is 4.8 days smaller (68% of its standard deviation). In column 2, I additionally include year fixed

[25]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.

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TABLE 3

Spillover Persistence and Stock Market Bubbles

Each column in Table 3 reports OLS estimates from regressions of Spillover Persistence on stock market bubble indicators:

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

where $\overline{\tau}_{i,t}$ 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 1 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 excludes 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, term spread changes, TED spread, and stock market return and volatility. Firm characteristics are size, leverage, and market-to-book ratio, all lagged by 1 year. Boom and bust years are the number of boom and bust years in the 5-year estimation window of ΔCoSP. Variable definitions are provided in Supplementary Material Table IA.1. t-statistics are shown in square 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.

	Dependent Variable					
	SPILLOVER_PERSISTENCE			$SPILLOVERPERSISTENCE_{t+4}$	SPILLOVER_PERSISTENCE	
	Sample					
	Baseline			Within Bubbles	Baseline	
	1	2	3	4	5	6
BOOM	−4.84***	−1.90***	−3.44**	2.61	3.62**	0.23
	[−3.03]	[−2.78]	[−2.59]	[1.62]	[2.02]	[0.23]
BUST	−2.22	−0.21	−1.34		−0.26	1.10
	[−1.26]	[−0.25]	[−1.43]		[−0.20]	[1.33]
BOOM × BURST_DISTANCE				−1.95***	−2.96***	−0.78**
				[−4.63]	[−5.37]	[−1.99]
ΔCoVaR		0.08				0.20
		[0.45]				[0.98]
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Market controls		Yes			Yes	Yes
Firm characteristics		Yes			Yes	Yes
Boom and bust length	Yes	Yes		Yes	Yes	Yes
Boom and bust years						Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes				Yes
No. of firms	665	665	456	232	575	575
No. of obs.	6975	6975	4835	1026	5773	5773
Adj. R^2	0.235	0.464	0.105	0.454	0.329	0.494
Adj. R^2 within	0.114	0.050	0.039	0.332	0.211	0.074
p-value for H0: Same coefficient on boom and bust	0.10	0.09	0.12			

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).[26] 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 (−1.9 days). This result suggests that bubble boom episodes 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

[26]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.

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bubbles and early years in SPILLOVER_PERSISTENCE's estimation window (which ranges 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:

$$\begin{aligned}\overline{\tau}_{i,t} = {} & \alpha_0 \text{BURST_DISTANCE}_{c,t} \times I_{c,t}^{Boom} \\ & + \alpha_1 I_{c,t}^{Bubble} + \beta L_{c,t}^{Bubble} + \gamma M_{c,t} + u_i + \varepsilon_{i,t},\end{aligned} \tag{16}$$

where $\text{BURST_DISTANCE}_{c,t}$ is the current distance to a bubble's burst. This specification 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 a 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 Supplementary Material Table IA.6, I estimate the regressions from Table 3 with SPILLOVER_PERSISTENCE based on ΔCoVaR (instead of ΔCoSP) as the dependent variable. The results are consistent with the baseline results.

V. Spillover Persistence and Fragility

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

A. 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 1-year–ahead leverage (total assets over the market value of equity) on its SPILLOVER_PERSISTENCE $\overline{\tau}_{i,t}$ in year t:

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

controlling for AVERAGE_ΔCoSP ($\overline{\psi}_{i,t}$), time-invariant differences across firms (u_i), lagged firm characteristics ($F_{i,t-1}$), and macroeconomic characteristics ($M_{c,t}$)

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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 (t-stat = 2.39). A 1-standard-

TABLE 4

Spillover Persistence and Fragility in the Financial System

Each column in Table 4 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 estimates from regressions of firm characteristics on SPILLOVER_PERSISTENCE (based on ΔCoSP) at the firm-year level. The dependent variable in columns 1 to 3 is 1-year–ahead LEVERAGE and in columns 4 and 5 1-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 1-year- and 2-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, term spread changes, TED spread, and stock market return and volatility. Firm characteristics are SIZE, LEVERAGE, and MARKET-TO-BOOK ratio, all lagged by 1 year. Bank characteristics are LIQUIDITY_RATIO, DEMAND_DEPOSITS, IMPAIRED_LOANS, and INTANGIBLE_ASSETS as a share of total assets, all lagged by 1 year. Variable definitions are provided in Supplementary Material Table IA.1. t-statistics are shown in square 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 1-standard-deviation change in Spillover Persistence. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	Dependent Variable							
	$LEVERAGE_{t+1}$			CDS_{t+1}		$100 \times CRISIS_{t+1}$		$100 \times CRISIS_{t+2}$
	Sample							
	Baseline	Ban & Bro				Baseline		
	1	2	3	4	5	6	7	8
SPILLOVER_PERSISTENCE	−0.07** [−2.39]	−0.09* [−1.72]	−0.06 [−1.10]	−0.01 [−1.30]	−0.01** [−2.10]	−0.58 [−1.65]	−0.47*** [−3.51]	−0.36*** [−2.81]
SPILLOVER_PERSIST.× SIZE			0.02 [0.62]		0.01** [2.49]			
SPILLOVER_PERSIST.× LEVERAGE			−0.17** [−2.51]		−0.01 [−1.22]			
SPILLOVER_PERSIST.× MARKET−TO−BOOK			−0.09*** [−2.73]		−0.02*** [−2.81]			
SPILLOVER_PERSIST.× LIQUIDITY_RATIO			0.05* [1.79]		0.02* [1.98]			
SPILLOVER_PERSIST.× DEMAND_DEPOSITS			−0.05 [−1.57]		−0.00 [−1.48]			
SPILLOVER_PERSIST.× IMPAIRED_LOANS			−0.03 [−1.00]		−0.03*** [−2.73]			
SPILLOVER_PERSIST.× INTANGIBLE_ASSETS			−0.07*** [−2.67]		−0.01** [−2.07]			
Macro controls	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Market controls		Yes	Yes		Yes		Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Bank characteristics		Yes	Yes	Yes	Yes		Yes	Yes
AVERAGE_ΔCoSP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes		Yes	Yes
No. of firms	793	195	195	77	77	633	633	620
No. of obs.	8476	1686	1686	689	689	6833	6833	6476
Adj. R^2	0.724	0.851	0.853	0.809	0.827	0.161	0.744	0.748
Adj. R^2 within	0.188	0.177	0.190	0.071	0.159	0.135	0.310	0.272
Standardized coefficient	−0.03	−0.04	−0.03	−0.04	−0.10	−0.10	−0.08	−0.06

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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 weaker balance sheets 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 from 0 (but with a relatively large t-stat of -1.3). Column 5 shows that the correlation is significantly negative (t-stat = -2.1) for banks with average characteristics. The coefficients on the interactions with bank characteristics have the same signs as with leverage as the 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 the dependent variable. 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.

B. 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 1-year–ahead banking crises on the SPILLOVER_PERSISTENCE of firm i in country c in year t:

$$\text{CRISIS}_{c,t+1} = \alpha\overline{\tau}_{i,t} + \beta\overline{\psi}_{i,t} + \gamma F_{i,t-1} + \eta M_{c,t} + u_i + \nu_t + \varepsilon_{i,t+1}, \tag{18}$$

controlling for AVERAGE_ΔCoSP ($\overline{\psi}_{i,t}$), time-invariant differences across firms (u_i), aggregate shocks (ν_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 $\overline{\psi}_{i,t}$ and including firm fixed effects. The estimate for α is negative, implying that lower SPILLOVER_PERSISTENCE is associated with a larger probability of 1-year–ahead banking crises. It is close to being significantly different from 0 at the 10% level (with a t-stat of -1.65). The magnitude implies that banking crises are by about 0.1 standard deviations (4 ppt) more likely following a 1-standard-deviation reduction in SPILLOVER_PERSISTENCE, which highlights the economic significance of SPILLOVER_PERSISTENCE for fragility.

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The relation between SPILLOVER_PERSISTENCE and future crises is robust to including the full set of controls (column 7). In this case, the coefficient is highly significant at the 1% level. 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 2 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 Supplementary Material Table IA.7, I present evidence that lower SPILLOVER_PERSISTENCE is also associated with a higher likelihood of crises occurring 3 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 (18) 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 a lower SPILLOVER_PERSISTENCE based on ΔCoVaR or MES (instead of ΔCoSP) does *not* significantly correlate with a larger probability of 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.

VI. Robustness Analysis

It is beyond the scope of this article 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's (2002) measure for stock market illiquidity. The results show that

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neither Spillover Persistence nor Average ΔCoSP is larger when stocks are less liquid (see Supplementary Material 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 autocorrelation of the system's equity return (see Supplementary Material Section 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, that is, caused by omitted variables.[27] 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 Supplementary Material Tables IA.8 to IA.10).

VII. 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 the effect of a firm's losses on the financial system, the larger is the Spillover Persistence. Motivated by the predictions of modern macro-finance models, this article 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, that is, 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 extend existing systemic risk measures.

This article 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

[27]This approach is called "prewhitening" and common in the forecasting literature (Giglio, Kelly, and Pruitt (2016), Dean and Dunsmuir (2016)).

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systemic risk and may prove useful for regulators to construct early-warning signals for fragility and to guide and implement policy.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S002210902400070X.

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