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Abstract

This paper proposes Spillover Persistence as a measure for financial fragility. The volatility paradox predicts that fragility builds up when volatility is low, which challenges existing measures. Spillover Persistence tackles this challenge by exploring a novel dimension of systemic risk: loss dynamics. I document that Spillover Persistence declines when fragility builds up, during the run-up phase of crises and asset price bubbles, and increases when systemic risk materializes. Variation in financial constraints connects Spillover Persistence to fragility. The results are consistent with the volatility paradox in recent macro-finance models, and highlight the usefulness of loss dynamics to disentangle fragility from amplification effects.

JEL classification: E44, G01, G12, G20, G32.

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

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1. Introduction

Fragility in the financial system plants the seeds for future crises, e.g., in the form of high leverage or risk-taking. Since it typically builds up in the background during quiet times, a key challenge for empirical risk measures is to detect fragility before systemic risk materializes and amplification effects arise. In this paper, I propose a measure for fragility at the firm level, *Spillover Persistence*, which is based on a novel dimension of systemic risk: loss dynamics. In a large sample of financial firms covering more than three decades, I document that Spillover Persistence declines when fragility builds up, but it increases when amplification effects arise. The analysis provides empirical evidence that loose financial constraints connect low Spillover Persistence to high fragility, both at the aggregate and at the firm level. These findings are consistent with the volatility paradox in recent macro-finance models, and show that loss dynamics are useful to detect fragility before systemic risk materializes.

Recent macro-finance theory characterizes endogenous risk dynamics. For example, in Brunnermeier and Sannikov (2014)'s model, when agents are financially constrained and face large losses (e.g., during a crisis), they engage in asset fire sales. Fire sales depress prices and, thereby, bolster future amplification of losses. In this case, today's losses increase the risk of losses in the future. Instead, when financial constraints are loose, agents absorb today's losses more easily and the effect of today's losses on future losses dies out more quickly. The volatility paradox predicts that fragility builds up in such quiet times, when financial constraints are loose and volatility is low, since agents are then encouraged to take more risks and leverage.[1]

These predictions motivate my framework. I introduce Spillover Persistence as a firm-level measure for fragility. It is the average time-lag at which the risk of losses in the financial system increases after a firm suffers losses. The longer-lasting the effect of a firm's losses on the financial system, the larger is Spillover Persistence. Consistent with the dynamics described above, I provide empirical evidence that Spillover Persistence captures the tightness of financial constraints and the resulting fragility and amplification effects. When financial constraints tighten, amplification effects arise and Spillover Persistence increases; in contrast, when financial constraints loosen, fragility builds up and Spillover Persistence declines.

Popular existing systemic risk measures build on contemporaneous volatility and correlation of losses across firms (e.g., Adrian and Brunnermeier (2016), Acharya et al. (2017), and Brownlees and Engle (2017)). Due to the volatility paradox, a weak spot of these measures

[1] The volatility paradox is featured, e.g., in the models of Acharya and Viswanathan (2011), Adrian and Boyarchenko (2012), Danielsson et al. (2012), and Brunnermeier and Sannikov (2014).

is to detect fragility *before* systemic risk materializes and volatility rises (as stressed, e.g., by Brunnermeier and Oehmke (2013)). Previous studies address the volatility paradox by using balance sheet and macroeconomic data.[2] Such approaches come with the potential drawback that they focus on specific sources of fragility although these can vary from crisis to crisis. This paper tackles the volatility paradox by exploring the *time-lagged* correlation of losses across financial firms (which reflects loss dynamics) instead of the *contemporaneous* correlation. The framework entirely builds on equity prices and is independent of contemporaneous volatility. As a result, it is readily applicable to every listed firm, does not make explicit assumptions about the sources of fragility, and is not subject to the volatility paradox critic.[3]

The framework has two building blocks. First, I introduce the Excess Conditional Shortfall Probability (ΔCoSP) as a firm-level measure of systemic risk. It captures the contribution of a firm's losses to the risk of subsequent losses in the financial system. ΔCoSP is motivated by Adrian and Brunnermeier (2016)'s ΔCoVaR but relies on time-lagged instead of contemporaneous correlation and it is independent of contemporaneous volatility. Second, I define Spillover Persistence as the average time-lag between losses of a given firm and subsequent losses of the financial system, weighted by the contribution to systemic risk. The construction of Spillover Persistence is similar to that of the Macaulay duration. When a firm's losses have a longer-lasting effect on the financial system, Spillover Persistence is larger.

I apply the framework to a large sample of more than 700 firms, which covers 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 individual firms are followed by an increase in the risk of large losses of the financial system at an average time horizon of one month. Importantly, Spillover Persistence substantially differs from existing systemic risk measures. For example, its correlation with ΔCoVaR is very small (less than 10%), and variation in ΔCoVaR explains less than 1% of the variation in Spillover Persistence. Thus, Spillover Persistence captures a novel dimension of systemic risk.

I document that Spillover Persistence is significantly larger during crises than normal

[2]Examples include Adrian and Brunnermeier (2016), who construct a forward-looking ΔCoVaR by projecting the original ΔCoVaR on lagged balance sheet and macroeconomic characteristics, and Duarte and Eisenbach (2021) and Greenwood et al. (2015), who use deleveraging pressure as a measure for fire sale vulnerability, which is mainly driven by banks' size, leverage, their assets' liquidity, and commonality of asset holdings across banks.

[3]A possible concern is that Spillover Persistence picks up stock market illiquidity instead of loss 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.

times, when overall financial conditions are tighter, and for firms with tighter balance sheet constraints. Banks and broker-dealers significantly increase their leverage and derivatives exposure when Spillover Persistence declines, holding other firm characteristics (such as size and equity valuation), macroeconomic characteristics, and time-invariant differences across firms fixed. These results suggest with a financial constraints channel, namely that tighter financial constraints lead to an increase in Spillover Persistence, and vice versa.

To explore the relation between Spillover Persistence and fragility, I examine the run-up phase of banking crises and stock market bubbles. First, I document that Spillover Persistence significantly declines before crises. Figure 1 illustrates this finding at the aggregate level. The effect is robust across various specifications, namely at the firm and country level, controlling for macroeconomic conditions (such as GDP and credit growth), firm characteristics (such as size and leverage), time-invariant differences across firms, and for variation in aggregate macroeconomic conditions over time. The correlation between Spillover Persistence and future crises is particularly strong when overall financial conditions and balance sheet constraints are less tight, consistent with the financial constraints channel. Importantly, controlling for contemporaneous systemic risk measures, which do not account for loss dynamics, neither affects the statistical nor economic significance of the correlation between Spillover Persistence and crises. Thus, it is variation in loss dynamics but not variation in contemporaneous systemic risk that drives the result.

[Place Figure 1 about here]

Previous literature argues that imbalances and fragility in the financial system build up during the run-up phase of asset price bubbles, and that amplification effects arise at later stages of bubbles and particularly when they burst (e.g., Borio and Lowe (2002), Brunnermeier and Oehmke (2013), Brunnermeier et al. (2020)). Consistent with this hypothesis, I document that Spillover Persistence is significantly lower during stock market bubble booms compared to non-bubble times. The effect is particularly pronounced at the run-up phase of bubbles compared to later stages: during an average bubble's lifetime, Spillover Persistence grows and is larger around the bubble's burst than during the early run-up phase. Spillover Persistence is thus useful to distinguish between fragility (during the run-up phase) and amplification (at the burst). The correlation between Spillover Persistence and bubble booms is stronger when overall financial conditions and balance sheet constraints are less tight, consistent with the financial constraints channel.

Finally, I examine the relation between Spillover Persistence and amplification. In Brunnermeier and Sannikov (2014)'s model, tight financial constraints associate with strong amplification due to pecuniary externalities such as fire sales, which boosts Spillover Persistence.

To test this mechanism, I exploit hurricane Katrina as an exogenous shock to the liquidity of US insurers that provided insurance in the hurricane-exposed region. Exposed insurers were forced to sell assets in order to pay insurance claims, consistent with a tightening of financial constraints. I show that the effect of hurricane Katrina on Spillover Persistence is significantly larger for insurers that were exposed to the hurricane relative to those that were not. This result supports the hypothesis that fire sale amplification boosts Spillover Persistence.

It is important for policymakers to identify when fragility in the financial system builds up, and to distinguish fragility from amplification. The reason is that it can be optimal to tighten regulation in order to fight a build-up of fragility, which however becomes harmful during times of amplification. For example, borrowing constraints can counteract a build-up of leverage but lead to stronger amplification once losses materialize (e.g., Kiyotaki and Moore (1997), Brunnermeier and Pedersen (2009), Adrian and Boyarchenko (2012), Farhi and Werning (2021)). I provide empirical evidence that Spillover Persistence detects a build-up of fragility at the aggregate as well as at the firm level, and before systemic risk materializes in crises and amplification effects arise. Thus, Spillover Persistence can be useful to align policies with fragility vs. amplification dynamics and to target specific firms or sectors.

Related literature. This paper explores a novel dimension of systemic risk: loss dynamics.[4] Thereby, it contributes to several literatures.

First, the paper connects to the modern macro-finance literature, which highlights the link between financial stability and financial conditions. Recent macro-finance models solve for full equilibrium dynamics with endogenous risk (e.g., Adrian and Boyarchenko (2012), He and Krishnamurthy (2012, 2013), Brunnermeier and Sannikov (2014), Modena (2021)). Pecuniary externalities amplify even small shocks, e.g., via leverage and fire sales, and thereby generate systemic (endogenous) risk. An important prediction of this literature is the volatility paradox, which says that fragility builds up in good times, when financial constraints are loose and volatility low, since agents are then encouraged to take more risks and leverage. I provide empirical evidence that these predictions are reflected in loss dynamics, i.e., in the time that the financial system's risk is alleviated after individual firms' losses. Consistent with the volatility paradox, I document a strong relationship between low Spillover Persistence, loose financial constraints, high leverage and risk-taking, and high financial fragility, both at the aggregate and firm level. The findings emphasize loss dynamics and endogenous risk-taking as important components of macro-finance models.

[4]Following Brunnermeier and Sannikov (2014)'s definition, systemic (endogenous) risk is the risk that is self-generated by the financial system. Chen et al. (2013) and Smaga (2014) provide detailed discussions about different definitions and interpretations of systemic risk.

Previous empirical studies examine the volatility paradox at the macroeconomic level and document that periods with low volatility and loose financial conditions precede periods with low GDP growth and crises (e.g., Adrian et al. (2018, 2019) and Danielsson et al. (2018)).[5] The contribution of this paper is to explore loss dynamics as a novel dimension of systemic risk that captures variation in financial constraints and to relate it to the volatility paradox at the firm level. Thereby, I take the analysis to the microeconomic level and explore not only *when* but also *where* and *how* fragility builds up.

Second, this paper contributes to the empirical literature on systemic risk by introducing Spillover Persistence as a new firm-level measure for financial fragility and amplification. Popular existing systemic risk measures, such as Adrian and Brunnermeier (2016)'s ΔCoVaR and Acharya et al. (2017)'s Marginal Expected Shortfall (MES), focus on *contemporaneous* systemic risk, i.e., simultaneous losses of the firm and system, and thereby rely on contemporaneous volatility and correlation to measure risk.[6] However, Billio et al. (2012) and Brunnermeier and Oehmke (2013) argue that, due to the volatility paradox, it is challenging for measures that rely on contemporaneous volatility to detect fragility in the financial system.[7] Spillover Persistence tackles this challenge by exploring loss dynamics. The correlation of Spillover Persistence with ΔCoVaR and MES is low, and the relation between Spillover Persistence and firm characteristics, banking crises, stock market bubbles, and hurricane Katrina is robust to controlling for these measures. Thus, loss dynamics are a novel and informative dimension of systemic risk.

Finally, my analysis reveals new empirical facts about loss dynamics and their relation to systemic risk. Spillover Persistence strongly declines before banking crises, with and without controlling for existing systemic risk measures and numerous firm and macroeconomic char-

[5]The related literature on leverage cycles documents that bank leverage negatively correlates with a bank's individual risk (e.g., Adrian and Shin (2010, 2014)). Complementing this literature, I focus on the financial system's risk instead of firms' individual risk.

[6]In contrast to global measures of systemic risk (such as CoSP-measures, ΔCoVaR, and MES), other measures focus on specific mechanisms that potentially create systemic risk, such as fire sales (e.g., Greenwood et al. (2015) and Duarte and Eisenbach (2021)), portfolio similarity (e.g., Cai et al. (2018) and Girardi et al. (2020)), and liquidity risk (e.g., Bai et al. (2018)). An overview of approaches to measure systemic risk is provided by Benoit et al. (2017).

[7]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."

acteristics that have been found to predict crises, such as leverage and credit growth (e.g., Schularick and Taylor (2012), Jordà et al. (2015), Krishnamurthy and Muir (2020)). Thus, changes in loss dynamics are an important indicator for fragility in the financial system and add to existing early-warning indicators for crises.

The paper also contributes to the literature on asset price bubbles and their relation with systemic risk and financial crises (e.g., Schularick and Taylor (2012), Jordà et al. (2015), and Brunnermeier et al. (2020)). Brunnermeier et al. (2020) document that ΔCoVaR is larger during both bubble booms and busts compared to non-bubble episodes. Complementing their result, I show that Spillover Persistence is significantly *smaller* during booms but not during busts compared to non-bubble episodes, and that it significantly increases during bubble booms. These findings hold both with and without controlling for ΔCoVaR. Spillover Persistence is thus useful to empirically distinguish between fragility and amplification, complementing previous measures.

Moreover, following the hypothesis that fire sales amplify losses in the financial system (e.g., Brunnermeier and Pedersen (2009)) and that amplification raises Spillover Persistence, I provide evidence that fire sale incentives for property & casualty insurers after hurricane Katrina associate with an increase in Spillover Persistence. This finding contributes to a growing literature that documents fire sales and their effects on the financial system (e.g., Coval and Stafford (2007), Ellul et al. (2011, 2015), Girardi et al. (2020), Chernenko and Sunderam (2020)).

This paper is organized as follows. Section 2 introduces the empirical framework to measure Spillover Persistence, reviews its properties, and describes its estimation and the data. Section 3 provides summary statistics and explores determinants for variation in Spillover Persistence. I investigate how Spillover Persistence relates to leverage and risk-taking in Section 4, to banking crises in Section 5, to asset price bubbles 6, and to fire sales in Section 7. Finally, Section 8 contains sensitivity analyses and Section 9 concludes.

2. Measuring Spillover Persistence

2.1. Conditional Shortfall Probability

I define the Excess Conditional Shortfall Probability (ΔCoSP) as the contribution of a firm i's losses to the risk of future losses in the system S. To capture potentially systemic events, I follow the previous literature and focus on large equity return losses.[8] I define by

[8]The focus on large equity return losses is common for systemic risk measures and shared, e.g., by Acharya et al. (2012, 2017), Adrian and Brunnermeier (2016), and Brownlees and Engle (2017).

$VaR^i(q)$ the $(1-q) \times 100\%$ percentile of the unconditional distribution of firm i's equity return loss $-r_t^i$,

$$\mathbb{P}(-r_t^i \geq VaR^i(q)) = q, \tag{1}$$

where r_t^i is the change in the log market value of a firm'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 firm's return r_t^i with the system's return r_t^S, $VaR^S(q)$ is the system's risk.[9]

ΔCoSP measures the extent to which firm i's large losses (that exceed $VaR^i(q)$) contribute to the risk of large future losses of the system (that exceed $VaR^S(q)$):

Definition 1. *For $\tau > 0$ and $q \in (0,1)$, define the Excess Conditional Shortfall Probability as the probability of large losses of the system τ days after large losses of the firm relative to an average day,*

$$\Delta\psi(\tau) = \mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q) \mid -r_t^i \geq VaR^i(q)\right) - \mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q)\right). \tag{2}$$

By definition of $VaR^S(q)$, the unconditional probability of large losses of the system is $\mathbb{P}\left(-r_{t+\tau}^S \geq VaR^S(q)\right) = q$. Normalization by q implies that if the firm's and system's losses are independent, then $\Delta\psi(\tau) = 0$. Instead, if $\Delta\psi(\tau) > 0$, then the probability of large losses of the system is $\Delta\psi(\tau) \times 100$ppt (percentage points) larger τ days after firm i faces large losses compared to an average day.

Figure 2 provides an example, using a standard nonparametric estimate ($\widehat{\Delta\psi}(\tau)$) for JP Morgan and the US financial system during 2003-2007. Intuitively, one would expect that the effect of a firm's losses on the system fades out with an increasing time-lag τ. Figure 2 supports this intuition, as $\widehat{\Delta\psi}(\tau)$ declines with a larger time-lag. Exploiting this property, I use the following parametric model to estimate ΔCoSP (see Online Appendix A for additional estimation details and justification of the parametric form):

$$\Delta\text{CoSP}(\tau) = e^{\alpha+\beta\tau}. \tag{3}$$

Figure 2 shows that the estimated model ($\Delta\text{CoSP}(\tau) = e^{\hat{\alpha}+\hat{\beta}\tau}$) closely matches the nonparametric estimate ($\widehat{\Delta\psi}$).

[Place Figure 2 about here]

[9] I define the system's return as the return of an index of all firms in the financial system, excluding the currently considered firm i (as described in Online Appendix B.1).

I propose two aggregate measures based on ΔCoSP. These disentangle the *average level* of systemic risk from *Spillover Persistence*.

Definition 2 (Average ΔCoSP)**.** *For $\tau^{max} > 1$, define Average $\Delta CoSP$ as the average increase in the probability of large losses of the system during the τ^{max} days after large losses of the firm,*

$$\bar{\psi} = \frac{1}{\tau^{max} - 1} \int_1^{\tau^{max}} \Delta CoSP(\tau)\, d\tau = \frac{1}{\beta(\tau^{max} - 1)} \left(e^{\alpha + \beta \tau^{max}} - e^{\alpha + \beta} \right). \tag{4}$$

Average ΔCoSP is a measure for the level of persistent systemic risk. It says that the probability of large losses of the system increases on average by $\bar{\psi} \times 100$ppt during the $\tau^{\max}$ days after large losses of the firm compared to an average day. As Figure 2 illustrates, $\bar{\psi}$ is the average of ΔCoSP across time-lags. It is worth emphasizing that $\bar{\psi}$ excludes contemporaneous systemic risk at $\tau = 0$. This separates persistent systemic risk ($\bar{\psi}$) from contemporaneous systemic risk (e.g., measured by ΔCoSP(0) and ΔCoVaR).

Definition 3 (Spillover Persistence)**.** *For $\tau^{max} > 1$, define Spillover Persistence as the average time-lag weighted by its contribution to Average $\Delta CoSP$,*

$$\bar{\tau} = \int_1^{\tau^{max}} \tau \cdot \frac{\Delta CoSP(\tau)}{\bar{\psi}(\tau^{max} - 1)}\, d\tau = \frac{1}{\bar{\psi}(\tau^{max} - 1)} \left(\frac{\beta \tau^{max} - 1}{\beta^2} e^{\alpha + \beta \tau^{max}} - \frac{\beta - 1}{\beta^2} e^{\alpha + \beta} \right). \tag{5}$$

Spillover Persistence is the average time-lag weighted by its contribution to systemic risk. The construction is analogous to that of the Macaulay duration, with the difference that time-lags are weighted by systemic risk instead of cash flows. Spillover Persistence says that a firm's losses correlate with subsequent losses of the system after $\bar{\tau}$ days on average. If losses only had a contemporaneous effect on the system, then $\bar{\tau} = 0$. If they had an effect only exactly after 3 days, then $\bar{\tau} = 3$. Instead, in Figure 2 ΔCoSP(τ) declines with the time-lag τ, which suggests that the effect of losses fades out over time. In this case, Spillover Persistence is determined by the slope of ΔCoSP(τ).

2.2. Properties of $\Delta CoSP$

Motivated by previous work on systemic risk, ΔCoSP uses the $q \times 100\%$ largest equity return losses as indicators for firm distress. Since these tail losses occur with probability q by construction, ΔCoSP is not mechanically linked to a firm's individual risk. This is a desirable property for systemic risk measures, since firms with a more risky business model do not *necessarily* contribute more or less to systemic risk than firms with a less risky business model. Since ΔCoSP is built on equity returns, it is also not mechanically driven by other firm characteristics, such as size or leverage.

Similar to Adrian and Brunnermeier (2016)'s ΔCoVaR, ΔCoSP measures the change in the system's risk when firm i is distressed relative to the average risk in the system. However, ΔCoSP differs from ΔCoVaR in two key aspects: (1) it incorporates a time-lag between losses of the firm and system, and (2) it uses the shortfall probability (SP) instead of the Value-at-Risk (VaR) as a measure for the system's risk. ΔCoVaR focuses on *contemporaneous* systemic risk, whereas the time-lag in ΔCoSP enables the estimation of the level and time horizon of *persistent* systemic risk. Using the Value-at-Risk to estimate the system's risk mechanically links ΔCoVaR to contemporaneous volatility in the system (see Adrian and Brunnermeier (2016, p.1713)), which impairs its ability to capture fragility during tranquil times (Brunnermeier and Oehmke (2013)). Instead, the shortfall probability is independent of contemporaneous volatility by construction. This property makes it a promising candidate to tackle the volatility paradox.

The concept of Granger (1969)-causality applies to ΔCoSP: the system's losses at time $t + \tau$, $\tau > 0$, cannot directly result in firm distress at time t.[10] 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 the tail correlation between a firm's and system's losses. Thus, it might also capture a firm's and system's common exposure to shocks. Since common exposure to shocks can be as important for financial stability as spillovers from firms to the system, Adrian and Brunnermeier (2016) and Brunnermeier et al. (2020) argue that the ability to capture both sources of systemic risk is an advantage rather than disadvantage of systemic risk measures. I provide several sensitivity analyses that suggest that my baseline results are not primarily driven by common exposure to omitted variables. First, I absorb aggregate effects of potential omitted variables by including time fixed effects in empirical models. Second, the existence of omitted variables that affect the system at both t and $t + \tau$ would lead to autocorrelation and predictable variation in the system's equity returns. I show in Section 8 that CoSP-measures (which are Average ΔCoSP and Spillover Persistence) do not significantly positively correlate with autocorrelation of the system's equity returns, and that my results are robust toward removing predictable variation in equity returns.

[10]This comes with the assumption that stock markets are liquid. In Section 8 I show that CoSP-measures are not driven by illiquidity of equity returns.

2.3. Data and estimation

The estimation of ΔCoSP uses daily equity market returns of a firm i and of the financial system. Time-lags and Spillover Persistence are measured in trading days. I retrieve equity market data from Thomson Reuters Datastream, which covers a large number of financial firms. The sample starts on January 1, 1985, and ends on December 31, 2017, covering three recessions (1990-1991, 2001, and 2007-2009) and several crises (1987, 1994, 1997, 1998, 2000, 2008, 2011). I start with a sample of all financial firms in the Datastream universe that are either currently listed or dead but with an available primary major equity quote in Datastream (as of February 2019).

For each firm, I obtain daily information on the unpadded and unadjusted stock price of common equity in local currency, the number of outstanding shares, and market capitalization in USD. I drop firms with less than one year of price data and I drop African and South American firms.[11] Following Adrian and Brunnermeier (2016), I focus on firms from the following financial sectors: banks (i.e., commercial banks or depository firms; 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).[12]

To estimate systemic risk in a multi-country setting, each firm is assigned (1) to one country and (2) to one of the following geographical regions based on its headquarter location: Europe, Asia (excluding Japan), North America, Japan, and Australia. By accounting for firms' geographical location, I acknowledge geographical variation in the macro-economic environment (such as interest rate levels and equity market volatility).

Losses in the financial system are daily return losses of a market value-weighted index of financial firms in the system. For each currently considered firm i, I define the relevant system as the set of other financial firms in the same geographical region. For instance, the financial system for JP Morgan contains all North American financial firms except for JP Morgan.[13]

I use backward-looking rolling estimation windows with a size of 5 years to estimate

[11] To omit a potential bias from public offerings, share repurchases and similar activities, I also drop observations for days on which the number of outstanding shares changed by more than 0.5% compared to the previous day. To ensure that securities are sufficiently liquid, I drop firm-day observations for which the market capitalization does not exceed 100thd USD. Moreover, I exclude all days on which at least 95% of the firms in the sample do not report a price.

[12] I classify a firm 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 firm if its SIC is between 6500 and 6599.

[13] Details are described in Online Appendix B.1.

ΔCoSP.[14] To alleviate estimation errors, I exclude firms from a given estimation window if there are less than 700 non-missing and non-zero observations of daily firm and system returns.[15]

The choice of ΔCoSP's reference level q is subject to a trade-off between capturing more severe shocks (smaller q) and relying on more observations to estimate ΔCoSP (larger q). I find $q = 5\%$ to be a reasonable choice.[16] ΔCoSP is estimated using the parametric model in Equation (3). Based on estimated ΔCoSP, I compute Average ΔCoSP and Spillover Persistence as described in Section 2.1. The maximum considered time-lag is $\tau^{\max} = 50$ days. The sample also includes ΔCoSP(0) as a measure for contemporaneous risk, which I compute using a standard nonparametric estimate. Estimation details are described in Online Appendix A.

I compare CoSP-measures to two closely related systemic risk measures. The main comparison is with ΔCoVaR since it is conceptually most closely related: (Average) ΔCoSP and ΔCoVaR both estimate a firm's *contribution* to systemic risk. ΔCoVaR is defined as

$$\Delta\text{CoVaR} = CoVaR_{-r^i=VaR^i(q)} - CoVaR_{-r^i=VaR^i(0.5)}, \tag{6}$$

where $\mathbb{P}(-r^S \geq CoVaR_E \mid E) = q$ for event E. Following Adrian and Brunnermeier (2016), ΔCoVaR is estimated using quantile regressions of weekly equity market returns.[17] As a robustness check, in some models I also include Acharya et al. (2017)'s Marginal Expected Shortfall (MES), which is defined as

$$MES = \mathbb{E}[-r^i \mid -r^S \geq VaR^S(q)]. \tag{7}$$

MES estimates a firm i's *exposure* to systemic risk. Following Acharya et al. (2017), I estimate MES for each firm-year as the firm's average return during days with the $q \times 100\%$ largest losses of the system.

I use the same reference level $q = 5\%$ for all systemic risk measures and winsorize ΔCoSP(0), MES, and ΔCoVaR at the 1% and 99% level, and Average ΔCoSP and Spillover

[14] A relatively long estimation window is needed to ensure that (1) economically significant losses occur within the time window, and (2) systemic risk measures are subject to a reasonably small estimation error.

[15] Since Spillover Persistence is particularly sensitive toward estimation errors from sequentially missing returns, I also winsorize each time series of equity returns by excluding periods with more than 5 subsequently missing returns and 1500-day periods with more than 180 missing returns.

[16] $q = 5\%$ is also close to reference levels used in similar studies on systemic risk. 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.

[17] Macroeconomic state variables used as explanatory variables in quantile regressions are reported in Table B.2 in Online Appendix B.2. Since my analysis is at annual frequency, I use the annual average of weekly ΔCoVaR.

Persistence at the 98% level (since these include a significant number of zero observations).

Finally, I enrich the sample of systemic risk measures 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 size of time and demand deposits, loans, 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). 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 firm and macroeconomic characteristics are in Online Appendix B.2.

3. Summary statistics and determinants

In this section, I discuss summary statistics for Spillover Persistence, explore how it relates to other systemic risk measures, and estimate the effect of financial conditions and firm characteristics on Spillover Persistence.

3.1. Summary statistics

After merging data for Spillover Persistence, Average ΔCoSP, and ΔCoVaR, the baseline sample includes 1,143 unique firms from 56 countries between 1989 and 2017.[18] Most firms are (commercial) banks, followed by real estate firms, broker-dealers, and insurers.[19] The total market value of firms in the sample is 9.47 trillion USD in December 2017. It corresponds to roughly 85% of the market value of financial firms worldwide and to roughly 75% in the subsample of US firms.[20] Thus, the sample is representative for the vast majority of publicly listed financial firms.

Table 1 depicts summary statistics for Spillover Persistence and systemic risk measures

[18]Here and in the following, in the context of systemic risk measures *year* refers to the last year in a 5-year estimation window. 46% of firm-year observations are for firms located in Europe, 36% in North America, 11% in Asia, 5% in Japan, and 2% in Australia.

[19]More specifically, 44% of firm-year observations are banks, 20% for real estate firms, 18% for broker-dealers, and 18% for insurers.

[20]The total market value of US firms in the sample is 3.84 trillion USD. 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.

in the baseline sample. The median of ΔCoSP(0) is 21ppt. This means that the occurrence of losses is contemporaneously correlated between firms and the financial system: in the median firm-year, if a firm suffers large losses, the probability of losses of the system on the same day is 21ppt larger than on an average day. Following a firm's losses, the average probability of losses of the system is 2.8ppt larger than on an average day, reflected by the Average ΔCoSP. The median Spillover Persistence is 21 days, which means that a firm's losses are followed by an increase in the probability of losses of the system at an average time horizon of 21 trading days, which is roughly one month.

[Place Table 1 about here]

As Figure 3 (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 3 (b) depicts the evolution of Spillover Persistence. While Spillover Persistence positively correlates with Average ΔCoSP (the correlation coefficient is 51% at the firm-year level), both measures clearly differ in the time series dimension.[21] To disentangle variation in Spillover Persistence from that in the level of systemic risk in the main analyses, I control for Average ΔCoSP in regressions with Spillover Persistence as explanatory variable. The correlation of Spillover Persistence is even lower with contemporaneous systemic risk measures, namely 8.1% with ΔCoVaR and 9.7% with MES at the firm-year level. Therefore, most of the variation in Spillover Persistence is orthogonal to the variation in contemporaneous systemic risk measures.

[Place Figure 3 about here]

3.2. Determinants of Spillover Persistence

Roughly 15% of Spillover Persistence's variation is explained by time-invariant heterogeneity across firms.[22] Aggregate fluctuations (globally or regionally) explain up to 22% of its variation. Hence, Spillover Persistence is neither to a large extent explained by macroeconomic changes nor is it highly persistent over time at the firm-level. Instead, the majority of variation (roughly 60%) comes from relative changes over time, i.e., differential trends of Spillover Persistence across firms.

[21] Table B.3 in Online Appendix B.2 reports the correlation between systemic risk measures and Spillover Persistence.

[22] Table B.4 in Online Appendix B.2 decomposes variation in Spillover Persistence into time-invariant variation and aggregate fluctuations.

In Table C.2 in Online Appendix C, I explore determinants of Spillover Persistence. First, I examine the role of overall financial conditions. To measure overall financial conditions, I follow Adrian et al. (2019) and use the Federal Reserve Bank of Chicago's National Financial Conditions Index (NFCI).[23] A larger value of NFCI corresponds to more tight financial conditions. I estimate that a one-standard deviation tightening in overall financial conditions associates with a 3.2 day increase in Spillover Persistence. This effect corresponds to roughly 45% of Spillover Persistence's unconditional standard deviation and, thus, is highly economically significant. Second, I examine other macroeconomic variables related to financial conditions. I find a highly significant correlation between banking crises and Spillover Persistence. During banking crises, Spillover Persistence is approximately 3 days larger than on average, which corresponds to roughly 40% of its standard deviation.[24] Moreover, I document that Spillover Persistence significantly increases with lower credit growth, and larger TED and credit spreads. These results show that Spillover Persistence is larger when financial conditions are tighter.

Third, I explore the cross-section of firms. Spillover Persistence is significantly larger for firms located in North America, particularly compared to those in Japan and Asia. Plausibly, these differences are due to the large interconnectedness of the US financial system, which might boost amplification effects. Size is an important determinant for Spillover Persistence: a 1% difference in total assets relates to a roughly 0.3 days larger Spillover Persistence. This finding is consistent with the idea that size is an important determinant for the propensity to amplify losses. Moreover, within the set of banks and broker-dealers, I find that Spillover Persistence is larger for banks that maintain a larger share of intangible assets. This result is consistent with the hypothesis that Spillover Persistence increases with tighter balance sheet constraints.

Finally, I explore the relation between Spillover Persistence and other risk measures. Spillover Persistence positively correlates with contemporaneous systemic risk measured by ΔCoVaR. However, ΔCoVaR explains less than 1% of the variation in Spillover Persistence. Thus, ΔCoVaR and Spillover Persistence capture different dimensions of systemic risk.

Spillover Persistence also positively correlates with the level of persistent systemic risk, measured by Average ΔCoSP. Thus, losses of firms with higher levels of systemic risk also relate to a more persistent increase in the risk of losses in the financial system. Nonetheless,

[23] The NFCI is a weighted average of more than 100 measures of financial activity, including conditions in money markets, debt and equity markets, as described by Brave and Butters (2011).

[24] I show that the large correlation between Spillover Persistence and crises cannot be explained by other macroeconomic characteristics (such as market funding conditions) or firm and bank characteristics. I additionally explore the robustness of the correlation between Spillover Persistence and crises in Table C.1 in Online Appendix C.

most of the variation in Spillover Persistence is orthogonal to variation in Average ΔCoSP.

Spillover Persistence does not positively correlate with a firm's individual risk, as measured by its Value-at-Risk. Therefore, the systemic risk perspective of Spillover Persistence differs from the firm perspective in studies on leverage cycles (e.g., Adrian and Shin (2014)). I also find that Spillover Persistence cannot be explained by market illiquidity of a firm's equity, as measured by Amihud (2002)'s illiquidity measure, which alleviates the concern that stock market illiquidity mechanically leads to large Spillover Persistence.[25]

4. Leverage and risk-taking

4.1. Empirical model and data

The previous section suggests that Spillover Persistence correlates with the tightness of financial constraints. Since the volatility paradox predicts that looser financial constraints correlate with an increase in firm leverage and risk-taking, I hypothesize that firm's increase their leverage and take more risks when Spillover Persistence declines. To test this hypothesis, I regress firm i's leverage (total assets over the market value of equity) and credit default swap (CDS) exposure (CDS notional relative to total assets) in year $t+1$ ($Y_{i,t+1}$) on its Spillover Persistence in year t ($\bar{\tau}_{i,t}$),[26]

$$Y_{i,t+1} = \alpha \cdot \bar{\tau}_{i,t} + \gamma \cdot \mathbf{F}_{i,t-1} + \eta \cdot \mathbf{M}_{c,t} + u_i + \varepsilon_{i,t+1}, \tag{8}$$

controlling for time-invariant differences across firms (u_i) and for firm characteristics ($\mathbf{F}_{i,t-1}$) in year $t-1$ and macroeconomic characteristics ($\mathbf{M}_{c,t}$) in firm i's headquarter country c in year t. In the most granular specifications, I also include year fixed effects, which absorb aggregate (firm-invariant) changes in the economic environment. Variable definitions are provided in Table B.1 in Online Appendix B.2. Standard errors are clustered at the firm and country-year levels, which accounts for autocorrelation at the firm level and for correlation across firms within country-years.

Consistent with the financial constraints channel, I expect that, at the margin, firms with a weaker balance sheet react more strongly to a loosening of financial conditions. Therefore, I hypothesize that the correlation of Spillover Persistence with leverage and CDS exposure is stronger for firms with tighter balance sheet constraints. To explore the role of balance

[25] I explore the relation between Spillover Persistence and stock market illiquidity in Online Appendix C.4 in more detail.

[26] With slight abuse of notation, I use t here and in the following to index years of variables in regression models, whereas it indexes days of equity return losses in Section 2.

sheet constraints, I interact $\bar{\tau}_{i,t}$ with firm characteristics (standardized to mean zero and unit variance). Table 2 summarizes the key variables in the sample.

[**Place Table 2 about here**]

4.2. Results

First, I examine whether Spillover Persistence correlates with leverage. In column (1) in Table 3, I find that leverage significantly increases when Spillover Persistence declines ($p < 10\%$), controlling for macroeconomic and firm characteristics, firm fixed effects, and Average ΔCoSP. A one-standard deviation decline in Spillover Persistence relates to an increase in leverage by 2% of its standard deviation. This results is consistent with the hypothesis that a decline in Spillover Persistence reflects a loosening of financial constraints.

[**Place Table 3 about here**]

The coefficient of Spillover Persistence doubles in size and is statistically more significant ($p < 5\%$) when I only examine the subsample of banks and broker-dealers in column (2), where I additionally control for bank characteristics. The coefficient increases even more when I absorb aggregate shocks by including year fixed effects in column (3). In this case, a one-standard deviation decline in Spillover Persistence relates to an increase in leverage by 6% of its standard deviation.

The effect of Spillover Persistence on leverage is twice as large for banks with a one-standard deviation larger share of impaired loans than on average (column (4)). Thus, the effect of impaired loans on the sensitivity of leverage toward Spillover Persistence is highly economically significant. As a large share of impaired loans reflects a weak balance sheet, this result is consistent with the financial constraints channel.

In column (5), I examine changes in banks and broker-dealers' CDS exposure. I find that a decline in Spillover Persistence significantly correlates with an increase in CDS exposure ($p < 10\%$), controlling for macroeconomic, firm, and bank characteristics as well as firm and year fixed effects. The effect is similar in magnitude to the effect of Spillover Persistence on leverage: a 1-standard deviation decline in Spillover Persistence relates to a 5%-standard deviation increase in CDS exposure. The correlation between CDS exposure and Spillover Persistence is significantly stronger for banks with a larger share of impaired loans and intangible assets (column (6)). Thus, the results are consistent with an effect of Spillover Persistence on risk-taking due to a financial constraints channel.

5. Fragility before banking crises

The volatility predicts that loose financial constraints contribute to the build-up of fragility in the financial system, e.g., by encouraging agents to increase leverage and risk-taking. Motivated by this prediction and by the negative correlation of Spillover Persistence with leverage and risk-taking documented in the previous section, I hypothesize that fragility in the financial system builds up when Spillover Persistence declines. In this section, I test the hypothesis by exploring the dynamics of Spillover Persistence during the run-up phase of banking crises.

5.1. Empirical model and data

Data about banking crises episodes and their economic costs and characteristics are from Laeven and Valencia (2018)'s country-level database. I consider countries with at least one crisis between 1989 and 2017. After merging with systemic risk measures, the "crises sample" includes 738 financial firms located in 26 countries. 18% of the firm-year observations in the sample are flagged as crisis-years (see Table 4). The output loss (in % of GDP) is 30% for an average country-year within crises. The distribution of systemic risk measures in the crises sample is similar to that in the baseline sample.

[Place Table 4 about here]

In the baseline model, I regress the banking crisis indicator for firm i's country c in year $t+1$ on firm i's Spillover Persistence ($\bar{\tau}_{i,t}$) in year t, controlling for Average ΔCoSP ($\bar{\psi}_{i,t}$), a vector of country and region-specific macroeconomic characteristics ($\mathbf{M}_{c,t}$) in year t,

$$\text{Crisis}_{i,t+1} = \alpha \cdot \bar{\tau}_{i,t} + \beta \cdot \bar{\psi}_{i,t} + \gamma \cdot \mathbf{M}_{c,t} + u_i + v_t + \varepsilon_{i,t+1}. \tag{9}$$

α is the correlation between Spillover Persistence and the likelihood of a future crises for an average firm relative to other firms.[27] The firm fixed effect u_i absorbs potential time-invariant differences across firms, e.g., that some firms experience more crises *on average* and exhibit larger Spillover Persistence *on average* compared to other firms. The year fixed effect v_t ensures that α does not pick up correlation between crises and Spillover Persistence due to potential omitted macroeconomic variables at the aggregate level. By controlling for Average ΔCoSP ($\bar{\psi}_{i,t}$), α is estimated off changes in $\bar{\tau}_{i,t}$ holding the level of firm i's

[27] Since crises are measured at country-year level, all firms in the same country c and year $t+1$ are assigned the same level of $\text{Crisis}_{i,t+1}$. By performing the regression at the firm level, the estimate gives more weight to countries with more firms. In Table C.4 in Online Appendix C, I show that the results also hold at the country level, i.e., with the same weight for each country.

(persistent) systemic risk constant. In other words, the estimation of α relies on variation in the slope of ΔCoSP(τ) across time-lags τ but not on its level. The hypothesis implies that declines in Spillover Persistence correlate with build-ups of fragility and, thereby, precede crises. Thus, I expect that $\alpha < 0$.

While year fixed effects absorb aggregate macroeconomic changes, I also control for current macroeconomic characteristics at the country- and region-level. Specifically, I include inflation, GDP growth, and credit growth, capturing business cycle and credit dynamics, and investment growth, reflecting the use of credit for investment versus consumption, at the country-level. These variables have been highlighted as important determinants for crises by previous studies (e.g., by Schularick and Taylor (2012) and Krishnamurthy and Muir (2020)). Moreover, I also control for current financial market conditions by including the logarithm of the 10-year government bond rate, the change in short-term interest rates, change in term spreads, TED spread, change in credit spread, equity market return and volatility at region level. In additional regressions, I also control for lagged firm characteristics (size, leverage, and market-to-book) and for contemporaneous systemic risk measures (ΔCoVaR and ΔCoSP(0)). Variable definitions are provided in Table B.1 in Online Appendix B.2. Standard errors are clustered at the firm and country-year levels, which accounts for autocorrelation at the firm level and for correlation across firms within country-years.

Moreover, I explore heterogeneity in the correlation between Spillover Persistence and future crises across macroeconomic and firm characteristics. For this purpose, I interact $\bar{\tau}_{i,t}$ in Equation (9) with macroeconomic and firm variables, such as financial conditions, firm size, leverage, and funding structure. I standardize all macroeconomic and firm characteristics to have a zero mean and unit standard deviation. Hence, when including interaction terms, the coefficient of $\bar{\tau}_{i,t}$ is the correlation between Spillover Persistence and crises for average financial conditions for a firm with average size, average leverage, etc.

5.2. Baseline Results

I start by exploring the correlation between crises and Spillover Persistence and Average ΔCoSP without including fixed effects or macroeconomic characteristics. The estimated coefficients in column (1) of Table 5 show that both measures significantly correlate with future crises ($p < 1\%$), but with opposite signs. A 1-standard deviation *increase* in Average ΔCoSP relates to a 14ppt larger crisis likelihood, and a 1-standard deviation *decrease* in Spillover Persistence relates to a 3ppt larger crisis likelihood. These effects are both economically significant compared to the average crisis likelihood of 18% in the sample. CoSP-measures also have substantial explanatory power, as they jointly capture 11% of the variation in the occurrence of crises. The negative coefficient of Spillover Persistence is consistent with the time-series dynamics in Figure 1 and supports the hypothesis that Spillover Persistence declines when fragility builds up before crises.

[**Place Table 5 about here**]

In column (2), I estimate the same model with ΔCoVaR instead of CoSP-measures as explanatory variable. A 1-standard deviation increase in ΔCoVaR associates with a 6ppt higher crisis likelihood, which is significantly different from zero ($p < 1\%$). Variation in ΔCoVaR explains 3% of the variation in banking crises, which is less than one third of the variation captured by CoSP-measures.

In column (3), I present estimated coefficients for the baseline model in Equation (9), which includes firm and year fixed effects and controls for macroeconomic characteristics. The remaining variation in Spillover Persistence and Average ΔCoSP is still highly significantly correlated with future banking crises ($p = 1\%$). The estimated coefficients drop by roughly 50% in absolute value compared to column (1), which suggests that approximately half of the correlation of Spillover Persistence and Average ΔCoSP with future crises in column (1) is explained by macroeconomic variables, aggregate shocks, and time-invariant heterogeneity across firms.

Additionally controlling for contemporaneous systemic risk by ΔCoVaR and firm characteristics in column (4) does neither alter the economic nor statistical significance of the coefficients of Spillover Persistence and Average ΔCoSP. Thus, the variation in CoSP-measures that correlates with banking crises is largely orthogonal to that of ΔCoVaR. Interestingly, the estimated coefficient of ΔCoVaR switches signs compared to the model without fixed effects and CoSP-measures. Thus, the positive correlation between ΔCoVaR and future crises is fully explained by fixed effects, macroeconomic variables, and CoSP-measures.[28]

The key methodological differences of CoSP-measures relative to ΔCoVaR are (1) the focus on loss dynamics and (2) that they are independent of contemporaneous volatility of the system. To assess which difference drives the significant correlation with crises in column (4), I replace ΔCoVaR with the contemporaneous ΔCoSP(0) as control variable in column (5). Similar to Average ΔCoSP, ΔCoSP(0) is also independent of contemporaneous volatility, but it is based on contemporaneous correlation and ignores loss dynamics. Thus,

[28] In additional, unreported regressions I find that the coefficient of ΔCoVaR becomes statistically insignificant when including year fixed effects, and becomes negative when additionally controlling for macroeconomic variables. Adrian and Brunnermeier (2016) also construct a forward-looking ΔCoVaR, which predicts future systemic risk by projecting ΔCoVaR on lagged firm and macroeconomic characteristics. By including most of their characteristics as control variables in my empirical model (such as firm size, leverage, market volatility, and fixed income spreads), I implicitly control for a large part of the variation in forward-looking ΔCoVaR as well.

if variation in loss dynamics is the key feature that captures fragility in column (4), the estimated coefficients of Average ΔCoSP and Spillover Persistence should not change in column (5) compared to (4). This is precisely what I find.[29] Thus, loss dynamics are the key characteristic of CoSP-measures that captures fragility before crises. Moreover, the coefficient of ΔCoSP(0) is not significantly different from zero in column (5) while controlling for ΔCoSP and Spillover Persistence. This suggests that there is no additional information about crises captured by contemporaneous systemic risk.

Finally, I examine whether CoSP-measures also relate to the economic *cost* of crises. If declines in Spillover Persistence capture a build-up of fragility, one would expect Spillover Persistence to negatively correlate with the severity of crises conditional on their occurrence. To test the hypothesis, I regress the output loss of crises conditional on their occurrence on lagged CoSP-measures. The estimated coefficients in column (6) show that Average ΔCoSP is significantly positively and Spillover Persistence significantly negatively correlated with output losses, consistent with the hypothesis.

These results are very robust. In Table C.3 in Online Appendix C I show that the statistical and economic significance of the results remain largely unchanged for banking crises that have systemic effects or crises that are not "borderline cases", and when I additionally control for the presence of stock market bubbles, for contemporaneous systemic risk using MES, for lagged crises and output losses, or predict the fiscal cost instead of the output loss of crises. Thus, the relation between CoSP-measures and crises is not specific to particular crises and cannot be explained by asset price bubbles or contemporaneous systemic risk measures. Moreover, in Table C.4 in Online Appendix C I show that the results also hold at the country level.

Figure 4 illustrates the dynamics of CoSP-measures before crises. To construct the figure, I use the baseline model in Equation (9) and vary the time-lag of the crisis indicator relative to explanatory variables. There is a clear pattern: the correlation of Spillover Persistence (and of Average ΔCoSP) with crises strengthens with closer proximity to crises. Since fragility builds up with closer proximity to crises, this result provides further support for the hypothesis that Spillover Persistence captures build-ups of fragility.

[Place Figure 4 about here]

[29]The p-value for the null hypothesis that the coefficients of Spillover Persistence (Average ΔCoSP) are significantly different in columns (4) and (5) is 99.5% (81.4%).

5.3. The role of financial conditions and bank characteristics

The financial constraints channel predicts that declines in Spillover Persistence reflect a loosening of financial constraints, which leads to a build-up of fragility especially when financial conditions are loose already. Therefore, I expect that the correlation between Spillover Persistence and crises is stronger when overall financial conditions and balance sheet constraints are less tight.

To test this hypothesis, I first explore time series variation in the US National Financial Conditions Index (NFCI) for US firms. In column (1) in Table 6, I add an interaction term between NFCI and Spillover Persistence to the baseline model in Equation (9). The coefficient on the interaction term is significantly positive ($p < 1\%$). Thus, the less tight financial conditions (the lower NFCI), the stronger is the correlation between declines in Spillover Persistence and future crises. Interestingly, the correlation between Spillover Persistence and future crises becomes negative only when financial conditions are less tight than on average.[30] This finding highlights the importance of financial conditions to explain the link between Spillover Persistence and fragility.

[**Place Table 6 about here**]

I dig deeper into variation in funding conditions in the multi-country sample of firms in column (2). Less tight funding conditions reflected in higher investment growth and lower TED spread significantly strengthen the (negative) correlation between Spillover Persistence and future crises. The finding is consistent with that from column (1) and with the financial constraints channel.

Finally, I explore cross-sectional heterogeneity in bank and broker-dealer characteristics. Motivated by the previous findings, I expect a stronger (negative) correlation between Spillover Persistence and future crises for banks with weaker balance sheets. To measure balance sheet constraints, I use bank leverage, the share of impaired loans, and intangible assets. Moreover, fragility in the banking system can result from maturity transformation, i.e., short-term funding and long-term lending (e.g., Diamond and Dybvig (1982)). Therefore, I expect a stronger (negative) effect for banks that are more active in maturity transformation, i.e., rely more heavily on deposit funding and invest more in loans than other banks.

In column (3), I interact these bank characteristics with Spillover Persistence. The interaction terms with demand deposits and loans enter with negative and strongly significant coefficients ($p < 1\%$ and $p < 5\%$, respectively). Thus, the correlation between Spillover Persistence and future crises is stronger for banks that more heavily engage in maturity

[30] In the regression sample, the correlation between Spillover Persistence and future crises is negative for the level of NFCI in 12 out of 28 years (i.e., 43%) between 1989 and 2016.

transformation than for other banks. Moreover, the interactions with the share of impaired loans and intangible assets enter with a significantly positive coefficient, and that with a bank's liquidity ratio with a significantly negative coefficient. Thus, declines in Spillover Persistence correlate significantly more with future crises for more liquid banks, and banks with a smaller share of impaired loans and of intangible assets. The findings support the hypothesis that less tight balance sheet constraints are an economic channel through which Spillover Persistence connects to fragility.

In column (4), I explore whether differential effects across banks are captured by differences in contemporaneous systemic risk. For this purpose, I additionally control for contemporaneous systemic risk using ΔCoVaR and its interaction with Spillover Persistence. However, the magnitude and statistical significance of coefficients of other interaction terms barely changes, which supports the robustness of my findings.

Finally, in column (5) I examine whether heterogeneity across banks can be explained by variation in overall financial conditions. For this purpose, I additionally control for the interaction between Spillover Persistence and NFCI. However, while the interaction term enters with a significantly positive coefficient (consistent with column (1)), the coefficients on demand deposits, loans, the liquidity ratio, share of impaired loans, and intangible assets barely change and remain significantly different from zero (except for the interaction terms of Spillover Persistence with impaired loans and liquidity ratio, which have $p < 13\%$). Therefore, both, overall financial conditions and firms' balance sheet constraints, are economically relevant channels that connect declines in Spillover Persistence to build-ups of fragility before crises.

6. Asset price bubbles

In this section, I explore fragility during asset price bubbles and their relation to Spillover Persistence. Previous literature argues that imbalances and fragility in the financial system build up during the run-up phase of asset price bubbles, whereas amplification effects arise at later stages of bubbles and particularly when they burst (e.g., Borio and Lowe (2002), Brunnermeier and Oehmke (2013), Brunnermeier et al. (2020)). Consistent with these bubble dynamics, I hypothesize that Spillover Persistence is lower during bubble booms (1) compared to average other years and (2) compared to the bubble bust phase, and that it increases during the boom phase and peaks around the burst.

6.1. Data

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 (2018), applied to the main stock price indices in 17 countries from 1987 to 2015.[31] By cutting each 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.

Bubble indicators are merged to the baseline sample of systemic risk measures and firm characteristics at the firm-year level.[32] The "bubbles sample" covers 33 bubbles, 17 countries, and 693 financial firms from 1989 to 2015.[33]

I saturate the sample with macroeconomic control variables that have been shown to correlate with asset price bubbles and financial fragility, such as inflation, GDP growth, credit-to-GDP growth, investment growth, and government bond rates.

[**Place Table 7 about here**]

The summary statistics in Table 7 show that 13% of the firm-year observations are labeled as stock market booms and 5% are bust periods. The average length of stock market booms (busts) is 2.16 (0.32) years, and an average firm-year within a bubble is roughly 2 years apart from the bubble burst (which may occur later or has occurred earlier). The distribution of CoSP-measures in the bubbles sample is similar to that in the overall sample.

6.2. Empirical model

First, in the baseline model 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 ($\mathbf{I}_{c,t}^{Bubble}$), controlling for the current boom and bust length ($\mathbf{L}_{c,t}^{Bubble}$), macroeconomic characteristics ($\mathbf{M}_{c,t}$), and time-invariant differences across firms (u_i),

$$\bar{\tau}_{i,t} = \alpha \cdot \mathbf{I}_{c,t}^{Bubble} + \beta \cdot \mathbf{L}_{c,t}^{Bubble} + \gamma \cdot \mathbf{M}_{c,t} + u_i + \varepsilon_{i,t}. \tag{10}$$

[31]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.

[32]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.

[33]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.

Additional specifications also include year fixed effects, which absorb aggregate fluctuations. I include the boom and bust length in order to alleviate concerns that estimates are driven by correlation between bubbles and early years of Spillover Persistence's estimation window (which is from $t-4$ to t). Additionally, I show that the results also hold when controlling for 1-year lagged Spillover Persistence in Online Appendix C, and I provide a robustness check for the baseline results by regressing Spillover Persistence on bubble indicators in the first year of the estimation window (which is $t-4$). Standard errors are clustered at firm and country-year levels, accounting for autocorrelation of bubbles and Spillover Persistence at the firm level.

Second, I dig deeper into the hypothesis that fragility dominates during the onset of bubbles whereas amplification effects arise around the bubble burst. For this purpose, I explore the dynamics of Spillover Persistence during bubbles by estimating

$$\bar{\tau}_{i,t} = \alpha_0 \cdot \text{Burst Distance}_{c,t} \times I_{c,t}^{Boom} + \alpha_1 \cdot \mathbf{I}_{c,t}^{Bubble} + \beta \cdot \mathbf{L}_{c,t}^{Bubble} + \gamma \cdot \mathbf{M}_{c,t} + u_i + \varepsilon_{i,t}, \quad (11)$$

where Burst Distance$_{c,t}$ is the current distance to a bubble's burst. This model tests for a linear 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.

Third, I hypothesize that loose financial conditions and maturity transformation are economic channels through which bubble booms relate to fragility. In this case, the run-up phase of bubbles more strongly (negatively) correlates with Spillover Persistence when overall financial conditions and firms' balance sheet constraints are less tight and firms engage in more maturity transformation. To test this hypothesis, I interact bubble indicators and the distance to bubble bursts with the US National Financial Conditions Index (NFCI), market funding conditions, and bank and broker-dealer characteristics (all standardized to zero mean and unit variance).

To address reverse causality concerns that not bubbles but other macroeconomic conditions spur changes in Spillover Persistence, I also run regressions that include additional macroeconomic characteristics, namely the (annual average of) the weekly change in short-term treasury bond yields, term spreads, the average TED spread, credit spread change, equity market return and volatility. Moreover, firms may contribute to the creation of bubbles, e.g., by providing excessive credit, or to the systemic nature of bubbles, e.g., by being highly leveraged.[34] Thus, correlation between Spillover Persistence and bubbles might be driven by correlation between Spillover Persistence and firm characteristics. To address this concern, I run additional regressions that include 1-year lagged firm-level control variables,

[34]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.

which are firm size (log of total assets), leverage, and market-to-book value, and regressions that additionally include 1-year lagged bank-specific control variables, namely liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets.

6.3. Baseline results

Column (1) in Table 8 shows that Spillover Persistence is significantly smaller during stock market boom episodes than in other years ($p < 1\%$). The economic significance is large: during booms, Spillover Persistence is roughly 50% of its standard deviation smaller. In column (2), I compare booms with bust phases of bubbles. Spillover Persistence is significantly lower ($p = 1\%$) during bubble booms than during busts, by roughly 50% of its standard deviation. These findings support the hypothesis that bubble booms associate with a build-up of fragility, captured by low Spillover Persistence.

[**Place Table 8 about here**]

I find that the negative correlation between Spillover Persistence and booms is very robust. In column (3), I additionally control for contemporaneous systemic risk by including ΔCoVaR as well as for additional macroeconomic characteristics, firm characteristics, and aggregate fluctuations (by including time fixed effects). The coefficient of the boom indicator declines from 3.7 to 1.9 days, suggesting that roughly half of the effect of bubble booms is reflected in these other variables. However, the remaining variation in bubble booms remains significantly correlated with Spillover Persistence ($p < 5\%$). Holding firm and macroeconomic characteristics constant, during booms Spillover Persistence is roughly 27% of its standard deviation smaller than outside of booms. The magnitude remains similar when I restrict the sample to only banks and broker-dealers and additionally control for granular bank characteristics (column (4)).

Finally, I explore an alternative lead-lag structure in column (5), where I examine the effect of bubbles in the first year that is used to estimate Spillover Persistence. The coefficient of the bubble boom indicator remains highly statistically significant and negative, with a similar magnitude as in prior specifications.

6.4. Spillover Persistence dynamics during booms

To shed light on the dynamics of Spillover Persistence during bubble booms, I estimate a linear trend. I hypothesize that Spillover Persistence is particularly low at the beginning of a bubble, reflecting high financial fragility, and larger around the burst, where amplification effects are stronger. In this case, there is a negative correlation between burst distance and Spillover Persistence during booms.

Consistent with the hypothesis, Table 9 shows that during booms Spillover Persistence significantly declines with the distance to a bubble's burst. In other words, it increases over time. In the baseline regression, I show that this effect holds within bubbles, i.e., for the subsample of all firm-year observations flagged as bubbles, controlling for macroeconomic characteristics, the current boom and bust length, and firm fixed effects (column (1)). The effect remains statistically significant with slightly smaller magnitude in the overall sample while controlling for the average effect of bubble booms and busts as well as firm characteristics (column (2)).

[**Place Table 9 about here**]

The distance effect during booms is robust in magnitude and statistical significance toward additionally controlling for contemporaneous systemic risk (measured by ΔCoVaR) and for the number of boom and bust years in the CoSP-estimation window (column (3)). This alleviates concerns (1) that Spillover Persistence dynamics are due to variation in the level of contemporaneous systemic risk and (2) that the number of boom or bust years that enter the CoSP-estimation window is an omitted variable for burst distance.[35] Moreover, the coefficient stays significant and slightly increases in (absolute) magnitude when I constrain the sample to only banks and broker-dealers and additionally control for granular bank characteristics (column (4)).

6.5. The role of financial conditions and bank characteristics

In this section, I explore whether the correlation between bubbles and Spillover Persistence differs with financial conditions and firms' balance sheet constraints.

First, I examine the role of overall financial conditions using heterogeneity in the National Financial Conditions Index (NFCI) for the subsample of US firms. I find that the correlation between Spillover Persistence and bubble booms is negative only if financial conditions are sufficiently loose, but not for average financial conditions (see column (1) in Table 10). The interaction between the boom indicator and NFCI is significantly positive ($p < 1\%$), which is consistent with the hypothesis that less tight financial conditions boost the build-up of fragility and lower Spillover Persistence during bubble booms.

[35] In Online Appendix C I additionally show that the results are robust to controlling for 1-year lagged Spillover Persistence, which provides additional evidence that early years in the estimation window for Spillover Persistence do not drive the results.

[Place Table 10 about here]

Second, I dig deeper into variation in funding conditions in the overall sample of firms in column (2). Less tight funding conditions reflected in higher investment growth and lower TED spread significantly strengthen the (negative) correlation between Spillover Persistence and bubble booms. The finding is consistent with that from column (1).[36]

Third, I explore cross-sectional heterogeneity in bank and broker-dealer characteristics. I measure the level of balance sheet constraints using bank leverage, liquidity, and the share of impaired loans and intangible assets, while controlling for macroeconomic characteristics, bank characteristics, bubble busts, boom and bust length, and firm fixed effects. Booms are more strongly correlated with low Spillover Persistence for banks with low leverage, high liquidity, and a small share of impaired loans and intangible assets (column (3)). The interaction with leverage, liquidity, and impaired loans is particularly significant ($p < 0.1\%$). A 1-standard deviation decrease in leverage relates to a 7 day increase in the (absolute value of the) correlation between booms and Spillover Persistence. A 1-standard deviation increase in liquidity relates to a 16 day increase in the (absolute value of the) correlation between booms and Spillover Persistence. The effect is thus highly economically significant, especially in comparison to the coefficient of booms for a bank with average characteristics (which is 4.6 days).

Moreover, the interaction of (demand and time) deposit funding with the boom indicator enters with a significant and negative coefficient. Thus, booms relate more strongly to low Spillover Persistence for banks that rely more heavily on deposit funding. The correlation is also economically significant: a 1-standard deviation increase in deposit funding relates to a 2 day increase in the absolute effect of booms.

The estimated coefficients on interaction terms remain largely unchanged when I additionally control for overall financial conditions and year fixed effects in column (4). Moreover, in columns (5) and (6) I interact the distance to bubble burst with bank characteristics and NFCI. The coefficients on interaction terms have the same signs as for the interactions with the bubble boom indicator. Overall these results are consistent with the hypothesis that loose financial conditions and balance sheet constraints as well as maturity transformation are economic channels that link Spillover Persistence to a build-up of fragility during bubbles.

[36] Interestingly, I also find that the interaction between bubble booms and credit growth enters with a significantly positive coefficient. This finding suggests that amplification and not fragility is stronger when bubbles are credit-fueled, consistent with Jordà et al. (2015)'s result that credit amplifies the economic costs of bubbles.

7. Amplification and fire sales

Whereas previous sections provide empirical evidence that Spillover Persistence negatively correlates with financial fragility, in this section I hypothesize that Spillover Persistence positive correlates with the presence of amplification effects. This hypothesis is consistent with the financial constraints channel, namely that a tightening in financial constraints raises Spillover Persistence, and vice versa. In the following, I provide empirical evidence for the hypothesis by exploiting hurricane Katrina as an exogenous shock to the financial constraints of property & casualty (P&C) insurers that were active in the hurricane-exposed region.

7.1. Empirical model and data

Hurricane Katrina made first landfall on August 25, 2005, and has been one of the costliest Atlantic hurricanes on record. It predominantly affected the US states Alabama, Louisiana, and Mississippi and triggered 41.1 billion USD in insurance claims being filed.[37] The volume of claims corresponds to more than twice the total premiums collected in 2004 by P&C insurers in these states. As a result, Katrina caused a massive liquidity need among P&C insurers, which resulted in substantial fire sales and price impact, as documented by Manconi et al. (2016) and Girardi et al. (2020). The hurricane is therefore a suitable event to explore the effect of a tightening of financial constraints and resulting fire sales on Spillover Persistence.

I estimate the effect of Katrina on the Spillover Persistence of US P&C insurers that were exposed to the hurricane relative to other insurers. Exposed insurers are identified as follows. 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.[38] Since the number of listed US insurers in my sample is small (namely 27), in additional analyses I also include Canadian and European insurers in the control group.[39]

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

[38] 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`).

[39] I provide details on the sample construction in Online Appendix B.2.5. European insurers faced significantly lower (almost absent) exposure to Katrina (see `https://www.globalreinsurance.com/sandp-katrina/rita-impact-modest-for-european-insurers/1321323.article`), except possibly for reinsurers, which I therefore exclude from the analysis. I assume that the same holds for Canadian in-

To isolate the impact of Katrina I estimate daily CoSP-measures based on 18-months backward-looking rolling windows (and, due to the shorter estimation window, with a 20-day maximum time-lag). Motivated by the models of Brunnermeier and Pedersen (2009), Allen and Carletti (2006), and Greenwood et al. (2015), I hypothesize that fire sales by exposed insurers mainly affect other financial firms that either hold assets similar to those of insurers or whose funding conditions rely on these assets' market liquidity. The majority of P&C insurers' assets is invested in corporate and municipal bonds (documented, e.g., by Girardi et al. (2020) and Ge and Weisbach (2020)). These assets typically trade in over-the-counter (OTC) markets, intermediated by broker-dealers.[40] Therefore, I expect that fire sales by P&C insurers after hurricane Katrina affect broker-dealers in particular. To capture spillovers to broker-dealers, I compute Spillover Persistence with respect to the broker-dealer system. In a robustness check, I alternatively use the non-financial system, which I expect to be less affected by fire sales than the broker-dealer system.[41] Table 11 provides summary statistics for the "hurricane sample".

[Place Table 11 about here]

In the baseline model, I regress Spillover Persistence of insurer i at 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, controlling for time-invariant heterogeneity at the insurer level (u_i) and for aggregate shocks (v_t),

$$\bar{\tau}_{i,t} = \alpha \cdot \text{Exposed}_i \times \text{post}_t + u_i + v_t + \varepsilon_{i,t}. \tag{12}$$

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 $\alpha > 0$, motivated by 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 US insurers, I use unclustered (heteroskedasticity-robust) standard errors in the sample of US insurers. Standard errors are clustered at the insurer-level in the sample of all North American and European insurers, which adjusts for autocorrelation of Spillover Persistence.

surers. Significant hurricane exposure by Canadian insurers would make the estimates more conservative.

[40]For example, Hendershott et al. (2020) highlight the importance of dealer-insurer relationships in the corporate bond market.

[41]I construct an index for the broker-dealer system analogously to that for the financial system but only include broker-dealers. To capture losses in the non-financial system, I use the total return index of Datastream Non-Financial indices for North America (946 constituents) and Europe (1833 constituents).

7.2. Results

Table 12 reports the estimated coefficients. The difference-in-difference estimate in column (1) is based on the sample of US insurers. Hurricane Katrina relates to an increase in Spillover Persistence by roughly 0.75 days for Katrina-exposed insurers relative to other insurers. The effect is statistically significantly different from zero ($p < 0.1\%$). It is also economically significant, as it corresponds to 18% of the standard deviation of Spillover Persistence in the sample.

[Place Table 12 about here]

In column (2), I include Canadian and European insurers in the control group. The difference between exposed and unexposed insurers remains highly statistically significant ($p < 0.1\%$) and increases to 1.1 days. A potential explanation for the difference in coefficients is that unexposed US insurers are more likely to face indirect exposure to hurricane Katrina than unexposed non-US insurers. In column (3), I additionally control for country-level trends. Therefore, the coefficient compares exposed to unexposed US insurers, as in column (1). The difference to the model in column (1) is that the relatively larger number of insurers (69 instead of 27) allows to cluster standard errors at the insurer level. This provides a robustness check that corrects standard errors for autocorrelation of Spillover Persistence. The coefficient remains significantly different from zero ($p < 3\%$), supporting the baseline result.

In the baseline results, I compute Spillover Persistence for spillovers to the broker-dealer system. The reason is that fire sales by exposed insurers are most likely to affect broker-dealers since both are active in similar segments of the financial market. Following this argument, the effect of fire sales should be smaller or absent for non-financial companies. To test this hypothesis, I re-estimate the baseline model for Spillover Persistence with respect to the non-financial system in column (4). The differential effect for exposed relative to unexposed insurers is not significantly different from zero and negligible in magnitude. This finding supports the hypothesis that the baseline effect of hurricane Katrina on Spillover Persistence is indeed due to fire sales by exposed insurers.

To test whether the results pick up differential pre-trends across insurers, I conduct a placebo analysis for the days before hurricane Katrina, from July 13 to August 24, 2005, with August 1 as placebo-event date. The result in column (5) shows no significant difference between exposed and unexposed insurers.[42]

[42] In Figure B.2 in Online Appendix B.2.5, I find a slight decrease in average Spillover Persistence for unexposed relative to exposed insurers before hurricane Katrina. The estimate in column (5) shows that the difference is not statistically significant, controlling for insurer and country-time fixed effects.

Finally, I examine to what extent the effect of hurricane Katrina is explained or picked up by contemporaneous systemic risk. In column (6) I control for ΔCoVaR. If changes in Spillover Persistence were explained by changes in contemporaneous systemic risk, the coefficient of the interaction between hurricane exposure and post-dummy should be smaller than in the baseline regression. In contrast, the coefficient of the interaction term is not significantly different in column (6) compared to the baseline model in column (3).[43]

I also examine directly whether ΔCoVaR picks up the effect of Katrina. On the one hand, ΔCoVaR is not designed to capture persistent effects of spillovers. Thus, if fire sales only affected loss dynamics but not contemporaneous systemic risk, there would be no differential effect of Katrina on ΔCoVaR across exposed and unexposed insurers. On the other hand, fire sales might also raise the level of contemporaneous systemic risk and, thereby, increase ΔCoVaR. In column (7), I do not find a significantly different effect of hurricane Katrina on ΔCoVaR for exposed relative to unexposed insurers ($p > 90\%$). This result suggests that fire sales do not necessarily increase contemporaneous systemic risk. Instead, the results are consistent with an effect of fire sales on loss dynamics, captured by Spillover Persistence.

8. Sensitivity analyses

It is possible that omitted variables explain the occurrence of losses of firms at day t and of the system at day $t + \tau$. In this case, ΔCoSP would pick up the common exposure to shocks in addition to potential spillovers from firms to the system. Adrian and Brunnermeier (2016) and Brunnermeier et al. (2020) argue that it is an advantage of systemic risk measures to pick up common exposure as well as spillovers since both can be sources of systemic risk. While it is beyond the scope of this paper to provide a causal identification of loss spillovers, below I provide empirical evidence that Spillover Persistence is not trivially explained by stock market illiquidity and that my results are not primarily due to exposure to common exposure to shocks.

First, if omitted variables affected all firms to the same extent, I would absorb their effect by including time fixed effects. The previous analyses show that the baseline results are very robust toward including time fixed effects.

Second, illiquidity of the securities whose prices are used to estimate ΔCoSP might bias Spillover Persistence, e.g., when information is priced in with delay. Therefore, one might be concerned that ΔCoSP picks up stock market illiquidity instead of loss spillovers. I address this concern by estimating whether variation in illiquidity explains variation in

[43]The p-value for the null hypothesis that the coefficient of the interaction between hurricane-exposure and post-dummy is the same in column (3) and (6) exceeds 90%.

CoSP-measures, 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 positively correlate with illiquidity, and that illiquidity explains less than 1% of the variation in Spillover Persistence.[44]

Third, and more generally, it is possible that omitted variables lead to persistent losses, specifically losses of the financial system on days t and $t + \tau$. The presence of such variables could raise the level of Spillover Persistence and would lead to autocorrelation in the system's return. However, I find that Spillover Persistence does not significantly positively correlate with autocorrelation of the system's return, and that variation in autocorrelation explains less than 3% of the variation in Spillover Persistence.[45]

A final concern is that omitted variables differently affect firm and system. If an omitted variable causes both the system and firm to face losses today and in the future, it would raise the level of Spillover Persistence. I address this concern by estimating an alternative ΔCoSP (and CoSP-measures) that is based on the system's return "shocks", defined as innovations in an autoregressive model of the system's return.[46] Thereby, I strip out predictable variation in the system's return, including the potential variation that could result from omitted variables which cause persistent losses to the system and firm. Based on the resulting time series of AR(1)-shocks, I re-estimate CoSP-measures and use them to re-estimate the baseline models that connect Spillover Persistence to leverage, crises, bubbles, and hurricane Katrina. The results remain robust in magnitude and statistical significance (see Online Appendix C.4).

These sensitivity analyses support the robustness of my results. They show that Spillover Persistence is not trivially explained by stock market illiquidity or autocorrelation of the system's return and that it remains informative about fragility and amplification dynamics after removing predictable variation, which could result from omitted variables.

9. Conclusion

Systemic risk measures often rely on contemporaneous volatility. However, macro-finance theory predicts that fragility builds up in the background during quiet times, when volatility is low (Brunnermeier and Sannikov (2014), Brunnermeier and Oehmke (2013)). This "volatility paradox" challenges the use of existing measures to identify fragility in the finan-

[44]I examine the correlation between (il-)liquidity measures and Spillover Persistence and Average ΔCoSP in Online Appendix C.4.

[45]I examine the correlation between autocorrelation coefficients and Spillover Persistence and Average ΔCoSP in Online Appendix C.4.

[46]This process is called "prewhitening" and common in the forecasting literature (e.g., see Giglio et al. (2016), Dean and Dunsmuir (2016), and references therein).

cial system and to distinguish a build-up of fragility from the materialization of systemic risk in crises, when amplification effects arise. The distinction between fragility and amplification is particularly relevant for policymakers that aim to design counter-cyclical regulation.

In this paper, I make progress by introducing an empirical framework that builds on a novel dimension of systemic risk: loss dynamics. I define Spillover Persistence as the average time-lag at which the risk of large losses of the financial system increases after a firm suffers large losses. The longer-lasting the effect of a firm's losses on the system, the larger is Spillover Persistence. The measure is motivated by recent macro-finance models, in which today's losses that hit constrained agents bolster the amplification of future shocks, and thereby raise the risk of future losses. The framework is applicable in many empirical settings, which supports future empirical work on loss dynamics, systemic risk, and its determinants.

I provide robust empirical evidence that Spillover Persistence captures variation in financial constraints, fragility, and amplification in the financial system. For this purpose, I exploit a broad multi-country setting with more than 700 financial firms from 1989 to 2017. I document that Spillover Persistence declines when financial constraints become less tight, and vice versa. The volatility paradox predicts that loose financial constraints contribute to the build-up of fragility in the financial system. Consistent with this prediction, I find that Spillover Persistence declines before banking crises, particularly when overall financial conditions are loose. Spillover Persistence also declines in early years of stock market bubbles, consistent with a build-up of fragility in these times. Instead, Spillover Persistence increases during crises and for insurers with high a propensity to fire-sell assets due to hurricane Katrina. The results highlight that loss dynamics are an important, informative, and novel dimension of systemic risk, which is useful to empirically detect a build-up of fragility before it materializes in crises.

The paper bridges recent advances in macro-finance theory and in the empirical literature on risks in the financial system. Thereby, I reveal a novel and relevant dimension of systemic risk and present 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 policy.

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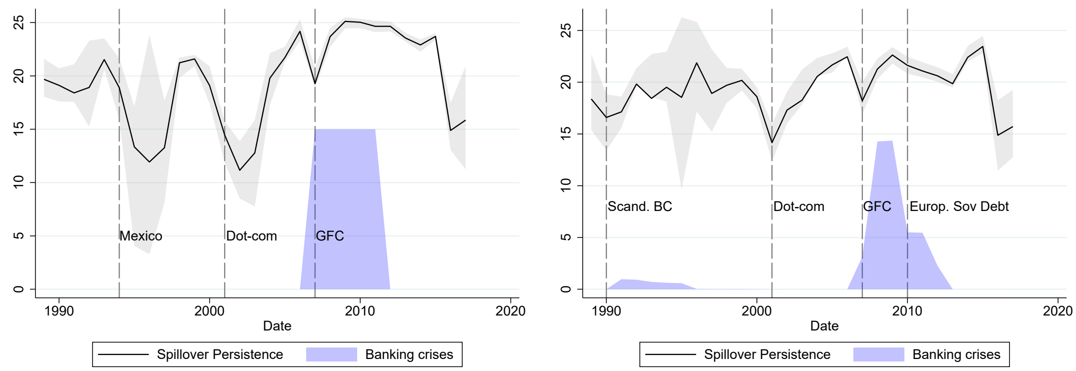
Figures and Tables

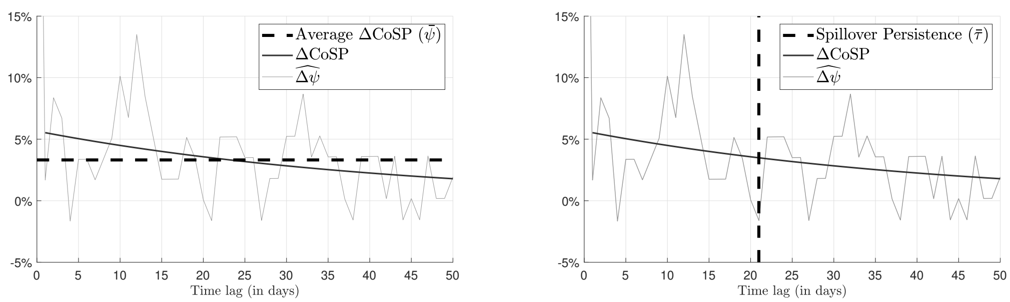
Fig. 1. Spillover Persistence, banking crises, and bubbles.
The figures depict the annual average Spillover Persistence and its 25th and 75th percentiles across financial firms in (a) the US and (b) Europe, weighted by total assets. Banking crises are illustrated in blue areas, with the height in (b) corresponding to the share of firms experiencing a crisis (weighted by total assets). Vertical dashed lines mark the onset of the Scandinavian banking crisis (1990), Mexican peso crisis (1994), burst of the dot-com bubble (2001), global financial crises (2007), and European sovereign debt crisis (2010).



(a) US.

(b) Europe.

Fig. 2. Illustration of ΔCoSP, Average ΔCoSP, and Spillover Persistence.
The figures depict estimates for ΔCoSP, Average ΔCoSP, and Spillover Persistence based on daily equity return losses of JP Morgan and the North American financial system from January 2003 to December 2007. The x-axis displays the time-lag between losses of JP Morgan and the financial system in days. $\Delta\text{CoSP} = e^{\hat{\alpha}+\hat{\beta}\tau}$ is the estimated parametric model for $\Delta\psi$, and $\widehat{\Delta\psi}$ is a standard nonparametric estimate, described in Online Appendix A.

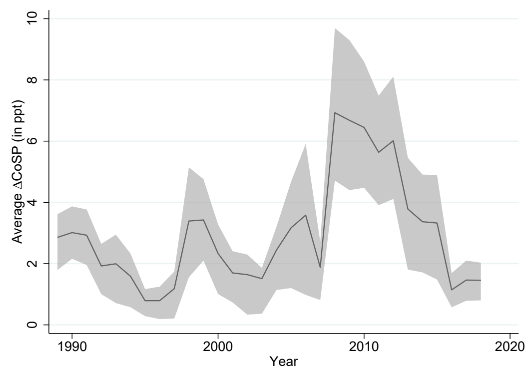


(a) ΔCoSP and Average ΔCoSP.

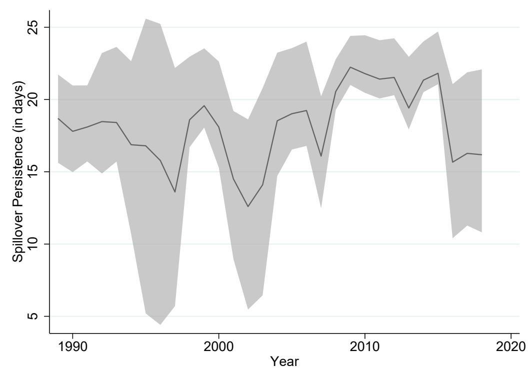
(b) ΔCoSP and Spillover Persistence.

Fig. 3. CoSP-measures: evolution over time.

The figures depict the annual mean and 25th and 75th percentiles of Average ΔCoSP and Spillover Persistence across firms. 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.



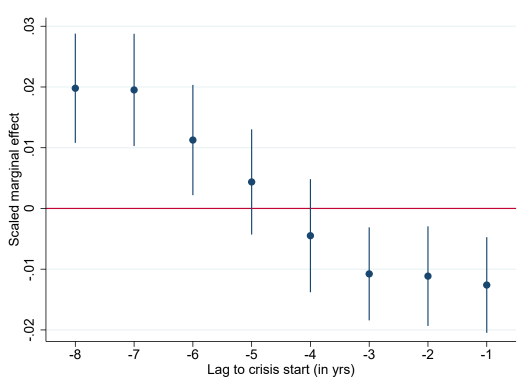
(a) Average ΔCoSP.



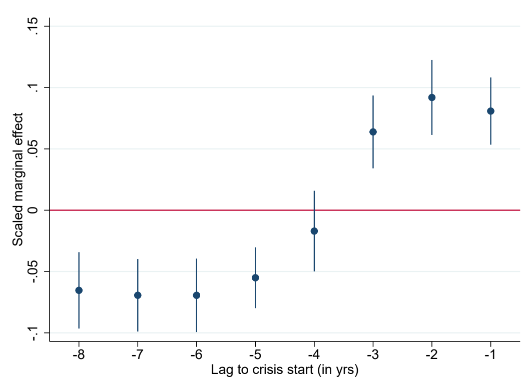
(b) Spillover Persistence.

Fig. 4. Correlation between CoSP-measures and crises at different time horizons.

The figures depict the estimated change in the likelihood of crises in year t (in percentage points) and its 95% confidence interval that relates to a 1-standard deviation increase in (a) Spillover Persistence and (b) Average ΔCoSP in year $t + x$, x displayed on the x-axis is the lag between CoSP-measures and crisis start. Estimates are based on Equation (9) by varying the time-lag between dependent variable relative to explanatory variables. Standard errors are clustered at firm and country-year levels.



(a) Spillover Persistence.



(b) Average ΔCoSP.

Table 1: Systemic risk measures: summary statistics.

The table depicts summary statistics for Spillover Persistence and systemic risk measures at the firm-year level. ΔCoSP(0), 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 yearly 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. Variable descriptions and data sources are provided in Table B.1.

	N	Mean	Median	SD	p5	p95
Spillover Persistence ($\bar{\tau}$, in days)	10,977	19.04	20.99	7.14	2.17	27.34
Average ΔCoSP ($\bar{\psi}$, in ppt)	10,977	3.60	2.83	2.92	0.02	9.59
ΔCoVaR (in ppt)	10,977	2.95	2.90	1.64	0.43	5.84
MES (in ppt)	10,960	2.15	1.72	1.83	0.07	5.97
ΔCoSP(0) (in ppt)	10,977	22.57	20.77	16.16	-1.54	51.81

Table 2: Risk-taking sample: summary statistics.

The table depicts summary statistics at the firm-year level in baseline regressions (1), (2), and (5) in Table 3 for leverage, leverage of banks and broker-dealers, and CDS exposure scaled by total assets, respectively. “Ban & Bro” indicates the subsample of firms included in BankFocus. Variable descriptions and data sources are provided in Table B.1.

	N	Mean	Median	SD	p5	p95
Leverage	9,710	11.49	6.09	15.88	0.80	39.72
Leverage (Ban & Bro)	1,607	14.12	9.40	13.70	3.01	41.17
CDS (Ban & Bro)	668	0.19	0.00	0.60	0.00	1.37
Spillover Persistence ($\bar{\tau}$, in days)	9,710	19.01	20.96	7.15	2.36	27.31
Average ΔCoSP ($\bar{\psi}$, in ppt)	9,710	3.68	3.01	2.94	0.02	9.72

Table 3: Spillover Persistence, leverage, and risk-taking.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variables are (1-4) leverage and (5-6) credit default swap notional scaled by total assets at year $t+1$. Average ΔCoSP and Spillover Persistence are estimated in 5-year rolling windows, where the last year is t. Firm characteristics are size, leverage (except in columns (1-4)), and market-to-book ratio at $t-1$; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets at $t-1$; and macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises at t. All firm and bank characteristics are standardized. Columns (2-6) only include firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:		Leverage$_{t+1}$			CDS$_{t+1}$	
Sample:	All			Ban & Bro		
Spillover Persistence	-0.048*	-0.100**	-0.132**	-0.120**	-0.007*	-0.003
	(0.070)	(0.044)	(0.021)	(0.034)	(0.083)	(0.537)
Spillover Persistence × Size				0.023		0.010*
				(0.512)		(0.089)
Spillover Persistence × Market-to-Book				-0.009		-0.011***
				(0.757)		(0.004)
Spillover Persistence × Liquidity ratio				-0.000		0.033
				(0.993)		(0.147)
Spillover Persistence × Demand deposits				-0.014		-0.008**
				(0.745)		(0.011)
Spillover Persistence × Time deposits				-0.023		0.001
				(0.602)		(0.645)
Spillover Persistence × Loans				0.048		0.006
				(0.145)		(0.364)
Spillover Persistence × Impaired loans				-0.229***		-0.020***
				(0.000)		(0.008)
Spillover Persistence × Intangible assets				-0.017		-0.012**
				(0.547)		(0.043)
Spillover Persistence × Leverage						-0.011
						(0.162)
Macro characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	No	Yes	Yes	Yes	Yes	Yes
Average ΔCoSP	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Standardized coefficients						
Spillover Persistence	-.022	-.047	-.063	-.057	-.047	-.019
No. of firms	831	190	190	190	77	77
No. of obs.	9,710	1,607	1,607	1,607	668	668
Adj. R^2	0.656	0.822	0.835	0.842	0.846	0.852
Adj. R^2 within	0.080	0.140	0.073	0.112	0.068	0.162

Table 4: Crises sample: summary statistics.

The table depicts summary statistics at the firm-year level used to estimate Equation (9). Variable descriptions and data sources are provided in Table B.1.

	N	Mean	Median	SD	p5	p95
Crisis (binary)	8,000	0.18	0.00	0.38	0.00	1.00
Output loss (in % of GDP)	8,000	5.30	0.00	12.65	0.00	30.00
Output loss (% of GDP, within crises)	1,382	29.93	30.00	13.01	12.30	45.00
Spillover Persistence ($\bar{\tau}$, in days)	8,000	19.19	21.10	7.06	2.24	27.21
Average ΔCoSP ($\bar{\psi}$, in ppt)	8,000	3.81	3.16	2.97	0.01	9.95
ΔCoVaR (in ppt)	8,000	3.22	3.15	1.60	0.64	6.08
ΔCoSP(0) (in ppt)	8,000	24.23	22.73	16.52	-0.49	53.23

Table 5: Fragility before crises.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is (1-5) a dummy variable that indicates the occurrence of a banking crisis and (6) the output loss (in % of GDP) of a banking crisis at year $t+1$. The definition of crises and the estimation of the output loss follow those by Laeven and Valencia (2018). The main independent variables are Spillover Persistence and Average ΔCoSP. These are estimated in 5-year backward-looking rolling windows, where the last year is t. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility at t. Firm characteristics are size, leverage, and market-to-book ratio at $t-1$. Column (6) is based on the subsample of observations with $\text{Crisis}_{t+1} = 1$. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year levels. Scaled coefficients reflect the change in the dependent variable for a standard deviation change in the independent variable. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			Crisis_{t+1}			Output loss_{t+1}
Sample:			Baseline			$\text{Crisis}_{t+1} = 1$
Spillover Persistence	-0.005***		-0.002***	-0.002***	-0.002***	-0.009**
	(0.001)		(0.010)	(0.008)	(0.008)	(0.016)
Average ΔCoSP	0.048***		0.026***	0.026***	0.028***	0.054***
	(0.000)		(0.000)	(0.000)	(0.000)	(0.002)
ΔCoVaR		0.040***		-0.023**		
		(0.001)		(0.041)		
ΔCoSP(0)					-0.001	
					(0.158)	
Macro characteristics	No	No	Yes	Yes	Yes	Yes
Firm characteristics	No	No	No	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	No
(1-5) Scaled & (6) standardized coefficients						
Spillover Persistence	-.03		-.01	-.01	-.01	-.004
Average ΔCoSP	.14		.08	.08	.08	.01
ΔCoVaR		.06		-.04		
ΔCoSP(0)					-.02	
No. of firms	738	738	738	738	738	395
No. of obs.	8,000	8,000	8,000	8,000	8,000	1,382
Adj. R^2	0.113	0.029	0.721	0.722	0.721	1.000
Adj. R^2 within	0.113	0.029	0.291	0.293	0.292	0.663

Table 6: Fragility before crises: financial conditions and bank characteristics.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is a dummy variable that indicates the occurrence of a banking crisis at year $t+1$. The definition of crises follows Laeven and Valencia (2018). Spillover Persistence and Average ΔCoSP are estimated in 5-year backward-looking rolling windows, where the last year is t. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility at t. Firm characteristics are size, leverage, and market-to-book ratio at $t-1$. Bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets at $t-1$. All macro, firm, and bank characteristics are standardized. Columns (3-5) only include firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at (1) firm and (2-5) firm and country-year levels, respectively. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Crisis$_{t+1}$		
Sample:	US	Baseline		Ban & Bro	
Spillover Persistence	0.005***	-0.001	-0.001	-0.001	0.003*
	(0.000)	(0.181)	(0.151)	(0.328)	(0.081)
Spillover Persistence × NFCI	0.010***				0.011***
	(0.000)				(0.001)
Spillover Persistence × Investment growth		-0.004***			
		(0.005)			
Spillover Persistence × Credit growth		-0.001			
		(0.310)			
Spillover Persistence × TED spread		0.002*			
		(0.055)			
Spillover Persistence × Equity volatility		-0.001			
		(0.238)			
Spillover Persistence × Size			-0.001	-0.001	-0.000
			(0.297)	(0.113)	(0.438)
Spillover Persistence × Leverage			-0.001	-0.001	-0.001
			(0.302)	(0.254)	(0.567)
Spillover Persistence × Market-to-Book			0.001	0.001	0.001
			(0.132)	(0.162)	(0.288)
Spillover Persistence × Liquidity ratio			-0.002*	-0.002*	-0.001
			(0.050)	(0.069)	(0.129)
Spillover Persistence × Demand deposits			-0.003***	-0.003***	-0.003***
			(0.001)	(0.000)	(0.002)
Spillover Persistence × Time deposits			0.001	0.001	0.001
			(0.166)	(0.164)	(0.136)
Spillover Persistence × Loans			-0.001**	-0.002**	-0.001**
			(0.018)	(0.013)	(0.018)
Spillover Persistence × Impaired loans			0.002**	0.002**	0.001
			(0.024)	(0.011)	(0.129)
Spillover Persistence × Intangible assets			0.001**	0.001**	0.001*
			(0.017)	(0.028)	(0.052)
Spillover Persistence × ΔCoVaR				0.001	
				(0.164)	
Macro characteristics	No	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Bank characteristics	No	No	Yes	Yes	Yes
NFCI	Yes	No	No	No	No
Average ΔCoSP	Yes	Yes	Yes	Yes	Yes
ΔCoVaR	No	No	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
No. of firms	203	738	175	175	175
No. of obs.	2,831	8,000	1,426	1,426	1,426
Adj. R^2	0.365	0.725	0.879	0.879	0.884
Adj. R^2 within	0.354	0.300	0.386	0.389	0.411

Table 7: Bubbles sample: summary statistics.

The table depicts summary statistics at the firm-year level used to estimate Equation (10). Bubble characteristics (boom and bust length and burst distance) are equal to zero outside of bubbles. Bubbles are identified using the BSADF approach as described in Brunnermeier et al. (2020). Variable descriptions and data sources are provided in Table B.1.

	N	Mean	Median	SD	p5	p95
Boom (binary)	7,592	0.13	0.00	0.33	0.00	1.00
Bust (binary)	7,592	0.05	0.00	0.22	0.00	0.00
Boom length (in years, within bubbles)	1,342	2.16	1.67	1.66	0.00	4.92
Bust length (in years, within bubbles)	1,342	0.32	0.00	0.56	0.00	1.33
Burst dist (in years, within bubbles)	1,342	2.02	1.42	1.37	0.58	4.92
Spillover Persistence ($\bar{\tau}$, in days)	7,592	19.53	21.44	7.01	2.17	27.12
ΔCoVaR (in ppt)	7,592	3.28	3.21	1.58	0.75	6.10

Table 8: Spillover Persistence during bubbles.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is (1-4) t or (5) $t+4$. Bubble indicators are based on the BSADF approach and 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. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, all for year t. Firm characteristics are size, leverage, and market-to-book ratio; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all for year $t-1$. Column (4) only includes firms that are part of BankFocus. Variable definitions are provided in Table B.1. Scaled coefficients reflect the change in the dependent variable as a share of its standard deviation when the independent variable increases from zero to one. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Spillover Persistence$_t$				Spillover Persistence$_{t+4}$
Sample:	Baseline			Ban & Bro	All
Boom	-3.671***	-3.573**	-1.897**	-1.751*	-1.983**
	(0.001)	(0.014)	(0.018)	(0.070)	(0.031)
Bust	-0.097		0.384	-0.281	-1.432
	(0.949)		(0.660)	(0.916)	(0.129)
Bubble		-0.097			
		(0.949)			
Macro characteristics	Yes	Yes	Yes	Yes	Yes
Additional macro characteristics	No	No	Yes	Yes	Yes
Firm characteristics	No	No	Yes	Yes	Yes
Bank characteristics	No	No	No	Yes	No
Boom & bust length	Yes	Yes	Yes	Yes	No
ΔCoVaR	No	No	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No
Scaled coefficients					
Boom	-.52	-.51	-.27	-.27	-.29
Bust	-.01		.05	-.04	-.21
No. of firms	693	693	693	153	640
No. of obs.	7,592	7,592	7,592	1,295	7,043
Adj. R^2	0.252	0.252	0.373	0.586	0.223
Adj. R^2 within	0.115	0.115	0.029	0.040	0.096

Table 9: Spillover Persistence and distance to the bubble burst.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is t. Bubble indicators are based on the BSADF approach and equal 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 excludes bubbles without burst. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, all for year t. Firm characteristics are size, leverage, and market-to-book ratio; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all for year $t-1$. Column (4) only includes firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence			
Sample:	Within Bubble	Baseline		Ban & Bro
Boom × Burst Distance	-2.253***	-1.645***	-1.665***	-3.328***
	(0.005)	(0.007)	(0.005)	(0.001)
Macro characteristics	Yes	Yes	Yes	Yes
Additional macro characteristics	Yes	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes
Bank characteristics	No	No	No	Yes
Boom & bust	Yes	Yes	Yes	Yes
Boom & bust-years	No	No	Yes	Yes
Boom & bust length	Yes	Yes	Yes	Yes
ΔCoVaR	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of firms	250	596	596	135
No. of obs.	1,163	6,270	6,270	1,119
Adj. R^2	0.369	0.296	0.318	0.560
Adj. R^2 within	0.182	0.144	0.171	0.513

Table 10: Spillover Persistence during bubbles: funding conditions and firm characteristics.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is t. Bubble indicators are based on the BSADF approach and equal 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. I exclude bubbles without burst in columns (4-5). Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, all for year t. Firm characteristics are size, leverage, and market-to-book ratio; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all for year $t-1$. All macro, firm, and bank characteristics are standardized. Columns (3-6) only include firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at (1) firm and at (2-6) firm and country-year levels, respectively. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Spillover Persistence					
Sample:	US	Baseline	Ban & Bro			
Boom	17.517***	-0.816	-4.582**	-0.925	-10.238**	-2.888
	(0.000)	(0.406)	(0.010)	(0.512)	(0.032)	(0.205)
Boom × NFCI	23.677***					
	(0.000)					
Boom × Investment growth		-2.091***				
		(0.000)				
Boom × Credit growth		1.179**				
		(0.021)				
Boom × TED spread		1.172*				
		(0.060)				
Boom × Equity volatility		0.354				
		(0.797)				
Boom × Size			0.335	0.118		
			(0.779)	(0.927)		
Boom × Leverage			7.424***	4.609**		
			(0.000)	(0.022)		
Boom × Market-to-Book			4.394***	2.429***		
			(0.000)	(0.006)		
Boom × Liquidity Ratio			-15.804***	-12.502**		
			(0.000)	(0.012)		
Boom × Demand Deposits			-2.539*	-1.771		
			(0.092)	(0.189)		
Boom × Time Deposits			-2.146**	-2.496**		
			(0.023)	(0.048)		
Boom × Loans			-1.789	-0.980		
			(0.234)	(0.494)		
Boom × Impaired Loans			8.169***	5.400***		
			(0.000)	(0.003)		
Boom × Intangible Assets			3.162*	2.807		
			(0.096)	(0.111)		
Boom × Burst Distance					4.853	-1.227
					(0.123)	(0.554)
Boom × Burst Distance × NFCI					4.148**	
					(0.029)	
Boom × Burst Distance × Size					-0.233	-0.172
					(0.458)	(0.556)
Boom × Burst Distance × Leverage					2.147*	1.625
					(0.093)	(0.205)
Boom × Burst Distance × Market-to-Book					1.097*	0.895
					(0.088)	(0.144)
Boom × Burst Distance × Liquidity Ratio					-4.139*	-4.501*
					(0.063)	(0.068)
Boom × Burst Distance × Demand Deposits					-0.228	-0.057
					(0.699)	(0.930)
Boom × Burst Distance × Time Deposits					-0.236	-0.339
					(0.669)	(0.562)
Boom × Burst Distance × Loans					-0.623	-0.649
					(0.235)	(0.197)
Boom × Burst Distance × Impaired Loans					3.324***	3.270**
					(0.006)	(0.032)
Boom × Burst Distance × Intangible Assets					1.060	1.098
					(0.168)	(0.167)
Macro characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Additional macro characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes	Yes	Yes
Bank characteristics	No	No	Yes	Yes	Yes	Yes
NFCI	Yes	No	No	No	Yes	No
Bust	Yes	Yes	Yes	Yes	Yes	Yes
Boom & bust length	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
No. of firms	201	693	153	153	135	135
No. of obs.	2,714	7,592	1,295	1,295	1,119	1,119
Adj. R^2	0.385	0.379	0.493	0.601	0.570	0.627
Adj. R^2 within	0.283	0.038	0.435	0.074	0.524	0.076

Table 11: Hurricane sample: summary statistics.

The table depicts summary statistics used to estimate Equation (12). Observations are at the firm-day-level for Spillover Persistence with respect to the broker-dealer system and firm-week-level for ΔCoVaR from August 8 to September 16, 2005, for all North American and European insurers. US P&C insurers are labeled as exposed if the ratio of total premiums written in Alabama, Louisiana, and Mississippi from 2004Q3 to 2005Q2 is among the 25% largest across all US insurers. Variable descriptions and data sources are provided in Table B.1.

	N	Mean	Median	SD	p5	p95
69 insurers (8 exposed)						
Spillover Persistence ($\bar{\tau}$, in days)	2,093	4.88	4.52	3.80	0.00	11.54
ΔCoVaR (in ppt)	521	2.38	2.44	1.19	0.43	4.33

Table 12: Effect of hurricane Katrina on Spillover Persistence.

This table reports difference-in-difference estimates for the effect of hurricane Katrina (August 25-29, 2005) on the Spillover Persistence of exposed US P&C (property & casualty) insurers relative to (1) other US insurers, and (2-6) other North American and European insurers. The regression is at (1-5) daily and (6-7) weekly frequency (1-4,6-7) from August 8 to September 16, 2005, in the baseline models and (5) July 13 to August 24, 2005, in the placebo analysis. Exposed = 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 US insurers. Spillover Persistence is estimated in 18-month backward-looking rolling windows. The system comprises all broker-dealer firms in a firm's geographic region. post-Katrina = 1 for estimation window end-dates on August 25, 2005 and afterwards, and zero otherwise. post-Placebo = 1 for estimation window end-dates on August 1, 2005 and afterwards, and zero otherwise. The sample includes primary insurers located in Northern America or Europe. Scaled coefficients are estimated coefficients scaled by the dependent variable's standard deviation. Standard errors are (1) unclustered and (2-7) clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Spillover Persistence						ΔCoVaR
Sample:	US insurers	All insurers			Placebo	All insurers	
System:	Broker-dealer			NonFin	Broker-dealer		
Exposed × post-Katrina	0.749***	1.120***	0.749**	-0.031		0.666**	-0.003
	(0.000)	(0.001)	(0.024)	(0.946)		(0.026)	(0.992)
Exposed × post-Placebo					0.025		
					(0.972)		
ΔCoVaR						0.008	
						(0.937)	
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	No	No	No	No	No
Country × Day FE	No	No	Yes	Yes	Yes	Yes	Yes
Scaled coefficients							
Exposed × post-Katrina	.18	.29	.2	-.009		.17	0
No. of firms	27	69	69	69	68	69	69
No. of obs.	820	2,093	2,093	1,911	2,138	521	521
Adj. R^2	0.893	0.847	0.872	0.816	0.914	0.860	0.431
Adj. R^2 within	0.015	0.015	0.007	-0.001	-0.001	-0.000	-0.003

Online Appendix

A. Estimation of CoSP

A.1. Estimation of CoSP

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 firm i and the system S, respectively, where the stationary distribution of $(r_t^x)_t$ satisfies $\mathbb{P}(-r_t^s \geq VaR^x(q)) = q$ 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

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

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

$$r_{CC}(\tau) = \frac{\mathbb{E}\left[(D_t^i - q)(D_{t+\tau}^S - q)\right]}{q(1-q)}. \tag{A.2}$$

I assume the following parametric model for the cross-correlation function: $r_{CC}(\tau) = \frac{1}{1-q} e^{\alpha + \beta\tau}$ for $\tau \geq 1$, which implies that

$$\Delta\text{CoSP}(\tau) = e^{\alpha+\beta\tau}, \quad \text{for } \tau \geq 1. \tag{A.3}$$

Given this model, I compute the Maximum-Likelihood estimates for α and β under the assumption that $\mathbb{1}_{\left\{-r_t^i \geq VaR^i(q),\, -r_{t+\tau}^S \geq VaR^S(q)\right\}}$ is iid for $t = 1, .., n_\tau$. It follows that

$$Y_\tau := \sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^i \geq \widehat{VaR}^i(q),\, -r_{t+\tau}^S \geq \widehat{VaR}^S(q)\right\}} \sim Bin\left(n-\tau, \psi(\tau) q\right), \tag{A.4}$$

where $\psi(\tau) = \Delta\psi(\tau) + q$ and $Bin(n,p)$ is the Binomial distribution and the Value-at-Risk estimate $\widehat{VaR}^x(q)$ is the $n(1-q)$-th order statistic of $-r^x$ if $n(1-q)$ is an integer (and $[n(1-q)]+1$)-th order statistic if it is not an integer), $x \in \{i, S\}$. I assume that $Y_1, Y_2, ..., Y_{\tau^{max}}$ are independently distributed. Then, the log-likelihood function for observations $y_1, y_2, ...$ is given by

$$\mathcal{L} = \sum_{\tau=1}^{\tau^{max}} \log \binom{n-\tau}{y_\tau} + y_\tau \log\left(q\psi(\tau)\right) + \left(n-\tau-y_\tau\right)\log\left(1-q\psi(\tau)\right) \tag{A.5}$$

and the score functions as

$$\frac{\partial \mathcal{L}}{\partial \alpha} = \sum_{\tau=1}^{\tau^{max}} \frac{\tau y_\tau}{q+e^{\alpha\tau+\beta}} e^{\alpha\tau+\beta} - q\frac{\tau(n-\tau-y_\tau)}{1-q(q+e^{\alpha\tau+\beta})} e^{\alpha\tau+\beta} \stackrel{!}{=} 0, \tag{A.6}$$

$$\frac{\partial \mathcal{L}}{\partial \beta} = \sum_{\tau=1}^{\tau^{max}} \frac{y_\tau}{q^I+e^{\alpha\tau+\beta}} e^{\alpha\tau+\beta} - q\frac{n-\tau-y_\tau}{1-q(q+e^{\alpha\tau+\beta})} e^{\alpha\tau+\beta} \stackrel{!}{=} 0. \tag{A.7}$$

Finally, I estimate α and β by numerically solving Equations (A.6) and (A.7).

I motivate the parametric model in two ways. First, I additionally compute a standard nonparametric estimator for $r_{CC}(\tau)$, which yields

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

as an estimator for $\Delta\psi(\tau)$. Note that $\widehat{\Delta\psi}(\tau)+q$ also equals the OLS estimator for 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 (otherwise, the equivalence holds asymptotically).[47]

Visual inspection of $\widehat{\Delta\psi}(\tau)$ shows that it is exponentially declining with the time lag τ and that the baseline estimator developed above appropriately captures the dynamics of $\Delta\psi(\tau)$ across time-lags (see Section 2). Thus, even if time series properties deviated from the distributional assumptions made above for parametric estimation, the resulting estimates would be reasonable.[48]

Second, I motivate the parametric form for ΔCoSP(τ) using an autoregressive model for large losses in the financial system, where a large loss of the firm persistently increases

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[47] 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 is $\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{-r_t^i \geq \widehat{VaR}^i\right\}} = q(n-\tau)$, in which case the OLS estimator coincides with $\widehat{\Delta\psi}(\tau)+q$.

[48] Additionally, I compute the average deviation between the two estimates for each firm and estimation window, $\delta_{i,t} = \sum_{\tau=1}^{50} \widehat{\Delta\psi}(\tau) - \Delta\text{CoSP}(\tau)$. The median deviation is -0.03 percentage points, with the 5% and 95% percentile being -0.65 and 0.07 percentage points, which is small relative to the estimates for ΔCoSP(τ). The distribution of $\delta_{i,t}$ is very stable over time. These results suggest that the parametric estimation model does not result in a systematic bias compared to the nonparametric estimate.

the subsequent likelihood of large losses in the system. For this purpose, let $(D_t^S, D_t^i)_t$, where $D_t^x \in \{0,1\}$ are indicators for firm and system distress with stationary probability distribution $\mathbb{P}(D_t^x = 1) = q$ for all $x \in \{S, I\}$, and assume the following time-series dynamics:

$$D_{t+1}^S = a + bD_t^i + cD_t^S, \tag{A.9}$$

where $a, b, c > 0$, and let D_t^i and D_τ^I be independently distributed for all $t \neq \tau$. In this model, random shocks of firms lead to persistent distress of the system. Since $\mathbb{E}[D_t^i] = \mathbb{E}[D_t^S] = q$, it is

$$a + bq + cq = q \quad \Leftrightarrow \quad \frac{a}{1-b-c} = q. \tag{A.10}$$

The stationary conditional probability distribution is defined by

$$\mathbb{P}(D_{t+1}^S = 1 \mid D_t^i) = a + bD_t^i + c\mathbb{E}[D_t^S] = a + bD_t^i + cq. \tag{A.11}$$

Iteration yields

$$\begin{aligned}
\mathbb{P}(D_{t+\tau}^S = 1 \mid D_t^i) &= a + b\mathbb{E}[D_{t+\tau-1}^i] + c\mathbb{E}[D_{t+\tau-1}^S] &\text{(A.12)}\\
&= a + bq + c\left(a + b\mathbb{E}[D_{t+\tau-2}^i] + c\mathbb{E}[D_{t+\tau-2}^S]\right) &\text{(A.13)}\\
&... &\text{(A.14)}\\
&= a\sum_{i=0}^{\tau-1} c^i + bq\sum_{i=0}^{\tau-2} c^i + bc^{\tau-1}D_t^i + c^\tau q. &\text{(A.15)}
\end{aligned}$$

Using that $\sum_{i=0}^n q^i = \frac{1-q^{n+1}}{1-q}$ for $q \neq 1$, it is

$$\mathbb{P}(D_{t+\tau}^S = 1 \mid D_t^i) = \frac{a}{1-c} - \frac{a}{1-c}c^\tau + \frac{bq}{1-c} - \frac{bq}{1-c}c^{\tau-1} + bc^{\tau-1}D_t^i + c^\tau q \tag{A.16}$$

and

$$\begin{aligned}
\mathbb{P}(D_{t+\tau}^S = 1 \mid D_t^i = 1) &= e^{\tau\log(c)}\underbrace{\left(e^{\log(b)-\log(c)} - e^{\log(\frac{bq}{1-c})-\log(c)} + \left(q - \frac{a}{1-c}\right)\right)}_{=:\gamma} + \frac{bq+a}{1-c}\\
&= e^{\tau\log(c)+\log(\gamma)} + q, &\text{(A.17)}
\end{aligned}$$

where in the last step I use that Equation (A.10) implies

$$\frac{bq+a}{1-c} = q\frac{b+1-b-c}{1-c} = q\frac{1-c}{1-c} = q. \tag{A.18}$$

Therefore, in this model $\mathbb{P}(D^S_{t+\tau} = 1 \mid D^i_t = 1) = q + \Delta\psi(\tau) = q + e^{\alpha+\beta\tau}$ for $\alpha = \log(\gamma)$ and $\beta = \log(c)$. Note that $\beta = \log(c) < 0$ since the model is well-defined only for $c < 1$, consistent with the empirical observation that ΔCoSP declines with an increasing time-lag.

A.2. Estimation of Average ΔCoSP

I use the estimated parametric model for $\Delta\text{CoSP}(\tau)$ to estimate Average ΔCoSP. Then, the estimator for Average ΔCoSP is given by

$$\bar{\psi} = \frac{1}{\tau^{\max}-1}\int_1^{\tau^{\max}} \Delta\text{CoSP}(\tau)\,d\tau. \tag{A.19}$$

First, note that

$$\int \Delta\text{CoSP}(\tau)\,d\tau = \int e^{\alpha+\beta\tau}\,d\tau = \frac{1}{\beta}e^{\alpha+\beta\tau}, \tag{A.20}$$

thus,

$$\int_1^{\tau^{\max}} e^{\alpha+\beta\tau}\,d\tau = \frac{1}{\beta}\left(e^{\alpha+\beta\tau^{\max}} - e^{\alpha+\beta}\right) \tag{A.21}$$

and

$$\overline{\psi} = \frac{1}{\tau^{\max}-1}\frac{1}{\beta}\left(e^{\alpha+\beta\tau^{\max}} - e^{\alpha+\beta}\right). \tag{A.22}$$

A.3. Estimation of Spillover Persistence

I use the estimated parametric model for $\Delta\text{CoSP}(\tau)$ to estimate Spillover Persistence. Then, the estimator for Spillover Persistence is given by

$$\bar{\tau} = \frac{1}{\bar{\psi}(\tau^{\max}-1)}\int_1^{\tau^{\max}} \tau\cdot\Delta\text{CoSP}(\tau)\,d\tau. \tag{A.23}$$

Since

$$\int \tau \cdot \Delta\text{CoSP}(\tau)\, d\tau = \int \tau \cdot e^{\alpha+\beta\tau}\, d\tau = \left(\frac{\tau}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta\tau}, \tag{A.24}$$

it is

$$\overline{\tau} = \frac{1}{\bar{\psi}(\tau^{\max} - 1)} \left(\left(\frac{\tau^{\max}}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta\tau^{\max}} - \left(\frac{1}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta} \right). \tag{A.25}$$

B. Empirical methodology and additional summary statistics

B.1. Firm's and system's equity 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:

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

The system's log equity return is

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

and the firm's log equity return is

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

B.2. *Data and summary statistics*

B.2.1. *Variable definitions*

Table B.1: Variable definitions and data sources.
Equity market data is at daily frequency, all other variables are at annual frequency. All 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 system in excess of the reference level $q = 0.05$.
ΔCoSP(0)	Likelihood of simultaneous losses of the system and firm in excess of the reference level $q = 0.05$. Winsorized at 1%/99%.
Average ΔCoSP ($\bar{\psi}$)	Average level of ΔCoSP across time lags 1,...,50 days. Winsorized at 98%.
Spillover Persistence ($\bar{\tau}$)	Average time-lag τ weighted by ΔCoSP across time lags 1,...,50 days. Winsorized at 98%.
ΔCoVaR	Change in the system's Value-at-Risk conditional on a firm being under distress relative to its median state. Winsorized at 1%/99%.
MES	Firm's average equity return loss conditional on large system losses on the same day. Winsorized at 1%/99%.
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.

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Table B.1 – *Continued from previous page*

Variable	Definition
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).
log(interest rate)	log(10-year government bond rate); annual average of weekly rate, continent-level. *Source*: see Table B.2.
3M yield change	Weekly change in 3-month government bond rates; annual average. *Source*: see Table B.2.
Term spread change	Weekly change in yield spread between 10-year and 3-month government bond rates; annual average. *Source*: see Table B.2.
TED spread	Spread between 3-month Libor (interbank) and 3-month government bond rates; average per year. *Source*: see Table B.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 B.2.
Market return	Weekly market return of system-specific MSCI indices; annual average. *Source*: see Table B.2.
Equity volatility	22-day rolling window market return of system-specific MSCI indices; annual average. *Source*: see Table B.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.

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Table B.1 – *Continued from previous page*

Variable	**Definition**
Market-to-book	Market value of equity / book value of equity.
Firm ILLIQ	Amihud (2002)'s measure for stock market illiquidity.
Firm risk	5% Value-at-Risk based on a firm's daily equity return loss.
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.
Time deposits	(Time + savings deposits)/ total assets.
Intangible assets	(Goodwill + other intangible assets) / total assets.
Loans	(Gross of mortgage, consumer, corporate, and other loans - Loans loss reserves) / total assets.
Impaired loans	Impaired & non-performing exposure on customer and inter-bank loans before loan loss reserves / total assets.
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.
Hurricane Katrina	
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 retrieved from S&P Global Market Intelligence.
post-Katrina	Indicator for August 25, 2005, and afterwards.
post-Placebo	Indicator for August 1, 2005, and afterwards.

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

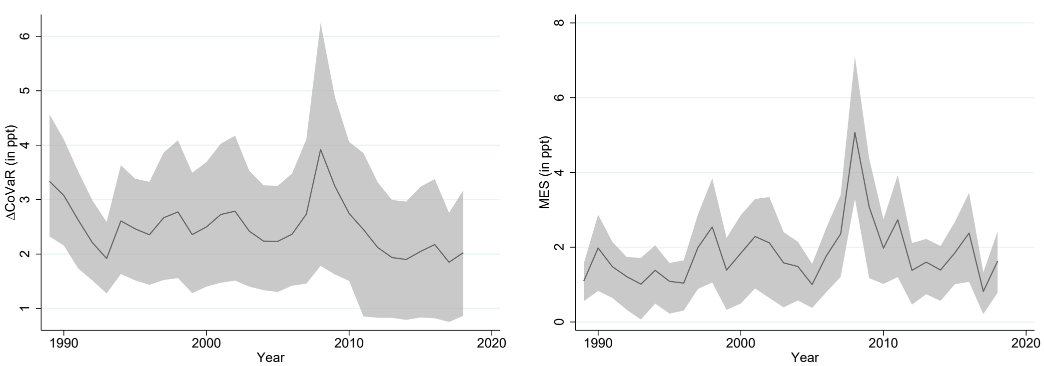
The table depicts the region-level macroeconomic variables, which also serve as state variables to estimate ΔCoVaR with quantile regressions, and compares them to the state variables used by Adrian and Brunnermeier (2016) for the US. The choice of state variables is motivated by that in Brunnermeier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

B.2.2. Systemic risk measures

Fig. B.1. 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 B.3: Correlation between Spillover Persistence and systemic risk measures.

This table reports the bivariate correlation between Spillover Persistence and systemic risk measures based on firm-year level observations from 1989 to 2017 in the baseline sample.

	Spillover Persistence	Average ΔCoSP	ΔCoVaR	MES
Spillover Persistence	1			
Average ΔCoSP	0.513***	1		
ΔCoVaR	0.0808***	0.299***	1	
MES	0.0972***	0.446***	0.517***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Decomposition of variation in Spillover Persistence.

This table reports the standard deviation of residuals and adjusted R^2 of regressions of Spillover Persistence on (1) a constant, (2) firm fixed effects, (3) year fixed effects, (4) year×continent fixed effects, (5) year×continent and firm fixed effects.

	(1)	(2)	(3)	(4)	(5)
	Baseline	Firm FE	Year FE	Year× Continent FE	Year× Continent & Firm FE
SD(Residuals)	7.13	6.25	6.52	6.27	5.39
Adj. R^2		0.15	0.16	0.22	0.36

B.2.3. 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).[49] Table B.5 provides the summary statistics after merging with systemic risk measures

Table B.5: Macroeconomic characteristics: summary statistics.

The table depicts summary statistics for macroeconomic characteristics based on country-year level observations from 1989 to 2017. *Sources*: OECD, BIS, St. Louis FRED, Thomson Reuters Datastream, Laeven and Valencia (2018), own calculations.

	N	Mean	Median	SD	p5	p95
Inflation (in ppt)	544	2.21	1.99	1.87	-0.05	5.40
Credit growth (in ppt)	544	2.29	1.87	5.43	-5.33	10.38
GDP growth (in ppt)	544	4.66	4.56	3.40	-0.66	9.56
Investment growth (in ppt)	544	-0.24	0.28	5.32	-9.21	6.89
log(interest rate)	544	1.04	1.39	1.01	-1.26	1.99
Crisis	544	0.13	0.00	0.34	0.00	1.00

In some regressions, I additionally include more 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).[50] I winsorize at 1% and 99% levels and find wide variation in all 6 macroeconomic variables, as Table B.6 shows after merging with systemic risk measures and baseline macroeconomic characteristics.

[49]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.

[50]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 B.1 and B.2.

Table B.6: Additional region-level macro characteristics: summary statistics.

The table depicts summary statistics for macroeconomic characteristics based on region-year observations (3-month yield change, term spread change, TED spread, credit spread change, market return, and equity volatility) from 1989 to 2017. Geographical regions are Europe, North America, Asia, Japan, and Australia. Table B.2 describes the data sources for each macroeconomic variable. *Sources*: St. Louis FRED, Thomson Reuters Datastream, own calculations.

	N	Mean	Median	SD	p5	p95
3M yield change (in bps)	74	-0.53	-0.10	2.27	-5.02	2.50
3M yield change (in bps)	74	-0.53	-0.10	2.27	-5.02	2.50
Term spread change (in bps)	74	0.11	-0.30	2.60	-2.88	2.93
TED spread (in bps)	74	32.31	26.74	31.59	0.05	93.71
Credit spread change (in bps)	74	-0.03	-0.09	1.86	-3.17	2.88
Market return (in ppt)	74	0.15	0.20	0.38	-0.53	0.61
Equity volatility (in ppt)	74	1.02	0.93	0.44	0.49	2.05

B.2.4. Firm and bank 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 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. After matching lagged firm characteristics to systemic risk measures and macroeconomic characteristics, the sample includes characteristics for 755 firms located in 29 countries from 1988 to 2016. I winsorize observations for each variable at the 1% and 99% levels. In the median firm-year, the firm has total assets of roughly 13 billion USD, while firm size varies greatly (Table B.7). The median market valuation is slightly larger than book equity (by 30%) and median leverage is 6, both with wide variation.

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.[51] 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 my measures for size and leverage

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

Table B.7: Firm & bank characteristics: summary statistics.

Based on firm-year observations from (1) 1988 to 2016 for total assets, size, market-to-book, and leverage, and (2) 1990 to 2016 for the Ban & Bro sample (which refers to firms in BankFocus) after matching with the sample of systemic risk measures. *Source*: Worldscope, Moody's BankFocus, own calculations.

	N	Mean	Median	SD	p5	p95
Total Assets (bn USD)	8,187	108.72	13.13	242.93	0.32	690.41
Size	8,187	2.59	2.57	2.32	-1.14	6.54
Market-to-Book	8,187	1.70	1.29	1.50	0.47	4.28
Leverage	8,187	11.09	5.88	15.44	0.79	39.12
Total Assets (Ban & Bro; bn USD)	1,623	220.00	42.66	442.19	3.32	1,264.03
Size (Ban & Bro)	1,623	3.95	3.75	1.74	1.20	7.14
Leverage (Ban & Bro)	1,623	13.79	9.35	13.98	2.99	39.58
Time Deposits (Ban & Bro)	1,623	0.21	0.18	0.16	0.01	0.50
Demand Deposits (Ban & Bro)	1,623	0.19	0.16	0.14	0.02	0.44
Loans (Ban & Bro)	1,623	0.57	0.62	0.19	0.15	0.80
Impaired Loans (Ban & Bro)	1,623	0.02	0.01	0.02	0.00	0.06
Intangible Assets (Ban & Bro)	1,623	0.02	0.01	0.03	0.00	0.07
Liquidity Ratio (Ban & Bro)	1,623	0.44	0.29	0.74	0.05	1.01
CDS (Ban & Bro)	648	0.24	0.00	0.68	0.00	1.68

for banks using BankFocus in all regressions for the sample of BankFocus firms. I winsorize all variables at the 1% and 99% levels.

After merging with systemic risk measures, in the median bank(/broker-dealer)-year in this sample total assets are roughly 43 billion USD and the leverage ratio is 9. The median bank is thus larger and more highly levered than the median firm in the broader sample that also covers non-banks. In the median bank-year, the share of time deposits (18% of total assets) is similar to that of demand deposits (16% of total assets). More than half of the assets are loans (62%). The amounts of impaired loans and of intangible assets are both relatively small (roughly 1% of total assets), whereas all variables display wide variation.

B.2.5. Exposure to hurricane Katrina

US insurance companies report premiums for direct insurance business (excluding reinsurance) 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

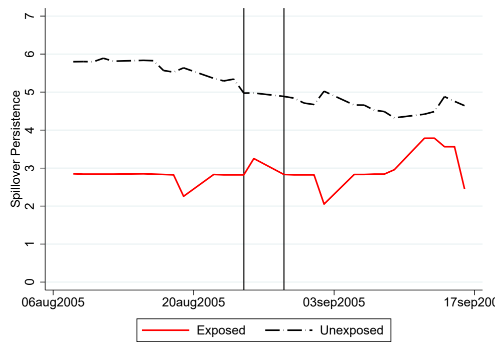


Fig. B.2. Spillover Persistence around hurricane Katrina.
The figure depicts the daily average Spillover Persistence across North American and European insurers that are (a) exposed and (b) un-exposed to hurricane Katrina, respectively. Vertical lines depict the dates of hurricane Katrina's first (August 25, 2005) and second (August 29, 2005) landfall.

CUSIP identifiers from S&P Global Market Intelligence and match these to CUSIPs and stock tickers, and check matches by hand. 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.[52] However, results are robust to including these 2 insurers in the treated group.

[52] 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*).

C. Additional empirical results and robustness

C.1. Determinants of Spillover Persistence

Table C.1: Spillover Persistence during crises.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking windows, where the final year is t. Macro characteristics are inflation, GDP growth, investment growth, credit growth (at country level), and short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, and log(interest rate) (at region level) at year t. Firm characteristics are size, leverage, market-to-book ratio, and cash flow, and bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all at year $t-1$. All firm and bank characteristics are standardized. Columns (3-4) only include firms that are part of BankFocus. Variable definitions are provided in Table B.1. Scaled coefficients are the coefficients scaled by the standard deviation of the dependent variable. Standard errors are clustered at firm and country-year levels. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence			
Sample:	All		Ban & Bro	
Crisis	2.777***	2.155**	3.709**	3.375***
	(0.000)	(0.015)	(0.011)	(0.009)
Crisis × Size				-0.682
				(0.126)
Crisis × Leverage				-0.499
				(0.405)
Crisis × Market-to-Book				-0.231
				(0.720)
Crisis × Liquidity ratio				0.534
				(0.200)
Crisis × Demand deposits				-0.644
				(0.291)
Crisis × Time deposits				0.002
				(0.998)
Crisis × Loans				0.198
				(0.627)
Crisis × Impaired loans				-0.332
				(0.660)
Crisis × Intangible assets				-0.634*
				(0.077)
Macro characteristics	No	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes
Bank characteristics	No	No	Yes	Yes
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	No	No
Scaled coefficients				
Crisis	.39	.3	.56	.51
No. of firms	849	849	194	194
No. of obs.	9,414	9,414	1,731	1,731
Adj. R^2	0.020	0.204	0.262	0.261
Adj. R^2 within	0.020	0.064	0.182	0.180

Table C.2: Spillover Persistence and macroeconomic and firm characteristics.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is t. Macroeconomic characteristics are for the final year of the estimation window, firm characteristics are lagged by one year. The omitted region in columns (4-5) is North America, and the omitted firm type in columns (5-6) is for (commercial) banks. Columns (7-8) only include firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at (1-2) firm and (3-10) firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. variable:	Spillover Persistence									
Sample:	US		All				Ban & Bro		All	
NFCI	3.208***									
	(0.000)									
Crisis		3.551***	2.861***			0.740**		1.197*		0.856**
		(0.000)	(0.002)			(0.042)		(0.051)		(0.027)
GDP growth		-0.295	-0.353***			-0.003		-0.085		-0.044
		(0.370)	(0.001)			(0.959)		(0.546)		(0.409)
Investment growth		0.181*	0.039			-0.019		0.080		0.001
		(0.077)	(0.563)			(0.585)		(0.407)		(0.966)
Credit growth		-0.721***	-0.107*			0.047		0.114		0.010
		(0.000)	(0.095)			(0.230)		(0.248)		(0.789)
Inflation		-0.259	-0.119			0.054		0.397		0.000
		(0.158)	(0.641)			(0.734)		(0.187)		(0.999)
3M yield change		0.755***	0.707***							
		(0.000)	(0.002)							
Term spread change		0.583***	0.288							
		(0.000)	(0.190)							
TED spread		0.018**	-0.003							
		(0.020)	(0.828)							
Credit spread change		0.512***	0.619***							
		(0.002)	(0.007)							
Market return		-0.541	0.621							
		(0.543)	(0.575)							
Equity volatility		-1.445	0.849							
		(0.136)	(0.480)							
log(Interest rate)		-1.050	-0.118							
		(0.254)	(0.752)							
Europe				-0.781**	-0.815**					
				(0.032)	(0.022)					
Japan				-4.064***	-4.138***					
				(0.001)	(0.001)					
Asia				-3.769***	-3.765***					
				(0.004)	(0.002)					
Broker-dealer				-0.035	0.561*	0.631*				
				(0.913)	(0.098)	(0.062)				
Insurer				1.343***	1.305***	1.340***				
				(0.000)	(0.000)	(0.000)				
Real estate				-0.210	0.659	0.728*				
				(0.533)	(0.108)	(0.068)				
Size					0.300***	0.262***	0.234	0.202		
					(0.000)	(0.001)	(0.119)	(0.137)		
Leverage					-0.004	0.002	-0.012	0.025		
					(0.729)	(0.872)	(0.684)	(0.283)		
Market-to-Book					0.051	0.035	-0.098	-0.079		
					(0.572)	(0.692)	(0.738)	(0.749)		
Liquidity Ratio							0.003	0.014		
							(0.979)	(0.861)		
Demand Deposits							-0.455	0.987		
							(0.832)	(0.503)		
Time Deposits							-2.252	0.840		
							(0.416)	(0.663)		
Loans							1.472	0.664		
							(0.272)	(0.572)		
Impaired Loans							-13.691	-10.498		
							(0.230)	(0.216)		
Intangible Assets							11.609**	4.065		
							(0.045)	(0.344)		
ΔCoVaR									0.407***	
									(0.000)	
Average ΔCoSP										1.356***
										(0.000)
Firm risk										-0.340***
										(0.001)
Firm ILLIQ										-0.000*
										(0.069)
Year FE	No	No	No	Yes	Yes	No	Yes	Yes	No	No
Year$\times$ Region FE	No	No	No	No	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	No	No	No	No	No	No	No
No. of firms	191	191	755	755	755	755	190	190	755	623
No. of obs.	2,699	2,699	8,187	8,187	8,187	8,187	1,633	1,631	8,187	4,612
Adj. R^2	0.153	0.253	0.185	0.212	0.218	0.262	0.357	0.449	0.008	0.356
Adj. R^2 within	0.048	0.160	0.059	0.032	0.040	0.015	0.014	0.013	0.008	0.198

C.2. Crises

Table C.3: Fragility before crises: robustness.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is (1) a dummy variable that indicates the occurrence of a systemic banking crisis, (2) a dummy that indicates the occurrence of a non-borderline banking crisis, (3-5) a dummy that indicates the occurrence of a banking crisis, (6) the output loss (in % of GDP) or (7) the fiscal cost (in % of GDP) of a banking crisis. The definitions of crises and the estimation of output loss and fiscal cost follow those by Laeven and Valencia (2018). The main independent variables are Spillover Persistence and Average ΔCoSP. These are estimated in 5-year backward-looking rolling windows, where the last year is t. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility at t. Firm characteristics are size, leverage, and market-to-book ratio at $t-1$. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year levels. Scaled coefficients reflect the change in the dependent variable for a standard deviation change in the independent variable. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. variable:	Systemic Crisis$_{t+1}$	Non-borderline Crisis$_{t+1}$		Crisis$_{t+1}$		Output loss$_{t+1}$	Fiscal cost$_{t+1}$
Spillover Persistence	-0.002**	-0.002***	-0.002***	-0.002***	-0.001**	-0.042***	-0.009*
	(0.016)	(0.009)	(0.005)	(0.009)	(0.013)	(0.005)	(0.060)
Average ΔCoSP	0.027***	0.027***	0.022***	0.026***	0.020***	0.714***	0.145***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
ΔCoVaR	0.013	-0.004			-0.020***	-0.428*	-0.144*
	(0.337)	(0.726)			(0.010)	(0.097)	(0.070)
Boom			-0.038				
			(0.565)				
Bust			-0.124*				
			(0.057)				
MES				-0.000			
				(0.993)			
Macro characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep. var	No	No	No	No	Yes	Yes	Yes
(1-5) Scaled & (6-7) standardized coefficients							
Spillover Persistence	-.01	-.01	-.01	-.01	-.01	-.02	-.02
Average ΔCoSP	.08	.08	.07	.08	.06	.17	.13
ΔCoVaR	.02	-.01			-.03	-.05	-.07
MES				0			
No. of firms	725	725	621	737	738	738	738
No. of obs.	7,876	7,876	7,138	7,991	8,000	8,000	8,000
Adj. R^2	0.595	0.679	0.744	0.721	0.774	0.769	0.711
Adj. R^2 within	0.287	0.296	0.329	0.291	0.426	0.535	0.469

In addition to my baseline analyses at the firm level, I also perform country-level regressions of crises likelihood on Spillover Persistence. For this purpose, I take each variable's average value across firms for each country-year. Countries enter the sample in the first year for which I observe at least 15 financial firms. This eliminates potential biases resulting from countries with only a small number of financial firms included in the sample.[53] Since larger

[53] 13 countries are left in the final country-level sample, including the US, Japan, Great Britain, France, Germany, India, Switzerland, and Italy. Without requiring a minimum number of firms within a country,

firms are typically more important for the financial system, I weight firms by their total assets when computing country averages.

Table C.4 illustrates the correlation between Spillover Persistence and banking crises at the country level. The results are consistent with those at the firm level. Without controlling for macroeconomic variables or including fixed effects, a 1-standard deviation decline in Spillover Persistence relates to a 7ppt larger likelihood of banking crises in the following year (column (1)).

The effect is slightly larger when controlling for macroeconomic characteristics and time-invariant differences across countries (column (2)) and is robust to additionally controlling for ΔCoVaR (column (3)), for contemporaneous ΔCoSP (column (4)), and for aggregate shocks by including year fixed effects (column (5)). Finally, Spillover Persistence at the country level also negatively correlates with the severity of crises as measured by their output loss (column (6)).

the model would give the same weight to countries with many financial firms in the sample (e.g., the US) and to countries with only a small number firms (e.g., Estonia). Plausibly, large differences in the number of listed financial firms arise when financial systems are not comparable across countries, e.g., the number of listed firms may be small because the financial sector is underdeveloped and/or concentrated, or listed firms are not representative for the financial sector. In both cases, it would bias the estimation.

Table C.4: Fragility before crises: country-level.

This table reports estimates from OLS panel regressions at the country-year level. The dependent variable is (1-5) a dummy variable that indicates the occurrence of a banking crisis, or (6) the output loss (in % of GDP) of a banking crisis at year $t + 1$. The definition of crises and the estimation of the output loss follow those by Laeven and Valencia (2018). The estimation is based on country-year level averages weighted by firms' total assets. The sample includes a country once there are at least 15 firms of the country present in the data. Spillover Persistence and Average ΔCoSP are estimated in 5-year backward-looking rolling windows, where the last year is t. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility at year t. Variable definitions are provided in Table B.1. Standard errors are clustered at region-year level. Scaled coefficients are the increase in the dependent variable for a standard deviation change in the independent variable. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			Crisis$_{t+1}$			Output loss$_{t+1}$
Spillover Persistence	-0.017*	-0.024**	-0.024**	-0.025***	-0.021**	-0.681**
	(0.078)	(0.013)	(0.013)	(0.010)	(0.012)	(0.030)
Average ΔCoSP	0.059**	0.061**	0.061**	0.055	0.097***	1.946**
	(0.013)	(0.025)	(0.025)	(0.216)	(0.001)	(0.010)
ΔCoVaR			0.021			
			(0.831)			
ΔCoSP(0)				0.003		
				(0.775)		
Macro controls	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	No
(1-5) Scaled & (6) standardized coefficients						
Spillover Persistence	-.07	-.1	-.1	-.1	-.09	-.27
Average ΔCoSP	.16	.17	.17	.15	.27	.52
ΔCoVaR			.03			
ΔCoSP(0)				.04		
No. of countries	12	12	12	12	12	12
No. of obs.	140	140	140	140	140	140
Adj. R^2	0.099	0.280	0.274	0.275	0.657	0.236
Adj. R^2 within	0.099	0.310	0.305	0.306	0.316	0.236

C.3. Bubbles

Table C.5: Robustness: Spillover Persistence during bubbles, controlling for lagged Spillover Persistence.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is (1-3) t or (4) $t+4$. Bubble indicators are based on the BSADF approach and 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. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, all for year t. Firm characteristics are size, leverage, and market-to-book ratio; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all for year $t-1$. Column (3) only includes firms that are part of BankFocus. Variable definitions are provided in Table B.1. Scaled coefficients reflect the change in the dependent variable as a share of its standard deviation when the independent variable increases from zero to one. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence$_t$			Spillover Persistence$_{t+4}$
Sample:	Baseline		Ban & Bro	All
Boom	-2.866***	-1.190*	-1.551***	-2.020***
	(0.001)	(0.057)	(0.001)	(0.007)
Bust	-1.270	0.131	-0.051	0.102
	(0.342)	(0.858)	(0.974)	(0.904)
1-year lagged dep. var.	Yes	Yes	Yes	Yes
Macro characteristics	Yes	Yes	Yes	Yes
Additional macro characteristics	No	Yes	Yes	Yes
Firm characteristics	No	Yes	No	Yes
Bank characteristics	No	No	Yes	No
Boom & bust length	Yes	Yes	Yes	No
ΔCoVaR	No	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
Scaled coefficients				
Boom	-.43	-.18	-.25	-.32
Bust	-.19	.02	-.01	.02
No. of firms	625	625	141	467
No. of obs.	6,674	6,674	1,199	5,450
Adj. R^2	0.424	0.497	0.657	0.385
Adj. R^2 within	0.327	0.212	0.185	0.305

Table C.6: Robustness: Spillover Persistence and distance to the bubble burst, controlling for lagged Spillover Persistence.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variable is Spillover Persistence. It is estimated in 5-year backward-looking rolling windows, where the last year is t. Bubble indicators are based on the BSADF approach and 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 excludes bubbles without burst. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility, all for year t. Firm characteristics are size, leverage, and market-to-book ratio; bank characteristics are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets, all for year $t-1$. Column (4) only includes firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence			
Sample:	Within Bubble	Baseline		Ban & Bro
Boom × Burst Distance	-0.519	-1.348***	-1.342***	-2.550***
	(0.375)	(0.000)	(0.001)	(0.000)
1-year lagged dep. var.	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Additional macro characteristics	No	Yes	Yes	Yes
Firm characteristics	No	Yes	Yes	Yes
Bank characteristics	No	No	No	Yes
Boom & bust	Yes	Yes	Yes	Yes
Boom & bust-years	No	No	Yes	Yes
Boom & bust length	Yes	Yes	Yes	Yes
ΔCoVaR	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of firms	224	537	534	124
No. of obs.	1,009	5,461	5,446	1,025
Adj. R^2	0.336	0.449	0.451	0.629
Adj. R^2 within	0.145	0.333	0.337	0.609

C.4. Liquidity and autocorrelation of stock returns

Daily turnover by value (VA) and volume (VO) comes from Thomson Reuters Datastream at the security-day-level. VO_t is the median daily turnover by volume (in thd USD) in a given time period. The Amihud measure is defined by (see Amihud (2002))

$$ILLIQ_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{|r_{t,i}|}{VA_{t,i}}, \tag{C.1}$$

where n_t is the number of days for which data is available in time period t, $r_{t,i}$ is the daily return at day i, and $VA_{t,i}$ is the daily turnover by value in thd USD. To calculate the turnover by volume of the system, I use the average daily turnover volume per firm. The Amihud measure for the system is similarly based on the system's (value-weighted) return and average daily turnover by value. Finally, I take averages across days in the same 5-year estimation-windows used to estimate Spillover Persistence and winsorize at 1% and 99%.

Table C.7: CoSP and financial market liquidity.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variables are (1-4) Spillover Persistence and (5-8) Average ΔCoSP, which are estimated in 5-year rolling windows. Firm (and system) turnover correspond to the average daily turnover volume in the corresponding 5-year estimation window (for an average firm of the system). Standard errors are clustered at firm and country-year levels. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Spillover Persistence				Average ΔCoSP			
log(Firm turnover)	0.119*	0.075			0.214***	0.268***		
	(0.059)	(0.677)			(0.000)	(0.000)		
log(System turnover)	0.225*	0.075			0.073	-0.086		
	(0.090)	(0.846)			(0.220)	(0.496)		
Firm ILLIQ			-0.000***	-0.000**			-0.000**	-0.000*
			(0.002)	(0.040)			(0.040)	(0.089)
System ILLIQ			-0.360	-0.442***			0.018	0.177
			(0.291)	(0.007)			(0.949)	(0.245)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of firms	1,204	1,098	962	834	1,204	1,098	962	834
No. of obs.	12,776	12,670	7,171	7,043	12,776	12,670	7,171	7,043
Adj. R^2	0.005	0.293	0.006	0.329	0.044	0.696	0.002	0.664
Adj. R^2 within	0.005	-0.000	0.006	0.003	0.044	0.011	0.002	0.002

To examine the effect of autocorrelation of equity prices on CoSP-measures, 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 1 to 10 days. Table C.8 reports the estimates. There is no significantly positive correlation between CoSP-measures and autocorrelation.

Table C.8: CoSP and autocorrelation.

This table reports estimates from OLS panel regressions at the firm-year level. The dependent variables are (1-2) Spillover Persistence and (3-4) Average ΔCoSP, which are estimated in 5-year rolling windows. $ACF_{1:10}$ is the system's autocorrelation, which corresponds to the average (across lags) autocorrelation coefficient of the system's daily returns in a given 5-year estimation window. Variable definitions are provided in Table B.1. Standard errors are clustered at firm and country-year level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Spillover Persistence		Average ΔCoSP	
$ACF_{1:10}$	-69.230***	39.639	-65.551***	-7.264
	(0.000)	(0.157)	(0.000)	(0.466)
Year FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
No. of firms	1,208	1,102	1,208	1,102
No. of obs.	12,974	12,868	12,974	12,868
Adj. R^2	0.023	0.291	0.140	0.689
Adj. R^2 within	0.023	0.001	0.140	0.001

Finally, I examine the effect of predictable variation in the system's equity returns on my results. If an omitted variable causes both the system and firm to face losses today and in the future, removing predictable variation from the system's return removes its effect on Spillover Persistence. For this purpose, I first estimate an AR(1) model for the system's return loss and then estimate CoSP-measures based on the system's AR(1)-residuals and the firm's actual equity return loss. This process is called "prewhitening". Table C.9 reports the estimates for baseline regressions using prewhitened Average ΔCoSP and Spillover Persistence. I find that all baseline results remain to hold.

Table C.9: Robustness: Baseline results with prewhitened Spillover Persistence.

Prewhitened ΔCoSP is computed based on a firm's equity return loss and the AR(1)-residuals of the system's equity return loss, prewhitened Spillover Persistence (Pre-wtd $\bar{\tau}$) and prewhitened Average ΔCoSP (Pre-wtd $\bar{\psi}$) are based on prewhitened ΔCoSP. In columns (1-7) prewhitened Spillover Persistence and prewhitened Average ΔCoSP are at the firm-year level and estimated in 5-year rolling windows, where the last year in the estimation window is t. In (8) prewhitened Spillover Persistence is at the firm-day level and estimated in 18-month rolling windows. The definition of bubble indicators, crises, and hurricane exposure is as in the baseline regressions. Macro characteristics are inflation, GDP growth, investment growth, log(interest rate), credit growth, and (only in (5-7)) banking crises. Additional macro characteristics are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility. Firm characteristics are size, market-to-book ratio, and leverage (except in column (7)). Bank characteristics are liquidity ratio, demand deposits, time deposits, loans, impaired loans, and intangible assets. Variable definitions are provided in Table B.1. Standard errors are (1-2, 5-7) clustered at firm and country-year levels, (3-4) clustered at region-year level, and (8) unclustered, respectively. ***, **, * indicate significance at the 1%, 5% and 10% levels respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Analysis:	Crises				Bubbles		Risk-taking	Amplification
Dep. variable:	Crisis_{t+1}				Pre-wtd Spillover Persistence_t		Leverage_{t+1}	Pre-wtd Spillover Persistence_t
Sample:	Firms		Countries		Baseline		Ban & Bro	US Insurers
Pre-wtd $\bar{\tau}$	-0.001**	-0.001**	-0.017*	-0.017**			-0.150***	
	(0.029)	(0.023)	(0.064)	(0.031)			(0.010)	
Pre-wtd $\bar{\psi}$	0.027***	0.028***	0.059**	0.096***			-0.095	
	(0.000)	(0.000)	(0.011)	(0.001)			(0.650)	
Boom					-3.236***	1.813		
					(0.004)	(0.229)		
Bust					0.151	1.044		
					(0.906)	(0.369)		
Boom$\times$Burst Distance						-1.650**		
						(0.016)		
Exposed $\times$ post-Katrina								0.478***
								(0.002)
ΔCoVaR		-0.023**						
		(0.042)						
Firm FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Country FE	No	No	No	Yes	No	No	No	No
Time FE	Yes	Yes	No	Yes	No	No	Yes	Yes
Macro characteristics	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Add. macro characteristics	Yes	Yes	No	Yes	No	Yes	No	No
Firm characteristics	No	No	No	No	No	Yes	Yes	No
Bank characteristics	No	No	No	No	No	No	Yes	No
Boom & bust length	No	No	No	No	Yes	Yes	No	No
No. of firms/countries	761	758	12	12	726	602	190	26
No. of obs.	8,388	8,369	140	140	8,766	6,303	1,607	776
Adj. R^2	0.724	0.724	0.093	0.652	0.237	0.291	0.835	0.940
Adj. R^2 within	0.299	0.301	0.093	0.305	0.101	0.138	0.076	0.011