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Tackling the Volatility Paradox: Persistence and Systemic Risk

Abstract

Macro-finance theory predicts that financial fragility builds up when volatility is low. This "volatility paradox"' challenges traditional systemic risk measures. I explore a new dimension of systemic risk, spillover persistence, which is the average time horizon at which a firm's losses increase future risk in the financial system. Using firm-level data covering more than 30 years and 50 countries, I document that persistence declines when fragility builds up: *before* crises, during stock market booms, and when banks take more risks. In contrast, persistence increases with loss amplification: *during* crises and fire sales. These findings support key predictions of recent macro-finance models.

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

JEL Classification: G01, G20, E44, G12.

A key challenge of empirical research on risk in the financial system is to measure endogenous risk, which is the risk self-generated by the system, e.g., due to amplification (Brunnermeier and Sannikov (2014)). Many studies build on contemporaneous volatility. However, the modern macro-finance literature predicts that larger contemporaneous volatility does not necessarily relate to larger endogenous risk. Most prominently, Brunnermeier and Sannikov (2014)'s volatility paradox postulates that crises are preceded by periods with *low* contemporaneous volatility. The volatility paradox thus challenges measures based on contemporaneous volatility and calls for identifying other characteristics that track endogenous and, ultimately, systemic risk.

In this paper, I explore variation in the persistence of loss spillovers as a measure for endogenous risk. Specifically, I introduce *Spillover Persistence* (or, short, *Persistence*) as a new firm-level measure for how fast the financial system reacts to a given firm's losses. I define Spillover Persistence as the time horizon at which the risk of large losses in the financial system increases after the firm suffers a large loss. The lower the level of Spillover Persistence, the more quickly the financial system's reaction is. I provide robust empirical evidence for a strong link between variation in Spillover Persistence and endogenous risk, namely fragility and amplification, in the financial system.

Persistence plays an important role in modern macro-finance theory. For example, in Brunnermeier and Sannikov (2014)'s model the risk of large future losses increases when constrained agents face losses today and therefore engage in fire sales, e.g., during crises, which bolster future amplification. Instead, when exogenous risk declines, today's losses are more easily absorbed and agents become less constrained. Then, Spillover Persistence declines, while agents are encouraged to take more risks, specifically increase dividends and leverage, which makes the system more fragile. I take two main predictions from the model: (1) declines in Spillover Persistence coincide with a build-up of financial fragility and increase in risk-taking, and (2) amplification, e.g., fire sales, and crises lead to larger Spillover Persistence.

I empirically test these predictions and reconcile them with the literature on empirical systemic risk measures in a broad multi-country setting, covering more than 30 years. My results suggest that Spillover Persistence is an important dimension of systemic risk: it is highly predictive for banking crises and their economic costs, captures the build-up of fragility during stock market booms and amplification effects of fire sales, and correlates with banks' risk-taking. Thus, my results strongly support the role of persistence of loss spillovers in macro-finance models in the vein of Brunnermeier and Sannikov (2014). In particular, I document a "swing and hit", i.e., u-shaped, pattern of Spillover Persistence around the onset of crises, as Figure 1 illustrates.

[Place Figure 1 about here]

More specifically, this paper makes three main contributions. First, I develop a measure for the persistence of systemic risk, *Spillover Persistence*, which leverages the existing systemic risk literature and builds in particular on Adrian and Brunnermeier (2016)'s ΔCoVaR. Spillover Persistence is the average time-lag between the occurrence of large losses of a given firm and of the financial system, weighted by the likelihood of large losses. In a broad sample of more than 1,200 financial firms covering 30 years and 56 countries, I find that today's losses have a persistent effect on the risk of future losses: large daily equity return losses of an average financial firm are followed by an increase in the risk of large losses in the financial system at an average time horizon of one month. This finding is consistent with the prediction of modern macro-finance theory that (temporary) losses do not immediately die out but amplify future losses. Spillover Persistence is significantly larger for broker-dealers and insurance companies, compared to commercial banks, and positively correlates with firm size and short-term funding. Importantly, there is very low correlation of Spillover Persistence with traditional systemic risk measures, such as Adrian and Brunnermeier (2016)'s ΔCoVaR or Acharya et al. (2017)'s Marginal Expected Shortfall (less than 10%). Thus, Persistence captures a novel dimension of systemic risk.

Second, I examine the relation between Persistence and fragility in the financial system. I find that Spillover Persistence significantly *declines* before the onset of banking crises. Figure 1 illustrates this dynamic for the US and European financial system. For example, Spillover Persistence declines before the onset of the 2007-08 crisis. I show that the relation between Spillover Persistence and crises is robust across various specifications, at the firm and country level, controlling for the level of systemic risk, macroeconomic conditions, firm characteristics, and firm- and year-fixed effects. Importantly, controlling for systemic risk measures that do not account for persistence in loss spillovers (such as ΔCoVaR) does not affect the statistical or economic significance of Persistence. This highlights the power of Spillover Persistence in capturing fragility relative to other measures.

I provide additional evidence that low Persistence connects to fragility by analyzing stock market price bubbles. The results show that Spillover Persistence significantly *declines* at the onset of stock market bubbles, which is a time that is typically associated with increased fragility in the financial system (Brunnermeier and Oehmke (2013a)).

In Brunnermeier and Sannikov (2014)'s model, declines in Persistence relate to build-ups of fragility because experts then take more risks, and more aggressive dividend policies in particular. Consistent with this mechanism, I empirically document that banks take more risks when Spillover Persistence declines. Specifically, banks increase dividend payments, leverage ratios, and derivatives exposure. These effects are particularly pronounced for banks with a weak loan portfolio and broker-dealers.

Third, I zoom in on the relation between Persistence and loss amplification. In Brunnermeier and Sannikov (2014)'s model, strong amplification effects during crises relate to fire sale externalities and lead to large Persistence. Supporting this prediction, I find that Spillover Persistence is significantly larger during crises than in normal times. To further push causal identification, I exploit hurricane Katrina as an exogenous firm-level shock to the liquidity of US property & casualty insurers that sold insurance in the hurricane-affected region (following Manconi et al. (2016), Chaderina et al. (2018), and Girardi et al. (2020)). My results provide robust evidence that the differential effect of Katrina on Spillover Persistence is significantly larger for insurers that were exposed to the hurricane relative to those that were not. Since Katrina resulted in enormous liquidity need and asset fire sales by exposed insurers (Chaderina et al. (2018)), the result strongly supports the hypothesis that fire sales lead to Persistence.

Overall, this paper reveals new empirical facts about the persistence of loss spillovers in the financial system and its relation to endogenous risk and amplification. My findings strongly support key predictions of macro-finance models in the vein of Brunnermeier and Sannikov (2014), namely that financial fragility builds up when Persistence declines, while amplification of losses leads to high Persistence. To the best of my knowledge, this paper is the first to translate these predictions into an empirical framework for systemic risk and to empirically quantify the effects.

I build my framework on a simple firm-level systemic risk measure that exploits tail dependence in daily equity return losses, which I call the *Excess Conditional Shortfall Probability* (ΔCoSP). Specifically, ΔCoSP is the probability of large (tail) losses in the system τ days after large losses of a given firm, normalized by the average probability of large losses in the system. Following the systemic risk literature, large (tail) losses are the 5% worst daily equity returns within a given estimation window. By weighting each time-lag τ with its associated level of systemic risk given by ΔCoSP, I calculate the *Spillover Persistence* – a firm-level measure for how fast the system reacts after a given firm suffers large losses.

A possible concern when using equity returns is that stock market illiquidity might mechanically cause serial-correlation, biasing Spillover Persistence upwards.[1] I address this concern by (1) excluding firms with illiquid securities (e.g., small firms), (2) documenting that Spillover Persistence does not significantly increase with Amihud (2002)'s illiquidity measure nor decrease with a stock's turnover volume, and (3) showing that Spillover Persistence does not significantly increase with auto-serial correlation in equity returns. Finally, I remove predictable variation in equity returns and show that all baseline results continue to hold.

The remainder of the paper is organized as follows. Section 1 provides a brief literature review and highlights this paper's contribution. In Section 2, I introduce the empirical framework to measure Spillover Persistence and review its properties. Section 3 describes the estimation of systemic risk measures and the data. In Section 4 I provide summary statistics for systemic risk measures and explore variation in Persistence and its relation to firm and macroeconomic characteristics. I relate Spillover Persistence to banking crises in Section 5, to asset price bubbles and bank risk-taking in Section 6, and to crises and fire sales in Section 7. Finally, Section 8 contains sensitivity analyses and Section 9 concludes.

1 Background and literature

This paper contributes to four strains of literature, namely that on (1) endogenous risk in the financial system, (2) fire sales, (3) asset price bubbles and banking crises, and (4) systemic risk measures.

Endogenous risk. Systemic risk is the risk of damage to the whole financial system, with potential spillovers to the real economy.[2] A key component of systemic risk is endogenous risk, namely the risk created by the endogenous response of agents in the financial system to initial losses. For example, fire sales, runs, leverage, and short-term funding have been highlighted as

[1] For example, Avramov et al. (2006) document that more illiquid stocks exhibit significantly more auto-serial correlation.

[2] I refer to Chen et al. (2013) and Smaga (2014) for a detailed discussion about the definition of systemic risk.

mechanisms that amplify losses, boosting endogenous risk.

A modern strain of the macro-finance literature solves for full equilibrium dynamics in continuous time economies with financial frictions (e.g., Adrian and Boyarchenko (2012), He and Krishnamurthy (2012, 2013), Brunnermeier and Sannikov (2014, 2016), Maggiori (2017), Dindo et al. (2020), Modena (2020)). In these models, shocks to agents' net worth are amplified by pecuniary externalities (e.g., fire sales) and leverage, thereby generating endogenous risk. My analysis is motivated in particular by Brunnermeier and Sannikov (2014)'s model, in which the interaction of financial constraints, leverage, and amplification of shocks generates Spillover Persistence: today's losses aggravate agents' financial constraints and leverage, which leads to more severe amplification and thus a higher probability of large losses in the future. Amplification is due to agents' leverage and due to feedback loops in prices (similar in its mechanism to Shleifer and Vishny (1992), Kiyotaki and Moore (1997), and Brunnermeier and Pedersen (2009)). Financial constraints bind in crises times, which results in high Spillover Persistence. In contrast, experts (which are productive agents) are unconstrained in good times, especially with low exogenous volatility. In these times, amplification and thus Spillover Persistence is weak. When exogenous volatility declines, fragility builds up because experts are encouraged to take more risks, namely increase dividend payouts and leverage. This is the "volatility paradox". Brunnermeier and Sannikov (2014) hence predict that (1) during crises and times with strong amplification, today's losses strongly predict losses in the future, i.e., Spillover Persistence is high, while (2) fragility and risk-taking by experts increases when Spillover Persistence declines. My findings provide empirical support for these key predictions.[3]

Another strain of literature closely relates to the volatility paradox by exploring leverage cycles. For example, Adrian and Shin (2014) document that leverage increases with banks' (own) Value-at-Risk and Adrian et al. (2018, 2019) document that periods with low volatility precede periods with low GDP growth. In the models of Acharya and Viswanathan (2011) and Adrian and Boyarchenko (2012) periods with loose financial conditions and low volatility motivate banks to increase leverage. I complement this literature by introducing Spillover Persistence as a new firm-level characteristic

[3]It is noteworthy that my empirical framework builds on losses in financial firms' market value, while in Brunnermeier and Sannikov (2014)'s model adverse shocks to the price of capital lead to a decline in experts' net worth (i.e., book value) but an increase in their market-to-book ratio. Therefore, it is theoretically ambiguous whether losses in experts' net worth translate into market value losses in their model.

that correlates with changes in leverage and fragility in the financial system. Importantly, Spillover Persistence is not based on a firm's individual risk (such as the Value-at-Risk in Adrian and Shin (2014)) but on the system's risk. As I argue above, Persistence relates to amplification effects and financial constraints of agents in the system.

Fire sales. Fire sales amplify initial shocks by pushing prices below fundamental value. For example, fire sales may constrain borrowing and interbank lending, as in Caballero and Krishnamurthy (2004), Lorenzoni (2008), Acharya (2009), Diamond and Rajan (2011), and Gale and Yorulmazer (2013), and impair other agents' balance sheets when these hold similar assets or are subject to price-dependent funding constraints (as in Brunnermeier and Sannikov (2014) and Brunnermeier and Pedersen (2009)).

A growing body of literature empirically documents forced asset sales and their price effects, e.g., by insurance companies (e.g., Ellul et al. (2011, 2015), Chaderina et al. (2018), Girardi et al. (2020)) and mutual funds (e.g., Coval and Stafford (2007), Chernenko and Sunderam (2020)). Typically, price impacts are very persistent. For example, Ellul et al. (2011) estimate that corporate bond prices decline for over 30 weeks after insurers are forced to sell. I provide evidence that fire sales boost Spillover Persistence: losses of insurers that engage more in fire sales have a relatively more persistent impact on the financial system.[4] Thus, my findings suggest that Spillover Persistence captures the amplification generated by fire sales.

Asset price bubbles and banking crises. Asset price bubbles coincide with increases in systemic risk (Brunnermeier et al. (2020)), and are indicative for financial crises particularly when they are paired with credit booms (Schularick and Taylor (2012), Jordà et al. (2015)). This paper uncovers the dynamics of Spillover Persistence during asset price bubbles and banking crises.

First, I show that declines in Spillover Persistence significantly forecast banking crises – even after controlling for numerous macroeconomic variables that have been found to predate crises, such as credit growth (e.g., Schularick and Taylor (2012), Jordà et al. (2015), Krishnamurthy and Muir (2017)).

Second, building on Brunnermeier et al. (2020)'s framework, I document that Spillover Persistence declines with the onset of asset price bubble booms and subsequently increases – particularly

[4]Similar to Chaderina et al. (2018) and Girardi et al. (2020), I empirically identify fire sale incentives by insurers' exposure to natural catastrophes, namely hurricane Katrina.

around bubble bursts. These dynamics – combined with my other results – suggest (1) that bubble booms correlate with an increase in fragility in the financial system, consistent with the view that bubble booms cause the build-up of systemic imbalances (e.g., Brunnermeier et al. (2020)), and (2) that bubble bursts relate to stronger amplification of losses.

Systemic risk measures. Systemic risk measures estimate the impact of a firm's losses on the financial system. Popular systemic risk measures are ΔCoVaR (Adrian and Brunnermeier (2016)) and Marginal Expected Shortfall (MES; Acharya et al. (2017)).[5] These measures focus on *contemporaneous* systemic risk, i.e., simultaneous losses of the firm and system, exploiting contemporaneous volatility and correlation. For example, Adrian and Brunnermeier (2016)'s ΔCoVaR is proportional to volatility of the financial system (see Adrian and Brunnermeier (2016, p.1413)) and Acharya et al. (2017)'s Marginal Expected Shortfall is proportional to a firm's beta times the expected shortfall of the financial system (see Benoit et al. (2017, p.137)). As Billio et al. (2012) and Brunnermeier and Oehmke (2013a) argue, due to the volatility paradox forward-looking systemic risk measures should not rely on contemporaneous volatility.[6] To circumvent the volatility paradox, Adrian and Brunnermeier (2016) regress (high-frequency) contemporaneous systemic risk measures on (low-frequency) macro- and firm-level characteristics. I show that Spillover Persistence adds additional information, as it significantly predicts future crises even after controlling for macro- and firm-level characteristics.

ΔCoSP, the systemic risk measure in my framework, is most closely related to Adrian and Brunnermeier (2016)'s ΔCoVaR. The two main differences are (1) that ΔCoSP incorporates a time lag between losses of the firm and the system and (2) that it uses the shortfall probability, i.e., the probability of large losses in the system, instead of the system's Value-at-Risk. Incorporating time lags enables me to estimate Persistence. Using the shortfall probability makes ΔCoSP independent from the system's contemporaneous volatility. I document that ΔCoSP substantially improves the prediction of financial crises and their impact on economic activity compared to other systemic risk

[5] Overviews of systemic risk measures are provided by Bisias et al. (2015) and Benoit et al. (2017).

[6] Brunnermeier and Oehmke (2013a, 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."

measures and macroeconomic variables.

ΔCoSP also relates to Granger causality (Billio et al. (2012)), with the difference that ΔCoSP focuses on correlation in the tails and also takes the level of correlation into account.[7] Adams et al. (2014) estimate impulse-response functions in a state-dependent sensitivity Value-at-Risk framework. They find that the systemic impact of loss spillovers can be very persistent over time with an effect over roughly one month time horizon, which is consistent with my baseline results. I complement this insight in several dimensions, especially by proposing a coherent approach to measure Persistence and by relating Persistence to endogenous risk, crises, fire sales, asset price bubbles, and bank characteristics.

2 Conditional Shortfall Probability

2.1 Methodology

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 particularly large equity return losses.[8] For this purpose, I define by $VaR^I(q)$ the $(1-q)\times 100\%$ percentile of the unconditional distribution of a firm I's equity return loss $-r_t^I$,

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

where r_t^I is the relative change in firm value 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, reflecting the smallest return loss that is not exceeded with probability $(1-q)\times 100\%$. Analogously, by replacing the firm's return r_t^I by the system's return r_t^S, $VaR^S(q)$ is the system's risk.[9]

ΔCoSP measures whether firm I's tail losses (that exceed $VaR^I(q)$) correlate with future tail

[7]Analogously to the Granger causality test proposed by Billio et al. (2012), the principle of Granger causality relies on ruling out one causal direction by the reasoning that an event at time $t+\tau$ cannot have caused an event at time t (Granger (1969)).

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

[9]I define the financial 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 Section 3).

losses of the system S (that exceed $VaR^S(q)$):

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

$$\Delta\psi(\tau) = \mathbb{P}\left(-r^S_{t+\tau} \geq VaR^S(q) \mid -r^I_t \geq VaR^I(q)\right) - q. \tag{1}$$

Normalization of $\psi(\tau)$ by q implies that if firm and system's (time-lagged) losses are independent, then $\Delta\psi(\tau) = 0$. If $\Delta\psi(\tau) > 0$, firm losses are associated with a subsequent increase in the likelihood of system losses by $\Delta\psi(\tau)$ percentage points. Therefore, $\Delta\psi(\tau)$ is a measure for firm I's contribution to systemic risk.[10]

Figure 2 depicts a standard nonparametric estimate for ΔCoSP(τ) as a function of the time-lag τ between large losses of JP Morgan and the US financial system during 2003-2007, $\widehat{\Delta\psi}$. Intuitively, the impact of a firm's losses on the system fades out with an increasing time-lag τ. Figure 2 supports this intuition and suggests that $\lim_{\tau\to\infty} \Delta\psi(\tau) = 0$ with exponential rate of convergence. Exploiting this property, I estimate CoSP assuming the following parametric model (see Appendix A for additional estimation details and justification of the parametric form):

$$\Delta\text{CoSP}(\tau) = e^{\alpha+\beta\tau}. \tag{2}$$

Figure 2 supports this modeling choice since 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]

I propose two aggregate measures based on ΔCoSP, which disentangle the *average level* from the *time persistence* of systemic risk. These two dimensions of ΔCoSP must not necessarily align.

[10]Note that ΔCoSP is proportional to the change in the likelihood of large system losses conditional on large firm losses compared to that conditional on the absence of large firm losses since

$$\Delta\psi(\tau) = (1-q)\left(\mathbb{P}\left(-r^S_{t+\tau} \geq VaR^S(q) \mid -r^I_t \geq VaR^I(q)\right) - \mathbb{P}\left(-r^S_{t+\tau} \geq VaR^S(q) \mid -r^I_t < VaR^I(q)\right)\right).$$

This definition for $\Delta\psi(\tau)$ is similar to that of Adrian and Brunnermeier (2016)'s ΔCoVaR, which is the change in the system's risk when the firm suffers a loss compared to when it does not. The important difference to ΔCoVaR is that $\Delta\psi(\tau)$ computes the system's risk *after* losses of the firm.

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

$$\bar{\psi} = \frac{1}{\tau^{max} - 1} \int_{1}^{\tau^{max}} \Delta CoSP(\tau)\, d\tau = \frac{1}{\beta(\tau^{max} - 1)} \left(e^{\alpha + \beta \tau^{max}} - e^{\alpha + \beta} \right). \tag{3}$$

Average ΔCoSP is a measure for the level of persistent systemic risk. It says that the probability of large system losses increases on average by $\bar{\psi} \times 100\%$ during the $\tau^{\max}$ days after large firm losses. As Figure 2 illustrates, $\bar{\psi}$ is the average of ΔCoSP across time lags. If firm and system losses are independent, then $\bar{\psi} = 0$. I emphasize that $\bar{\psi}$ precludes contemporaneous systemic risk at $\tau = 0$. This separates persistent systemic risk ($\bar{\psi}$) from contemporaneous systemic risk (such as measured by ΔCoSP(0) and ΔCoVaR).

Definition 3 (Spillover Persistence)**.** *For $\tau^{max} > 1$, define the Spillover Persistence as the average time horizon over which large firm losses increase the probability of large system losses weighted by the level of systemic risk,*

$$\bar{\tau} = \int_{1}^{\tau^{max}} \tau \cdot \frac{\Delta CoSP(\tau)}{\bar{\psi}(\tau^{max} - 1)}\, d\tau = \frac{1}{\bar{\psi}(\tau^{max} - 1)} \left(\frac{\beta \tau^{max} - 1}{\beta^2} e^{\alpha + \beta \tau^{max}} - \frac{\beta - 1}{\beta^2} e^{\alpha + \beta} \right), \tag{4}$$

where $\tau^{max} > 1$.

Spillover Persistence is an average of all time lags weighted by systemic risk.[11] It says that large firm losses affect the system after $\bar{\tau}$ days on average.

If firm losses had only a contemporaneous effect on the system, then $\bar{\tau} = 0$. If the system reacted only on day 3 after a firm's losses, then $\bar{\tau} = 3$. Instead, in Figure 2 we observe that ΔCoSP (exponentially) declines with the time lag τ. $\bar{\tau}$ is the average time lag weighted by ΔCoSP, i.e., the average time-horizon at which firm losses increase risk in the system. It is thus inversely related to how fast the system reacts to the firm's losses, on average.

2.2 Properties of CoSP

Motivated by previous work on systemic risk (e.g., Adrian and Brunnermeier (2016), Acharya et al. (2017)), I use the $q \times 100\%$ largest equity return losses as indicators for firm distress. Since

[11] Note that $\bar{\tau}$ is very similar to Macaulay (1938)'s duration, with the difference that time lags are weighted by systemic risk instead of the present value of cash flows.

these tail losses occur with probability q by definition and independent of firm volatility, ΔCoSP is not mechanically linked to the firm's business 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.

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, there are two main methodological differences between ΔCoVaR and ΔCoSP: (1) a time lag between losses of the firm and system, and (2) 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, while the time lag in ΔCoSP enables the estimation of the level and time horizon of *persistent* systemic risk. Using VaR 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 reflect a build-up of fragility during tranquil times (Brunnermeier and Oehmke (2013a)). Instead, the shortfall probability $\mathbb{P}(-r^S_{t+\tau} \geq VaR^S(q))$ is independent from contemporaneous volatility of the system by definition. This property makes it a promising candidate to tackle the volatility paradox.

Extending contemporaneous systemic risk measures, ΔCoSP underlies Granger (1969)-causality: system losses at time $t+\tau$, $\tau > 0$, cannot cause firm distress at time t.[12] However, it is worth stressing that, similar to previous systemic risk measures, ΔCoSP does not *causally* identify loss spillovers. Instead, it estimates the correlation between a firm's tail losses and subsequent tail losses in the system. Thus, it is possible that other (omitted) variables cause both the firm and the system to suffer losses at t and $t+\tau$, respectively. I undertake substantial efforts to rule out this effect. If omitted variables affect all firms to the same extent, I absorb their effect with time fixed effects in my analysis. The existence of omitted variables that affect the system at both t and $t+\tau$ would cause auto-serial correlation in the system's equity returns. I show in Section 8 that CoSP-measures (that is Average ΔCoSP and Spillover Persistence) do not significantly positively correlate with autocorrelation of the system's equity returns. Finally, in Section 8 I show that my results are robust toward removing predictable variation in equity returns.

[12] 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.

3 Data and estimation

I apply the CoSP framework to a large set of international financial firms. This section describes the data and estimation strategy for systemic risk measures.

The inputs to systemic risk measures are daily equity market returns of a firm I (based on unpadded and unadjusted prices of common equity) and daily equity market returns of the system S. Thus, a one-unit time lag $\tau = 1$ corresponds to a one (trading) day-difference. I retrieve equity market data from Thomson Reuters Financial Datastream, which covers a large number of international financial firms. The sample starts on January 01, 1985, and ends on December 31, 2018, covering three recessions (1990-1991, 2001, and 2007-2009) and several crises (1987, 1994, 1997, 1998, 2000, 2008, 2011). I start with the following firms:

1) Publicly traded financial firms that are included in either the *Datastream World Financials Index* (1,820 firms) or *Datastream UK Financials Index* (251 firms) as of February 2019.[13]
2) Dead firms (as of February 2019) that are classified by Datastream as financial firms and for which a primary major equity quote is available (6,850 firms).

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.[14] 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).[15]The resulting equity market data covers 6.8 million firm-day observations of 1,810 firms in 69 countries with a total market capitalization of 9.95 trillion USD at the end of 2018.

[13]It is not sufficient to use only the *Datastream World Financials Index* since it lacks many UK firms.

[14]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 firm's market capitalization does not exceed 100,000 USD. Moreover, I exclude all days on which at least 95% of the firms in the sample do not have a price reported, since these days most likely reflect non-trading days, e.g., bank holidays (this excludes 24 days).

[15]I classify a firm as bank if its SIC is between 6000 and 6199 or equal to 6712 (corresponding to bank holdings), as broker-dealer if its SIC is between 6200 and 6299, as insurer if its SIC is between 6300 and 6399 (excluding insurance brokers), and as real estate firm if its SIC is between 6500 and 6599.

I estimate systemic risk in a multi-country setting. For this purpose, I assign each firm (1) to one country and (2) to one of the following geographical regions (based on headquarter location): Europe (36%), Asia (excluding Japan; 30%), North America (22%), Japan (9%), and Australia (3%), where the number in parentheses is the relative number of firms matched to the respective region in the equity market sample. 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 given by 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 example, the financial system for JP Morgan contains all North American financial firms except for JP Morgan.[16]

Systemic risk likely changes over time. To account for time variation, I compute systemic risk measures for rolling time windows with a size of 5 years for each firm.[17] To alleviate estimation errors, I exclude firm-system pairs from a given estimation window if there are less than 700 non-missing and non-zero observations of daily firm and system returns.[18]

The choice of CoSP's reference level q is subject to a trade off between capturing more severe shocks (smaller q) and relying on more observations to estimate CoSP (larger q). I find $q = 5\%$ to be a reasonable choice.[19] I estimate CoSP using the parametric model $\Delta\text{CoSP}(\tau) = e^{\alpha+\beta\tau}$ for $\tau \geq 1$, as described in Appendix A, and use the estimated model to compute $\bar{\psi}$ and $\bar{\tau}$.[20] The maximum considered time lag in $\bar{\psi}$ and $\bar{\tau}$ is $\tau^{\max} = 50$ days.

[16] Details are described in Online Appendix B.1. Brunnermeier et al. (2020) follow a similar approach to calculate ΔCoVaR in a multi-country setting. The main differences are that they (1) exclude Asian firms, (2) only focus on the banking system (including broker-dealers but excluding insurers and real estate firms), and (3) that they include the currently considered firm (*risk-triggering firm*) when calculating the system index. The latter difference may potentially bias the results. For example, if a firm is very large compared to other firms in the system, it drives the system's performance and mechanically increases correlation between the firm and system. To avoid such bias, I construct a different system index for each firm, excluding the considered firm. Moreover, I take a broader perspective by including insurers and real estate firms in the financial system, following Adrian and Brunnermeier (2016).

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

[18] Since CoSP is prone to 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 for the estimation of CoSP. I require 700 observations after winsorizing to include a firm-system-estimation window observation.

[19] $q = 5\%$ 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.

[20] I justify this model by comparing it to a nonparametric estimate and an autoregressive model for system losses in Section 2.2 and Appendix A.

I compare CoSP to two closely related systemic risk measures. The main comparison is with ΔCoVaR, which is defined as

$$\Delta\text{CoVaR} = CoVaR_{-r^I = VaR^I(q)} - CoVaR_{-r^I = VaR^I(0.5)}, \tag{5}$$

where $\mathbb{P}(-r^S \geq CoVaR_E \mid E) = q$ for event E. Similar to ΔCoSP(τ), ΔCoVaR measures the change in the system's risk (here, its VaR) when a firm becomes distressed relative to its median state. I estimate ΔCoVaR using quantile regressions as proposed by Adrian and Brunnermeier (2016, Section III.B), based on weekly equity market returns.[21]

In some robustness checks, I also include the contemporaneous ΔCoSP, $\psi(0)$, as a measure for contemporaneous risk, which I compute using a standard nonparametric estimate (see Online Appendix A), as well as Acharya et al. (2017)'s MES, defined by

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

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

For all systemic risk measures, a larger value corresponds to higher systemic risk and I use the same reference level $q = 0.05$. To account for estimation errors, I winsorize $\Delta\psi(0)$, MES, and ΔCoVaR at the 1% and 99% level of firm-estimation window observations, and Average ΔCoSP and Spillover Persistence at the 98% level (since these are non-negative by definition and 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), equity valuation (market-to-book value), and dividends and cash flow (both relative to total assets) – and additional bank characteristics obtained from Moody's Analytics Bank Focus – namely time and demand deposits, loans, impaired loans, intangible assets, CDS notional (all relative to total assets), and liquidity ratio (liquid assets over deposits and short-term funding).

[21]Following Adrian and Brunnermeier (2016), for each firm I estimate quantile regressions based on the whole available time series with macroeconomic state variables as dependent variables (reported in Table B.2). Since my analysis is on annual frequency, I use the yearly average of weekly ΔCoVaR in the analysis. In unreported regressions, I find that my results are robust to using the end-of-year ΔCoVaR.

Moreover, I include a wide range of macroeconomic characteristics, such as inflation, GDP growth, credit growth, banking crises, equity market volatility 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.

4 Exploring variation in Spillover Persistence

In this section, I provide descriptive statistics for CoSP and other systemic risk measures and explore correlation between Spillover Persistence and macroeconomic and firm characteristics. The baseline sample includes 1,234 unique firms from 56 countries for which an estimate for Spillover Persistence is available in at least one year between 1989 and 2018.[22] The total market value of firms in the sample is 8.3 trillion USD on December 31, 2018, which corresponds to roughly 70% of the market value of financial firms globally.[23] Thus, the sample includes a vast majority of publicly listed financial firms.

Table 1 provides summary statistics for systemic risk measures and Persistence. The median of $\Delta\psi(0)$, a contemporaneous systemic risk measure, is 19ppt. This means that the occurrence of losses is positively correlated across firms and the financial system: if the median firm suffers large losses, the likelihood of system losses on the same day is 19 percentage points larger than on average. Subsequently, the likelihood of system losses declines, as the descriptive statistics for Average ΔCoSP show. The average probability of system losses in the 50 days *subsequent* to the median firm suffering large losses is only 2.5 percentage points larger than on average.

Descriptive statistics for Spillover Persistence show that a median firm's losses are followed by a larger risk of losses in the financial system at an average time horizon of 21 trading days, which corresponds to approximately one month. Thus, the median firm losses increase the risk of future losses in the system.

[22]Here and in the following, in the context of systemic risk measures *year* refers to the last year in a 5-year rolling time window used to estimate systemic risk measures. 42% of firm-year observations are for firms located in Europe, 30% for North America, 19% for Asia, 5% for Japan, and 4% in Australia. 45% of firm-year observations are for banks, 18% for broker-dealers, 17% insurers, and 20% real estate firms.

[23]The total market value of US firms in the sample is 3.13 trillion USD, which corresponds to roughly 60% of the total market value of the US financial sector. 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 31, 2018, record a total market value of 11.51 trillion USD and 5.53 trillion USD, respectively. The FTSE WORLD FINANCIALS and FTSE USA FINANCIALS index report similar, yet slightly smaller, levels.

[Place Table 1 about here]

The median ΔCoVaR is 2.4 percentage points, meaning that a system's conditional Value-at-Risk is 2.4 percentage points larger if the median firm is under distress relative to its median state (see Table 1). The median MES is 1.5 percentage points, meaning that a median firm's average daily equity return is -1.5% on days during which the financial system is under distress.[24]

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. Despite a positive correlation with Average ΔCoSP (which is 51%), both measures clearly differ in the time series dimension, suggesting that they pick up different information.[25] The correlation of ΔCoVaR with Average ΔCoSP is 30% and with Spillover Persistence it is 9%. The correlation of MES with Average ΔCoSP and Spillover Persistence is 43% and 9%, respectively. These estimates for bivariate correlations show that – while all measures overlap to some extent in the information they capture – a large share of the information captured by the level of persistent systemic risk (Average ΔCoSP) and especially that captured by Spillover Persistence is orthogonal to the information picked up by contemporaneous systemic risk, i.e., by ΔCoVaR and MES.

[Place Figure 3 about here]

Only 22% of variation in Spillover Persistence is explained by time-invariant cross-sectional differences across firms.[26] Similarly, aggregate fluctuations (globally or regionally) explain only 14% to 22% of its variation. These findings suggest that persistence is neither highly persistent over time nor explained by macroeconomic changes. Instead, the majority of variation (roughly 60%) reflects relative changes over time, i.e., differential trends of Spillover Persistence across firms.

In Table 2, I explore the relation between Spillover Persistence and firm and macroeconomic characteristics. Column (1) examines the role of macroeconomic characteristics, controlling for

[24] My estimates for MES and ΔCoVaR are very close to those from other studies. For example, Acharya et al. (2017) estimate a median MES of 1.47% based on the time period from June 2006 to 2007 for 102 large US-based financial firms. Adrian and Brunnermeier (2016) estimate an average weekly ΔCoVaR of 1.172% at the $q = 1\%$ reference level based on the weekly equity market returns of 1,823 US financial firms from 1971 to 2013.

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

[26] I report a variance decomposition for Spillover Persistence in Table B.4 in Online Appendix B.2.

time-invariant differences across firms. Banking crises have the most important effect on Persistence in terms of statistical significance. During crises, Persistence is 3 days larger, which corresponds to 16% of the average level of Persistence.

Column (2) focuses on cross-sectional differences in Persistence, controlling for year fixed effects. Persistence is significantly larger in North America than other regions, particularly relative to Japan and Asia. A potential reason is the high interconnectedness particularly of the US financial system, which might boost amplification losses. Moreover, I find that Persistence is significantly larger for insurance companies than for (commercial) banks. This finding is consistent with the hypothesis that insurers amplify fire sale spirals, which I explore in Section 7.

[**Place Table 2 about here**]

Columns (3) and (4) dig deeper into the role of firm characteristics. The results show that firm size is an important determinant for Persistence: an increase in 1% of total assets relates to an increase by roughly 0.3 days (0.04 standard deviations) in Persistence. Interestingly, controlling for firm characteristics, Persistence is significantly larger for broker-dealers than for (commercial) banks, consistent with the high interconnectedness of these institutions (column (3)). These results are not driven by country-specific macroeconomic characteristics or region-specific trends (column (4)). Moreover, controlling for firm characteristics, Persistence is not significantly different for "globally systemically important" firms (so-called "SIFIs", which are determined by the Financial Stability Board (2011)) compared to other firms (column (4)).[27] This finding suggests that Spillover Persistence is not driven by macroprudential regulatory efforts after the 2007-08 financial crisis.

In columns (5) and (6), I zoom in on banks and broker-dealers, using the subsample of firms included in Moody's Analytics BankFocus (the "Ban & Bro" sample). The estimates highlight deposit funding as an important driver for Persistence. A 1ppt increase in demand deposits relative to total assets relates to a roughly 7 day increase in Spillover Persistence, controlling for region-level trends and time-invariant differences across banks (column (6)). This finding is consistent with short-term funding as a source of instability and amplification of losses (e.g., see Diamond and Rajan (2011) and Brunnermeier and Oehmke (2013b)).

[27] I do not include the SIFI indicator in all regressions since it is only available starting in 2011 for banks and broker-dealers, and from 2014 to 2016 for insurers.

Finally, columns (7) and (8) explore the relation between Spillover Persistence and other risk measures, controlling for region-level trends. I find that Persistence strongly positively relates to the level of systemic risk as measured by ΔCoVaR (column (7)) and Average ΔCoSP (column (8)). Thus, losses of firms with higher levels of systemic risk have a more persistent effect on the financial system, on average. Nonetheless, given the R^2 of 35% in column (8), more than 60% of the variation in Spillover Persistence is orthogonal to the variation in risk measures and region-level trends.

Persistence does not positively correlate with a firm's own risk, as measured by its Value-at-Risk. Therefore, the systemic risk perspective of Spillover Persistence differs from the firm-individual risk perspective in related studies (e.g., Adrian and Shin (2014)). I also find that Persistence cannot be explained by illiquidity of a firm's equity, as measured by Amihud (2002)'s illiquidity measure.[28]

5 Persistence and the run-up of crises

I hypothesize that declines in Spillover Persistence correlate build-ups of fragility in the financial system. To test the hypothesis, in this section I examine Spillover Persistence during the run-up phase of banking crises.

5.1 Empirical model and data

To test the relation between Spillover Persistence and banking crises, I use Laeven and Valencia (2018)'s banking crisis indicators and characteristics, available on country-level from 1970 to 2017. I only include countries for which I observe at least one crisis between 1989 and 2017. After merging with systemic risk measures, the "crises sample" includes 778 financial firms in 27 countries from 1989 to 2017. The descriptive statistics in Table 3 show that 17% of the firm-year observations in the sample are marked as crisis-years. I also include the output loss (in % of GDP) as a measure for the economic cost of crises. The distribution of systemic risk measures in the crises sample is comparable to that in the baseline sample.

[Place Table 3 about here]

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

In the baseline model, I regress banking crisis indicators in country c in year $t+1$ on Spillover Persistence ($\bar{\tau}_{it}$) of firm i in country c in year t, controlling for Average ΔCoSP ($\bar{\psi}_{it}$), a vector of country and region-specific macroeconomic characteristics ($\mathbf{M}_{ct}$) in year t and firm- and time-fixed effects,[29]

$$\text{Crisis}_{i,t+1} = \alpha \cdot \bar{\tau}_{it} + \beta \cdot \bar{\psi}_{it} + \gamma \cdot \mathbf{M}_{ct} + u_i + v_t + \varepsilon_{i,t+1}. \tag{6}$$

By controlling for $\bar{\psi}_{it}$, α estimates the effect of $\bar{\tau}_{it}$ on the likelihood of crises while holding firm i's the average level of systemic risk constant. Hence, the model disentangles variation in the level and in the persistence of spillovers and, as a result, the identification of α relies only on variation in the slope of $\Delta\psi(\tau)$. The hypothesis is that declines in Spillover Persistence reflect build-ups of fragility. Thus, I expect that $\alpha < 0$, i.e., that future crises become likely when Spillover Persistence declines.

I control for the effect of macroeconomic characteristics on the likelihood of crises, which are inflation, GDP growth, and investment growth (all on country-level), and the logarithm of the 10-year interest 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 contemporaneous systemic risk, measured by ΔCoVaR or $\Delta\psi(0)$ at time t. Since the crisis-indicator is measured at the country-level, it correlates across firms within country-years. Therefore, I cluster standard errors at country-year level. I alleviate concerns that clustering of crises across years or across countries affects the results by additional multi-way clustering of standard errors at the firm and year levels.

Moreover, I explore heterogeneity in the effect of Spillover Persistence across firms, asking whether variation in some firms' Spillover Persistence is more predictive for crises than that of other firms. For this purpose, I interact $\bar{\tau}_{it}$ in Equation (6) with firm type and zoom in on bank characteristics, such as size, leverage, and funding structure. I lag each firm characteristic by one year relative to $\bar{\tau}_{it}$ and subtract its average value. Hence, when including the interaction terms, the coefficient of $\bar{\tau}_{it}$ can be interpreted as the relation between crises and Persistence for a bank with

[29] With slight abuse of notation, I use t here and in the following to index years of variables in regression models, while I have used it in Section 2 to index days of equity return losses. Since crises are measured at country-level, all firms in the same country c are assigned the same level of $\text{Crisis}_{i,t+1}$ in firm-level regressions.

average size, average leverage, etc.

Finally, I perform additional analyses at the country-year level. For this purpose, I take each variable's mean 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 for which only a small number of firms is included in the sample.[30] Since larger firms are typically more important for the financial system, I weight firms by their total assets when computing country averages.

Country-level analyses estimate the effect for an average country's average firm, while firm-level analyses estimate the effect for an average firm in the sample. These effects may potentially differ since in country-level analyses firms in countries with a small number of firms have more weight relative to those in countries with a large number of firms. Instead, in firm-level regressions each firm has the same weight. I show that my results are consistent across both settings.

5.2 Firm-level results

The baseline regression in Table 4 shows that both the level and persistence of (persistent) spillovers significantly predict banking crises (column (1)): a one-standard deviation increase in Average ΔCoSP relates to a 8ppt larger crisis likelihood, and a one-standard deviation *decrease* in Spillover Persistence relates to a 1ppt larger crisis likelihood. Both effects are statistically significant (at the 1% level, respectively), and economically significant compared to the average crisis likelihood of 17% in the sample. Thus, both measures capture a build-up of fragility in the financial system before crises.

[Place Table 4 about here]

The negative coefficient for Spillover Persistence is consistent with the dynamics in Figure 1, which shows that Spillover Persistence declines during the run-up of crises. It supports the hypothesis that fragility builds up when Spillover Persistence declines.

[30]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, 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.

Controlling for contemporaneous systemic risk by ΔCoVaR does not alter the economic nor statistical significance of Spillover Persistence and Average ΔCoSP (column (2)). This finding suggests that CoSP measures are more informative about the fragility of the financial system than contemporaneous systemic risk measures, such as ΔCoVaR.[31] Indeed, by including Average ΔCoSP and Spillover Persistence in the model in column (2) the proportion of explained variation increases by 15 percentage points relative to not including them.[32] Thus, Persistence is highly informative about banking crises - in excess of the information captured by macroeconomic characteristics and ΔCoVaR.[33]

As I argue in Section 2.2, the key distinction of CoSP-measures compared to ΔCoVaR are (1) the focus on persistent systemic risk and (2) the independence from contemporaneous volatility of the system. To assess which characteristic drives the (relatively stronger) ability to capture build-ups of fragility, I replace ΔCoVaR with contemporaneous CoSP $\Delta\psi(0)$ in column (3). Similar to Average ΔCoSP, $\Delta\psi(0)$ is also independent from contemporaneous volatility, but it exclusively relies on contemporaneous tail correlation and does not capture persistence. Thus, if persistence of loss spillovers was the key feature that improves the ability to capture fragility, we would expect no changes in the statistical significance and size of the coefficient of Average ΔCoSP and Spillover Persistence in column (3) compared to (2) and that the coefficient on $\Delta\psi(0)$ is not significantly different from zero. This is precisely what I find in Table 4.

Finally, I also provide evidence that CoSP-measures do not only improve the prediction of whether banking crises *occur*, but also of their economic *costs*. For this purpose, I relate variation in the output loss of crises conditional on a crisis occurring at $t+1$ to the level of Spillover Persistence during the crisis' run-up phase. Consistent with my baseline results, I find that Average ΔCoSP is significantly positively and Spillover Persistence significantly negatively correlated with the output

[31]It is worth noting that ΔCoVaR is significantly positively correlated with the occurrence of banking crisis once excluding Average ΔCoSP, Spillover Persistence, and macro control variables from the model. However, its statistical significance vanishes once including macro controls, and the coefficient becomes significantly negative once including CoSP measures.

[32]The share of explained variation in relative changes in banking crisis occurrence (within R^2) is 13% with ΔCoVaR and macro controls as independent variables and firm and year fixed effects (i.e., column (2) without Average ΔCoSP and Spillover Persistence), and it is 29% in the model in column (2). Similarly, the share of explained variation (overall R^2) is 60% with ΔCoVaR and macro controls as independent variables and firm and year fixed effects (i.e., column (2) without Average ΔCoSP and Spillover Persistence), and it is 75% in the model in column (2).

[33]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 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.

loss (column (4)). Thus, a decline in Spillover Persistence does not only predict a higher likelihood but also stronger severity of banking crises.

These baseline results are very robust. In Table C.1 in Online Appendix C I show that the statistical and economic significance of the results remain largely unchanged when predicting only banking crises that have systemic effects or only crises that are not "borderline cases" and when controlling for stock market bubbles, for contemporaneous systemic risk by using Acharya et al. (2017)'s MES, and for lagged crises and output losses, and for a fiscal cost instead of output loss indicator. Thus, the relation between persistence and crises is not specific to particular crises and cannot be explained by asset price bubbles or traditional systemic risk measures.

Figure 4 illustrates the dynamics of the marginal effect of CoSP-measures before crises. To construct the figure, I build on the baseline regression in Equation (6) and vary the time lag of the crisis indicator (the dependent variable), holding CoSP-measures and macroeconomic characteristics (independent variables) fixed. There is a clear pattern: the correlation of crises with Spillover Persistence declines (becomes "more negative") and that with Average ΔCoSP increases (becomes "more positive") with closer proximity to crises. This provides further support for the hypothesis that declines in Persistence reflect build-ups of fragility.

[Place Figure 4 about here]

Next, I examine to what extent firm characteristics explain or affect the predictive power of Spillover Persistence for banking crises. In column (1) in Table 5, I re-estimate Equation (6) but additionally include firm characteristics as control variables. The economic and statistical significance of the coefficients on $\bar{\psi}_{it}$ and $\bar{\tau}_{it}$ barely changes, providing further support for the robustness of the baseline results.

The predictive power of Persistence for crises may differ across firms. Intuitively, some firms are more important (e.g., more "central") in the Persistence system. Moreover, some firms might react more severely to changes in persistence than others (an effect I explore in Section 6.2). Taken together, higher importance and stronger reaction can make a firm's change in Persistence a stronger indicator for crises relative to other firms. I explore such heterogeneity by interacting firm characteristics with Spillover Persistence in the baseline model. Column (2) analyzes heterogeneity across firm types. I find that a decline in Spillover Persistence of broker-dealers is significantly less predictive for crises than that of (commercial) banks. This result is consistent with the finding that broker-dealers take relatively less risks when Persistence declines, compared to (commercial) banks, which I present in Section 6.2.

[Place Table 5 about here]

I dig deeper into heterogeneity across bank characteristics in column (3). Banks' funding structure and asset composition are the most important source of heterogeneity, in terms of statistical significance. A decline in Spillover Persistence for banks that rely more on demand deposit funding, maintain less intangible assets and a smaller share of impaired loans than other banks is a relatively stronger indicator for banking crises. Since I do not find that the same characteristics relate to a significantly stronger reaction to changes in Persistence in Section 6.2, the result suggests that these banks' Persistence is a more important indicator for financial fragility than that of other banks.

5.3 Country-level results

Table 6 illustrates the effect of Spillover Persistence on crisis likelihood at the country level. The results are consistent with those at the firm level. In the baseline regression with country fixed effects and macro controls, a one-standard deviation decrease in Spillover Persistence relates to an 8ppt increase in the likelihood of a banking crisis in the next year (column (1)). This effect is significant at the 5% level and remains (statistically and economically) largely unchanged when additionally controlling for ΔCoVaR (column (2)). The effect is similar for predicting the occurrence of banking crises at a 2-year horizon (column (3)) and when controlling for contemporaneous systemic risk measured by $\Delta\psi(0)$ instead of ΔCoVaR (column (4)). Moreover, Spillover Persistence at the country level also negatively correlates with the output loss of crises (columns (5)).

[Place Table 6 about here]

6 Low persistence, asset price bubbles, and risk-taking

In the following, I explore possibly reasons for the link between declines in Spillover Persistence and build-ups of fragility in the financial system. Specifically, I document (1) that Persistence declines when stock market price bubbles begin to emerge and (2) that banks engage in more risky behavior when Persistence declines. Asset price bubbles and increased risk taking are commonly associated with an increase in fragility and can increase the likelihood of future crises (e.g., Brunnermeier and Oehmke (2013a), Brunnermeier and Sannikov (2014), Schularick and Taylor (2012)), which provides a possible explanation for the strong predictive power of declines in Spillover Persistence for future banking crises.

6.1 Asset price bubbles

In this section, I examine the connection between Spillover Persistence and asset price bubbles. The run-up phase of a bubble typically coincides with imbalances in the financial system and financial fragility (Brunnermeier and Oehmke (2013a)). Consistent with the hypothesis that low persistence relates to high financial fragility, I find that Spillover Persistence is significantly lower during the start of stock market booms than during normal times and during later bubble phases.

6.1.1 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.[34] 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 distance to a bubble's burst.

I merge the bubble indicators to the baseline sample of systemic risk measures at the firm-year level.[35] In the baseline regression, the "bubbles sample" covers 40 bubbles in 17 countries from 1990 to 2015, and 724 financial firms.[36]

[Place Table 7 about here]

[34] 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.

[35] I label a year as stock market boom or bust year if the respective bubble phase is present in at least 6 months of this year.

[36] 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.

The descriptive statistics in Table 7 show that 12% 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 2.13 (0.31) 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 Spillover Persistence, Average ΔCoSP, and ΔCoVaR in the bubbles sample is similar to that in the overall sample.

I saturate the sample with macroeconomic control variables that have been shown to interact with asset price bubbles and financial crises. I include inflation, GDP growth, and credit-to-GDP growth, capturing business cycle and credit dynamics. In all regressions, I also control for investment growth, reflecting the use of credit for investment versus consumption as important channel for bubbles to result in financial crises (highlighted, e.g., by Schularick and Taylor (2012)). These variables are at country-year level. I also include the logarithm of the 10-year interest rate (at region level) to control for the bank-sovereign nexus, as in Brunnermeier et al. (2020).

6.1.2 Empirical model. First, in the baseline model I follow the setup in Brunnermeier et al. (2020) and regress Spillover Persistence $\bar{\tau}_{it}$ of firm i in country c in year t (estimated based on years $t-4$ to t) on the vector of boom and bust indicator $\mathbf{I}_{ct}^{Bubble}$, controlling for a vector that includes the current boom and bust length ($\mathbf{L}_{ct}^{Bubble}$), 1-year lagged macroeconomic characteristics $\mathbf{M}_{c,t-1}$, and firm-fixed effects (u_i),

$$\bar{\tau}_{it} = \alpha \cdot \mathbf{I}_{ct}^{Bubble} + \beta \cdot \mathbf{L}_{ct}^{Bubble} + \gamma \cdot \mathbf{M}_{c,t-1} + u_i + \varepsilon_{it}.$$

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. Additionally, I show that the results also hold when additionally controlling for 1-year lagged Spillover Persistence in Appendix C.2, and I provide a robustness check for the baseline results by regressing Spillover Persistence on bubble indicators in the first year ($t-4$) of the estimation window. Standard errors are clustered at firm and country-year levels, accounting for autocorrelation in Spillover Persistence at the firm level.

Second, I explore the dynamics of Spillover Persistence during asset price bubbles by estimating

$$\bar{\tau}_{it} = \alpha_0 \cdot \text{Burst Distance}_{ct} \cdot I_{ct}^{Boom} + \alpha_1 \cdot \mathbf{I}_{ct}^{Bubble} + \beta \cdot \mathbf{L}_{ct}^{Bubble} + \gamma \cdot \mathbf{M}_{c,t-1} + u_i + \varepsilon_{it},$$

where Burst Distance$_{ct}$ is the current distance to a bubble's burst. This model tests for linear trends of Spillover Persistence in the boom phase of bubbles. If $\alpha_0 < 0$, then Spillover Persistence increases during bubble booms, i.e., increases when distance to the burst declines.

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 (all at region level). 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.[37] Thus, correlation between Persistence and bubbles might be driven by correlation between Spillover Persistence and firm characteristics. To address these concerns, I run additional regressions that include 1-year lagged firm-level control variables, which are firm size (log of total assets), leverage, dividends as a share of total assets, 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.

6.1.3 Baseline results. I first illustrate the relation between Spillover Persistence and bubbles in Table 8. The results show that Spillover Persistence is significantly lower during stock market boom episodes than in other years (column (1)). The economic significance is large: during booms, Spillover Persistence is roughly 50% of its standard deviation lower than otherwise. This effect differs from the effect of bubble busts, which do not relate to a significantly different level of persistence than other years. In column (2), I directly compare booms and busts. I find that Spillover Persistence is indeed significantly lower (at the 1.4% level) during a bubble boom than during a bust, namely by 45% of its standard deviation.

[Place Table 8 about here]

[37]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.

I show that this baseline effect of bubble 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 time fixed effects. Still, the coefficient for bubble booms remains significantly negative with large economic significance. This continues to hold 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 bubble indicators for the first year that is used to estimate Spillover Persistence. The effect of a bubble boom remains highly statistically significant and negative, with a similar magnitude as in the baseline regression. In Appendix C.2 I show that the results are robust to additionally controlling for 1-year lagged Spillover Persistence.

6.1.4 Persistence dynamics during booms. To shed light on the dynamics of persistence during bubbles, I estimate a linear trend during the bubble boom. I hypothesize that Spillover Persistence is particularly low at the beginning of a bubble, reflecting an increase in fragility, and larger around the burst, where amplification effects become 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 Spillover Persistence significantly declines with the distance to a bubble's burst during booms. In other words, it increases over time during booms. In the baseline regression, I show that this effect holds within bubbles, i.e., for the sample of all year-firm 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 a similar magnitude in the overall sample while controlling for bubble booms and busts as well as additional macroeconomic and firm characteristics (column (2)).

[Place Table 9 about here]

The distance effect during booms is robust in magnitude and statistical significance to additionally controlling for contemporaneous systemic risk (measured by ΔCoVaR) and the number of boom and bust years in the CoSP-estimation window (column (3)). This alleviates the concerns (1) that effects are driven by variation in systemic risk and (2) the number of boom or bust years that enter the CoSP-estimation window is an omitted variable for the effect of burst distance. Moreover, the effect stays significant and increases in magnitude when I constrain the sample to only banks and broker-dealers and additionally control for granular bank characteristics (column (4)). In Appendix C.2 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 explain the results.

Overall, my findings show that Spillover Persistence is significantly smaller during early years of the run-up phase of stock market booms: relative to an average year, relative to the bubble bust phase, and relative to later boom years.

6.2 Risk-taking

I hypothesize that during times with declining Spillover Persistence financial firms are encouraged to take more risks, e.g., pay more dividends and raise leverage. To test the hypothesis, I regress firms' dividend payments (relative to total assets) and leverage on Spillover Persistence. Additionally, I use credit default swap exposure (measured by CDS notional relative to total assets) as a measure for risk-taking. Table 10 summarizes the key variables in the sample.

[Place Table 10 about here]

To alleviate the concern that I pick up correlation between risk-taking and macroeconomic or firm characteristics or variation in the level of risk, I control for a large set of macroeconomic and firm characteristics, as well as granular bank characteristics and Average ΔCoSP. In the most refined specifications, I also include firm and year fixed effects – controlling for time invariant differences across banks and for aggregate bank-invariant changes in the economic environment.

First, I examine whether changes in Spillover Persistence for an average financial firm correlate with changes in the amount of dividends paid to shareholders, controlling for macroeconomic and firm characteristics and firm and year fixed effects. In column (1) in Table 11, I find that a decline in persistence significantly correlates with a subsequent increase in dividends. A one-standard deviation decline in persistence relates to a 3%-standard deviation increase in dividends paid. I examine heterogeneity in this effect across banks and broker-dealers in column (2). The results show that dividend payouts increase relatively more with declines in Spillover Persistence when banks are larger and less liquid.

[Place Table 11 about here]

Second, I examine whether changes in Spillover Persistence correlate with changes in leverage for bank and broker-dealers, motivated by the importance of leverage for these intermediaries. The results in column (3) imply that the effect of Persistence on leverage is larger in magnitude than that on dividends. A one-standard deviation decline in Spillover Persistence relates to a 6%-standard deviation increase in leverage.

I find that the relation between Persistence and leverage is significantly stronger for banks and broker-dealers with a large cash flow and a large share of impaired loans (column (4)). One interpretation of this result is that weaker banks, which have an impaired asset portfolio but do not yet suffer cash flow losses, react more strongly to changes in persistence.

Finally, I examine changes in banks and broker-dealers' credit default swap (CDS) exposure. I find that declines in Persistence significantly and negatively relate to a larger CDS exposure, controlling for macroeconomic, firm, and bank characteristics as well as firm and year fixed effects (column (5)). While the direction of this effect is similar to that on dividends and leverage, and it is even larger in magnitude: a 1-standard deviation increase in Spillover Persistence relates to a 10%-standard deviation increase in CDS exposure. Thus, the relation between Spillover Persistence and derivatives exposure is particularly strong, compared to that with dividends and with leverage.

The effect of persistence on CDS exposure is particularly large for broker-dealers (compared to commercial banks), and for relatively smaller banks with high equity valuation and a large share of impaired loans (column (6)). The relatively larger effect for broker-dealers seems intuitive, as these are generally more involved in derivatives trading. The heterogeneity in impaired loans as well as equity valuation is similar to that in the effect on leverage, and consistent with the hypothesis that weaker banks react more strongly to changes in Persistence.

7 High persistence and amplification

This section explores times with high Spillover Persistence. I hypothesize that stronger amplification of losses leads to higher levels of Persistence, as in Brunnermeier and Sannikov (2014)'s model. Consistent with the hypothesis, in this section I provide empirical evidence that Spillover Persistence is substantially larger (1) *during* banking crises compared to non-crises times and (2) for firms that engage in fire sales compared to other firms.

7.1 Amplification during crises

In the previous Section 4 I document that the level of Spillover Persistence is larger during banking crises than in other years. In the following, I explore this effect in greater detail. For this purpose, I regress Spillover Persistence $\bar{\tau}_{i,t+x}$ of firm i in year $t+x$, $x \geq 0$, on the banking crisis indicator for year t in firm i's country c,

$$\bar{\tau}_{i,t+x} = \alpha \cdot \text{Crisis}_{ct} + \eta \cdot \mathbf{M}_{ct} + \gamma \cdot \mathbf{F}_{i,t-1} + u_i + \varepsilon_{it}.$$

I control for relevant macroeconomic characteristics $\mathbf{M}_{it}$ in year t and firm characteristics $\mathbf{F}_{i,t-1}$ in year $t-1$ to alleviate the concern that unobserved characteristics cause correlation between crises and Spillover Persistence. Macroeconomic characteristics are observed at country-year level (inflation, GDP growth, investment and credit growth, and crises) and at region-year level (3-month yield, term spread, and credit spread changes, TED spread, equity market return and volatility, and interest rate) for year t. Firm characteristics are size, leverage, market-to-book, and cash flow, and bank characteristics are the liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets for year $t-1$. I disentangle the effect of firm and bank characteristics from that of macroeconomic characteristics by using a 1-year time lag. Standard errors are clustered at the country-year and firm level, alleviating concerns that autocorrelation in Spillover Persistence biases standard errors.

Consistent with the analysis in Table 2, the results in Table 12 indicate that Spillover Persistence significantly increases during banking crises (column (1)). The effect is economically significant: during crises, Spillover Persistence is roughly 2.7 days larger than during normal times, which corresponds to 14% of Spillover Persistence's standard deviation. The effect almost doubles in size for banks and broker-dealers, for which Spillover Persistence increases by 4.3 days during crises, i.e., 23% of its standard deviation (column (2)).

[Place Table 12 about here]

I find the effect of crises on Spillover Persistence to be very persistent over time, with similar magnitude and statistical significance at a 1-year (columns (3) and (4)) and 2-year lag (column (5)). By interacting the crisis indicator with bank characteristics, I examine heterogeneity in the effect of crises on Spillover Persistence. The results show that the effect is significantly stronger for banks that enter a crises with a large loan portfolio with few impaired loans (column (4)). Since crises impair loan quality and loans are highly illiquid (e.g., see Greenwood et al. (2015)), this result is consistent with crises relating to fire sale spirals that amplify initial losses and, thereby, boost Spillover Persistence. To alleviate potential concerns that the results are driven by the 5-year estimation window for Spillover Persistence, I show in Appendix C.3 that the estimated effects of crises are similar in statistical and economic significance when I additionally control for 1-year lagged Spillover Persistence. Overall, the results strongly support the hypothesis that amplification during crises boosts the level of Spillover Persistence.

7.2 Fire sales

To dig deeper into the role of amplification, I hypothesize that fire sales by insurance companies increase Spillover Persistence. This hypothesis is motivated by the importance of amplification effects in Brunnermeier and Sannikov (2014) and by Ellul et al. (2011) and Chaderina et al. (2018)'s observation that the price reaction following insurers' fire sales is extremely persistent – up to 35 weeks. Forced liquidation of assets at fire sale prices can impair other agents' funding liquidity – either due to correlated holdings (as in Allen and Carletti (2006), Greenwood et al. (2015), Chernenko and Sunderam (2020)) or because funding constraints react to market illiquidity (as in Brunnermeier and Pedersen (2009)). These spillovers fuel liquidity spirals, during which prices and funding conditions further deteriorate (Brunnermeier and Pedersen (2009)). If liquidity spirals occur, the initial forced selling of assets leads to more amplification of losses in the future, which raises the risk of large future losses. This mechanism implies that fire sales lead to larger Spillover

Persistence. In the following I test this hypothesis using hurricane Katrina as an exogenous shock to the liquidity need of US property & casualty (P&C) insurers, forcing them to liquidate assets.

7.2.1 Empirical model and data. Hurricane Katrina on August 23, 2005, has been one of the costliest Atlantic hurricanes on record. It predominantly affected the US states Louisiana and Mississippi and triggered 41.1 billion USD in insurance claims being filed.[38] The volume of claims corresponds to almost 4 times the total premiums collected in 2004 by P&C insurers in these states (NAIC (2005)). Therefore, Katrina caused massive liquidity need among P&C insurers, resulting in substantial asset liquidations (Chaderina et al. (2018)).[39]

I test the impact of Katrina on Spillover Persistence of US P&C insurers that were exposed to the hurricane relative to other insurers.[40] Following Girardi et al. (2020), I label US P&C insurers as exposed if their ratio of premiums written in Louisiana and Mississippi in 2004 relative to that in all US states is among the 25% largest in the cross-sectional distribution of US P&C insurers.[41] I include all European and North American insurers in the analysis, which allows me to control for differential trends between P&C and life insurers, as well as between the US and other countries.[42]

To isolate the impact of Katrina I estimate CoSP in 18-months rolling windows and with a 20-day maximum time-lag. The dependent variable in regressions is then the change in Spillover Persistence within one month after Katrina,

$$\Delta_t \bar{\tau} = \bar{\tau}_{\text{09-22-2005}} - \bar{\tau}_{\text{08-22-2005}}.$$

Fire sales should mainly hit other firms that keep similar assets on their balance sheet (as in Allen and Carletti (2006) and Greenwood et al. (2015)). The majority of P&C insurers' assets is invested

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

[39] Girardi et al. (2020) also use Katrina as a shock to the liquidity need of US P&C insurers and show that insurers with a more similar portfolio experience a larger drop in their portfolio return after the hurricane. Manconi et al. (2016) exploit hurricane-induced bond sales by US P&C insurers as an exogenous shock to bondholder concentration. Chaderina et al. (2018) examine the liquidity of assets sold by US P&C insurers after hurricanes.

[40] Since life insurers were relatively unaffected by the hurricane, they provide a reasonable 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`).

[41] The list of exposed insurers comes from Girardi et al. (2020), which the authors kindly made available to me.

[42] European insurers had significantly lower (almost absent) exposure to Katrina (see `https://www.globalreinsurance.com/sandp-katrina/rita-impact-modest-for-european-insurers/1321323.article`), except possibly reinsurers, which I therefore exclude from the analysis.

in corporate, municipal, and government bonds (NAIC (2005)). (Commercial) banks also hold significant volumes of bonds and thus are likely affected.[43] To capture fire sale spillovers to banks, I compute $\bar{\tau}$ with respect to the banking system.Table 13 provides summary statistics for the "fire sales sample".

[Place Table 13 about here]

In the most refined model, I regress the change in Spillover Persistence between pre- and post-Katrina of an insurer i in country c on an indicator whether the insurer is exposed to Katrina, controlling for insurer-type (P&C vs life) and country fixed effects as well as the change in Average ΔCoSP during the same time period, $\Delta_t \bar{\psi}$,

$$\Delta_t \bar{\tau}_i = \alpha \cdot \text{Exposed}_i + \beta \cdot \text{P\&C}_i + \gamma \cdot \Delta_t \bar{\psi} + v_c + \varepsilon_i.$$

Standard errors are clustered at the country level. The hypothesis predicts that P&C insurers' change in Spillover Persistence is larger for exposed insurers relative to others ($\alpha > 0$).

7.2.2 Results. Table 14 reports the estimated coefficients. The difference-in-difference estimate in column (1) shows that Spillover Persistence increases significantly more for insurers exposed to hurricane Katrina relative to other insurers. The statistical and economic significance increases when I additionally control for country and insurer-type fixed effects in column (2). These results are consistent with the hypothesis that fire sales after hurricane Katrina lead to an increase in Spillover Persistence.

[Place Table 14 about here]

Variation in Spillover Persistence reflects not only changes in the time persistence of systemic risk, but may also reflect changes in the level of systemic risk. To disentangle these two dimensions, I additionally control for changes in Average ΔCoSP, $\Delta_t \bar{\psi}$, in column (3). The effect of exposure to hurricane Katrina on changes in Spillover Persistence remains highly significant, suggesting that the effect of fire sales on Spillover Persistence is not driven by changes in the severity of spillovers.

[43] In 2005Q1, 10% of US commercial banks' assets was invested in treasury and municipal securities and corporate and foreign bonds (Board of the Governors of the Federal Reserve System (2005)).

I conduct several robustness checks. First, a placebo test around July 23, 2005, does not provide a significantly positive effect for exposed insurers (columns (4)), suggesting that the baseline estimates do not pick up differential trends. Second, I re-estimate Spillover Persistence using a larger maximum time-lag (column (5)) as well as longer estimation windows (column (6)). In all cases, the results strongly support the baseline results. Since Katrina forced exposed US P&C insurers to sell an enormous volume of assets relative to other insurers, these results strongly support the hypothesis that fire sales increase Spillover Persistence.

8 Sensitivity analyses

A potential concern of measuring persistence with CoSP is that it may not reflect loss spillovers but that omitted variables cause losses on days t and $t+\tau$ (see Section 2.2). I address this concern in four ways.

First, if omitted variables hit all firms to the same extent, I absorb their effect by including year fixed effects. I show that my baseline results remain very robust.

Second, high level of illiquidity of the securities whose prices are used to estimate CoSP might correlate with a high level of Spillover Persistence. The reason is that illiquidity can cause auto-serial correlation between stock returns when information is priced in with delay. Therefore, one might be concerned that CoSP picks up stock market illiquidity instead of loss spillovers. I address this concern by estimating whether variation in illiquidity explains variation in CoSP-measures, using a firm's turnover by volume as a measure for stock market liquidity as well as Amihud (2002)'s measure for illiquidity. The results show that neither Spillover Persistence nor Average ΔCoSP positively correlate with illiquidity.[44]

Third, and more generally, omitted variables that cause correlation between equity returns on days t and $t+\tau$ would raise the level of Spillover Persistence. I address this concern by regressing both CoSP-measures on the level of autocorrelation of the system's equity return. Contrary to the potential concern, I find that Persistence is significantly *negatively* related to autocorrelation in the system's return.[45] Thus, I do not find evidence that Spillover Persistence results from omitted

[44] I report OLS estimates for the correlation between illiquidity measures and Spillover Persistence and Average ΔCoSP in Online Appendix C.4. The results hold with and without controlling for firm and time fixed effects.

[45] I report OLS estimates for the correlation between autocorrelation coefficients and Spillover Persistence and Average ΔCoSP in Online Appendix C.4. The negative correlation between autocorrelation and CoSP-measures

variables that cause auto-serial correlation of the system's returns.

A final concern is that omitted variables differently affect firm and system. I address this concern by using the system's equity return loss "shocks" to measure CoSP, defined as innovations to an autoregression of the system equity return loss.[46] Thereby, I strip out predictable variation in the system's return loss, potentially caused by omitted variables that cause losses of the system today and in the future. Based on the resulting time series of AR(1)-shocks, I re-estimate CoSP-measures and use them to re-estimate the baseline models. The results remain robust in magnitude and statistical significance (see Online Appendix C.4).

These sensitivity checks support the robustness of my results. They strongly suggest that CoSP indeed captures loss spillovers from firms to the financial system, and do not result from spurious correlation due to omitted variables. While it is beyond the scope of this paper to ensure a causal identification of spillovers, my results show that Spillover Persistence is not trivially explained by other measures and is highly informative about fragility and amplification in the financial system.

9 Conclusion

Systemic risk measures often rely on contemporaneous volatility. However, modern macro-finance theory predicts that *endogenous risk* in the financial system, the main component of systemic risk, builds up in low volatility environments (Brunnermeier and Sannikov (2014), Brunnermeier and Oehmke (2013a)). This "volatility paradox" limits the use of contemporaneous volatility as a building block to measure endogenous risk.

In this paper, I propose a new empirical framework that builds on a different dimension of risk: time persistence. Specifically, I define the *Spillover Persistence* as the average time horizon at which a firm's tail losses raise the risk of tail losses in the financial system. The lower the Spillover Persistence, the more quickly the system reacts to a firm's losses. The measure is motivated by Brunnermeier and Sannikov (2014)'s model, in which today's losses that hit constrained agents lead to amplification of shocks in the future, thereby raising the risk of large future losses.

I provide robust empirical evidence that Spillover Persistence strongly correlates with fragility

becomes insignificant once I include firm and time fixed effects. This provides further support for that fixed effects in my baseline models remove the effect of autocorrelation.

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

and amplification in the financial system. For this purpose, I exploit a broad multi-country setting with more than 1,200 international financial firms from 1985 to 2018. First, I document that declines Spillover Persistence capture build-ups of fragility related to banking crises. Persistence declines during the run-up of crises, particularly when crises are costly. This result is robust toward controlling for a wide range of macroeconomic characteristics and traditional systemic risk measures.

Second, I provide two possible explanations for the negative relation between Persistence and fragility: stock market booms and risk-taking by banks. Specifically, I show that Spillover Persistence declines at the onset of stock market booms, which are periods characterized by increasing imbalances in the financial system. Moreover, I document that banks and broker-dealers adapt more aggressive dividend policies and significantly increase their leverage and derivative exposure when Spillover Persistence declines. The negative correlation between risk-taking and Spillover Persistence is consistent with Brunnermeier and Sannikov (2014)'s volatility paradox: agents in their model more easily absorb shocks when exogenous volatility declines, which leads to lower Spillover Persistence but also encourages them to adapt more aggressive dividend policies and increase their leverage.

Finally, I provide empirical evidence that amplification of losses leads to higher Spillover Persistence. This occurs during crises compared to non-crises times and for insurers that have larger fire sale incentives compared to other insurers.

My framework bridges recent advances in macro-finance theory and the empirical analyses of risks in the financial system. Thereby, I explore a new and highly relevant dimension of systemic risk, persistence of loss spillovers, 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 guide policy.

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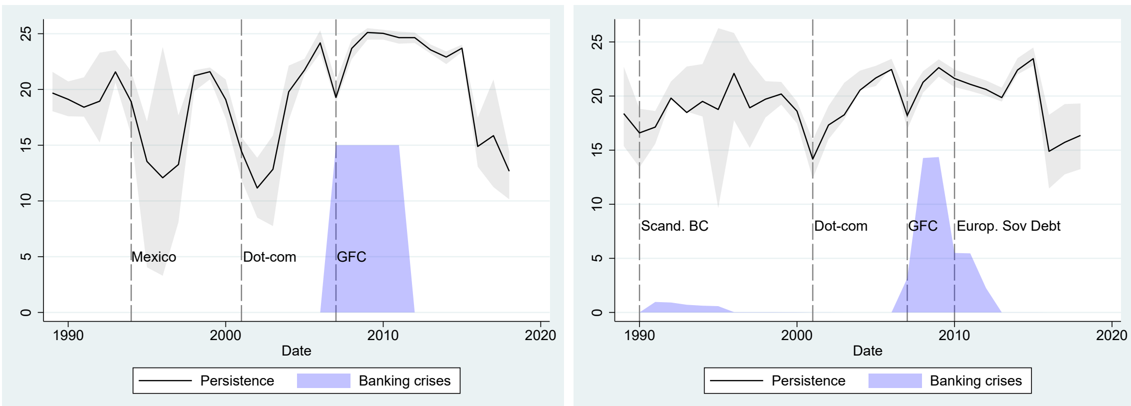
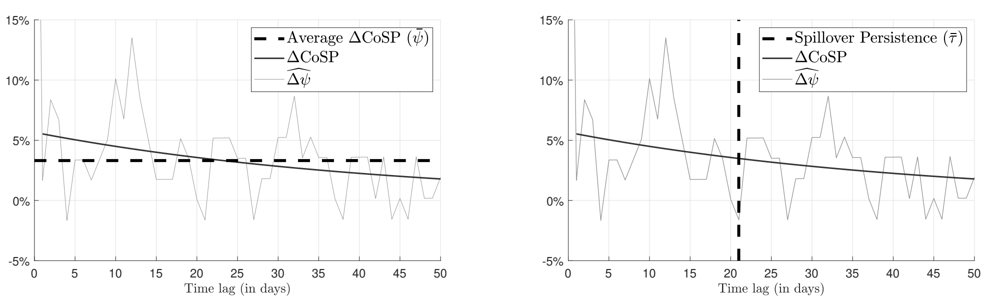
Figures and Tables

Figure 1. Spillover Persistence and crises.
The figures depict the annual average Spillover Persistence and 25th and 75th percentile across financial firms in (a) the US and (b) Europe, weighted by total assets. Banking crises from Laeven and Valencia (2018) 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 crises (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.

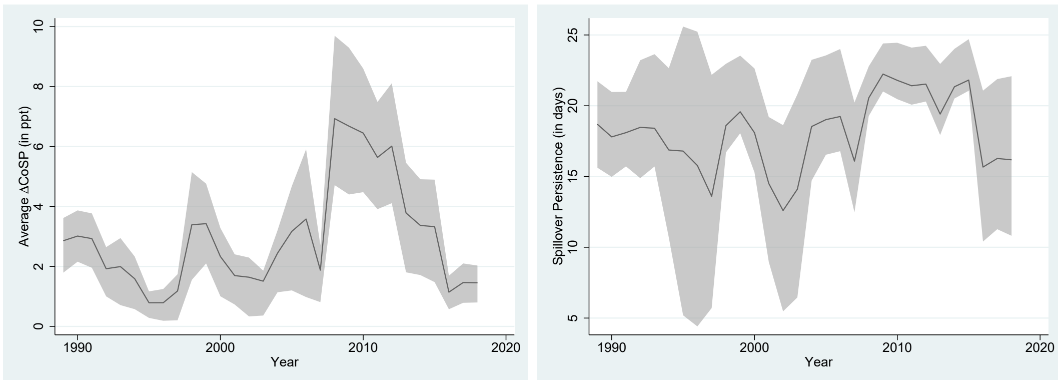
Figure 2. ΔCoSP, Average ΔCoSP, and Spillover Persistence for JP Morgan with respect to the financial system during 2003-2007.
The x-axis displays the number of days since large losses of JP Morgan. The estimation is based on daily equity returns for JP Morgan and equity returns of a value-weighted index of all other North American financial institutions as described in Section 3. $\Delta\text{CoSP}(\tau) = e^{\hat{\alpha}+\hat{\beta}\tau}$ is the estimated parametric model for $\Delta\psi$, while $\widehat{\Delta\psi}$ is a standard nonparametric estimate, described in Appendix A.



(a) CoSP and Average ΔCoSP ($\overline{\psi}_{2007} = 3.31\%$) (b) CoSP and Spillover Persistence ($\overline{\tau}_{2007} = 21$)

Figure 3. CoSP-measures: Evolution over time.

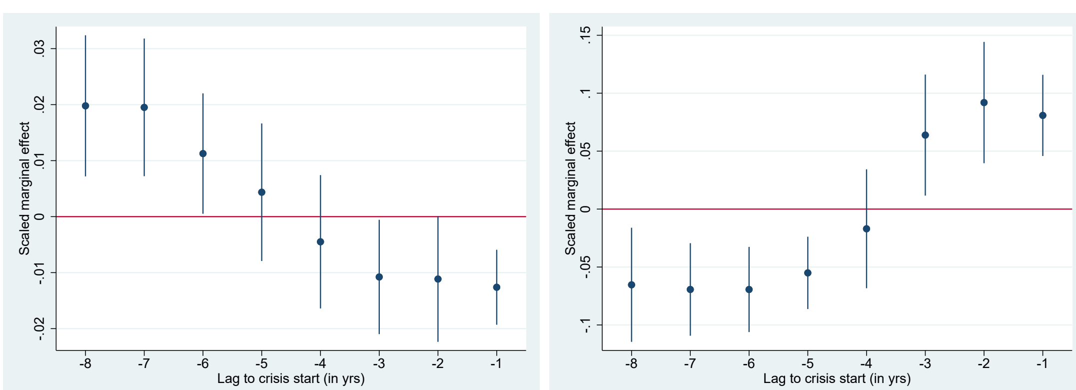
Figures depict the annual mean and interquantile range of Average ΔCoSP and Spillover Persistence across firms. Both measures are estimated based on daily equity market returns for 5-year rolling windows. *Year* corresponds to the end-year of the respective time window used for estimation.



(a) Average ΔCoSP. (b) Spillover Persistence.

Figure 4. Predicting crises at different time horizons.

The figures depicts the average marginal effect and 95% confidence interval of a 1-standard deviation increase in (a) Spillover Persistence and (b) Average ΔCoSP on the likelihood (in percentage points) of a crisis in x years, where the lag x between CoSP-measures and crisis start is on the x-axis. The effects are estimated using the model in Equation (6) by varying the time-lag between dependent variable relative to all independent variables. Standard errors are clustered at year, firm, and country-year levels.



(a) Spillover Persistence. (b) Average ΔCoSP.

Table 1. Systemic risk measures: descriptive statistics.

The table depicts descriptive statistics for Spillover Persistence and systemic risk measures at firm-year level. $\Delta\psi(0)$, Average ΔCoSP, and Spillover Persistence are estimated with daily equity return losses in 5-year rolling windows with end-years 1989 to 2018, ΔCoVaR is the yearly average of the weekly ΔCoVaR, which is estimated with weekly equity return losses using quantile regressions, and MES is based on daily equity return losses for a given year.

	N	Mean	Median	SD	Min	Max
$\Delta\psi(0)$ (in ppt)	13,880	21.43	19.26	15.86	-6.33	58.68
Average ΔCoSP ($\bar{\psi}$, in ppt)	13,697	3.30	2.49	2.81	0.00	10.94
Spillover Persistence ($\bar{\tau}$, in days)	13,697	18.56	20.59	7.36	0.00	31.97
ΔCoVaR (in ppt)	21,826	2.42	2.38	1.85	-1.86	7.51
MES (in ppt)	24,064	1.90	1.52	1.75	-0.93	8.58

Table 2. Spillover Persistence and macroeconomic and firm characteristics.
Average ΔCoSP and Spillover Persistence are estimated in 5-year windows, macroeconomic and firm characteristics are for the final year of the CoSP-estimation window. The omitted region in columns (2) and (3) is North America, and the omitted firm type in (2) - (4) is (commercial) bank. Columns (5) and (6) include only 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)	(7)	(8)
Dependent variable:	Spillover Persistence							
Sample:	All				Ban & Bro		All	
Crisis	3.025***			1.252	1.334*	2.680**	1.032***	1.060***
	(0.003)			(0.207)	(0.100)	(0.015)	(0.007)	(0.009)
GDP growth	-0.292***			-0.139*	-0.117	-0.103	-0.048	-0.056
	(0.009)			(0.071)	(0.290)	(0.415)	(0.362)	(0.248)
Investment growth	0.126*			0.059	0.012	0.017	0.052	0.031
	(0.059)			(0.277)	(0.852)	(0.800)	(0.134)	(0.256)
Credit growth	-0.094			0.167*	0.123	-0.012	0.038	0.029
	(0.151)			(0.054)	(0.142)	(0.921)	(0.383)	(0.426)
Inflation	0.029			-0.249	-0.033	0.278	-0.145	-0.025
	(0.912)			(0.218)	(0.910)	(0.313)	(0.348)	(0.837)
3M yield change	0.241							
	(0.261)							
Term spread change	0.024							
	(0.890)							
TED spread	0.012							
	(0.374)							
Market return	0.105							
	(0.908)							
Equity volatility	0.053							
	(0.961)							
log(Interest rate)	0.030							
	(0.935)							
Europe		-0.732*	-0.720*					
		(0.066)	(0.080)					
Japan		-2.486***	-2.676***					
		(0.009)	(0.002)					
Australia		-1.666*	-1.389					
		(0.068)	(0.128)					
Asia		-2.079***	-1.969***					
		(0.000)	(0.000)					
Broker-dealer		0.406	1.042***	1.433**				
		(0.137)	(0.001)	(0.016)				
Insurer		1.220***	1.362***	1.382***				
		(0.000)	(0.000)	(0.006)				
Real estate		0.120	0.859**	0.000				
		(0.685)	(0.024)	(1.000)				
Size			0.293***	0.440***	0.322*	0.776		
			(0.000)	(0.002)	(0.064)	(0.376)		
Leverage			-0.003	-0.016	-0.034	-0.042		
			(0.744)	(0.324)	(0.172)	(0.126)		
Market-to-Book			-0.021	0.027	0.020	0.517		
			(0.777)	(0.867)	(0.943)	(0.278)		
Dividends			0.001	0.015	0.288	-0.111		
			(0.977)	(0.867)	(0.435)	(0.788)		
SIFI				-0.487				
				(0.313)				
Liquidity Ratio					-0.116	-0.358		
					(0.282)	(0.201)		
Demand Deposits					2.847*	6.761*		
					(0.069)	(0.093)		
Time Deposits					-2.360	-1.846		
					(0.290)	(0.562)		
Loans					-0.593	0.593		
					(0.655)	(0.846)		
Impaired Loans					-7.732	-12.246		
					(0.356)	(0.451)		
Intangible Assets					0.358	-17.294		
					(0.946)	(0.114)		
ΔCoVaR							0.484***	-0.232***
							(0.000)	(0.009)
Firm risk							-0.148	-0.354***
							(0.209)	(0.000)
Firm equity illiq							-0.000**	-0.000**
							(0.026)	(0.015)
Average ΔCoSP								1.563***
								(0.000)
Year FE	No	Yes	Yes	No	No	No	No	No
Year× Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	No	Yes	No	No
No. of obs.	9,364	13,697	11,258	2,303	1,623	1,609	5,743	5,743
R^2	0.265	0.155	0.167	0.328	0.468	0.617	0.203	0.351
R^2 within	0.047	0.021	0.030	0.043	0.030	0.025	0.022	0.204

Table 3. Crises sample: descriptive statistics.
Based on firm-year level observations used to estimate the baseline model in Equation (6). Crises are identified on country-year level following Laeven and Valencia (2018). Variable descriptions are provided in Table B.1.

	N	Mean	Median	SD	Min	Max
Crisis	8,898	0.17	0.00	0.38	0.00	1.00
Output loss (in % of GDP)	8,897	5.04	0.00	12.35	0.00	93.20
Output loss (% of GDP, within crises)	1,577	23.02	25.30	17.15	0.00	93.20
Spillover Persistence (in days)	8,898	18.98	20.95	7.18	0.00	31.97
Average Δ CoSP (in ppt)	8,898	3.65	2.91	2.94	0.00	10.94
Δ CoVaR (in ppt)	8,879	3.15	3.09	1.60	-1.86	7.51

Table 4. Predicting crises.
Spillover Persistence and Average ΔCoSP are estimated in 5-year 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. Column (4) is for the subsample of observations with $\text{Crisis}_{t+1} = 1$. Variable definitions are provided in Table B.1. Standard errors are clustered at year, firm, and year-country levels. 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)
Dependent variable:		Crisis_{t+1}		Output loss_{t+1}
Sample:		All		$\text{Crisis}_{t+1} = 1$
$\text{Spillover Persistence}_t$	-0.002***	-0.002***	-0.002***	-0.010**
	(0.003)	(0.003)	(0.003)	(0.031)
Average ΔCoSP_t	0.027***	0.028***	0.030***	0.050**
	(0.001)	(0.001)	(0.000)	(0.017)
ΔCoVaR_t		-0.022**		
		(0.029)		
$\Delta\psi(0)_t$			-0.084	
			(0.250)	
Macro controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
Scaled coefficients				
$\text{Spillover Persistence}_t$	-.01	-.01	-.01	-.07
Average ΔCoSP_t	.08	.08	.09	.15
ΔCoVaR_t		-.03		
$\Delta\text{CoSP}(0)_t$			-.01	
No. of obs.	8,898	8,879	8,898	1,458
R^2	0.746	0.746	0.746	1.000
R^2 within	0.285	0.287	0.286	0.639

Table 5. Predicting crises: heterogeneity.

Spillover Persistence and Average ΔCoSP are estimated in 5-year windows, where the last year is t. Macro controls are inflation, GDP growth, investment growth, log(interest rate), and credit growth at t; additional macro controls are 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 firm and bank characteristics are de-meaned. The omitted firm type in columns (2) and (3) is (commercial) banks. Column (3) includes only firms that are part of BankFocus. Variable definitions are provided in Table B.1. Standard errors are clustered at year, firm, and year-country levels. ***, **, * indicate significance at the 1%, 5% and 10% levels respectively. P-values are in parentheses.

	(1)	(2)	(3)
Dependent variable:		Crisis_{t+1}	
Sample:	All		Ban & Bro
Spillover Persistence_t	-0.002***	-0.002***	-0.002
	(0.005)	(0.006)	(0.146)
Average ΔCoSP_t	0.026***	0.026***	0.013
	(0.001)	(0.001)	(0.100)
Spillover Persistence_t × Broker-dealer		0.002*	0.007
		(0.058)	(0.107)
Spillover Persistence_t × Insurer		0.001	
		(0.331)	
Spillover Persistence_t × Real estate		0.001	
		(0.426)	
Spillover Persistence_t × Size_{t-1}			-0.000
			(0.512)
Spillover Persistence_t × Leverage_{t-1}			-0.000
			(0.351)
Spillover Persistence_t × $\text{Market-to-Book}_{t-1}$			0.001
			(0.273)
Spillover Persistence_t × Liquidity ratio_{t-1}			-0.003
			(0.111)
Spillover Persistence_t × Demand deposits_{t-1}			-0.019**
			(0.013)
Spillover Persistence_t × Time deposits_{t-1}			0.005
			(0.372)
Spillover Persistence_t × Loans_{t-1}			-0.002
			(0.524)
Spillover Persistence_t × Impaired loans_{t-1}			0.087*
			(0.051)
Spillover Persistence_t × Intangible assets_{t-1}			0.047*
			(0.074)
Macro controls	Yes	Yes	Yes
Additional macro controls	Yes	Yes	No
Firm characteristics	Yes	Yes	Yes
Bank characteristics	No	No	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Standardized coefficients			
Spillover Persistence_t	-.01	-.02	-.01
Average ΔCoSP_t	.08	.08	.04
No. of obs.	8,486	8,486	1,560
R^2	0.745	0.745	0.868
R^2 within	0.279	0.279	0.287

Table 6. Predicting crises: country-level.
Based on country-year-level averages weighted by firms' total assets. I include countries once there are at least 15 firms present in the sample. Crises indicators and costs are based on Laeven and Valencia (2018). Spillover Persistence and Average ΔCoSP are estimated in 5-year windows, where the last year is t and corresponds to macroeconomic control variables. 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. Variable definitions are provided in Table B.1. Standard errors are clustered at year and country levels. 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)
Dependent variable:	$Crisis_{t+1}$		$Crisis_{t+2}$		Output $loss_{t+1}$
Spillover $Persistence_t$	-0.019**	-0.018*	-0.021*	-0.025**	-0.553*
	(0.050)	(0.052)	(0.063)	(0.045)	(0.066)
Average $\Delta CoSP_t$	0.054	0.054	0.076*	0.059	1.806
	(0.186)	(0.190)	(0.072)	(0.186)	(0.151)
$\Delta CoVaR_t$		-0.032	0.168		2.218
		(0.826)	(0.259)		(0.669)
$\Delta\psi(0)_t$				0.824	
				(0.382)	
Macro controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Scaled coefficients					
Spillover $Persistence_t$	-.08	-.08	-.09	-.1	-2.27
Average $\Delta CoSP_t$	.15	.15	.21	.17	5.06
$\Delta CoVaR_t$		-.04	.23		3.07
$\Delta\psi(0)_t$				.1	
No. of obs.	157	157	145	145	157
R^2	0.376	0.377	0.290	0.290	0.340
R^2 within	0.353	0.354	0.262	0.263	0.287

Table 7. Bubbles sample: descriptive statistics.
Based on firm-year observations. Bubble characteristics (boom and bust length, and burst distance) equal zero outside of bubbles. Bubbles are identified using the BSADF approach as described in Brunnermeier et al. (2020). Variable descriptions are provided in Table B.1.

	N	Mean	Median	SD	Min	Max
Boom (binary)	8,733	0.12	0.00	0.33	0.00	1.00
Bust (binary)	8,733	0.05	0.00	0.21	0.00	1.00
Boom length (in years, within bubbles)	1,480	2.13	1.67	1.63	0.00	5.33
Bust length (in years, within bubbles)	1,480	0.31	0.00	0.54	0.00	3.08
Burst dist (in years, within bubbles)	1,480	1.97	1.42	1.35	0.00	5.33
Spillover Persistence (in days)	8,733	19.22	21.24	7.15	0.00	31.97
Average ΔCoSP (in ppt)	8,733	3.85	3.21	2.99	0.00	10.94
Δ CoVaR (in ppt)	8,054	3.26	3.18	1.58	-1.86	7.51

Table 8. Spillover Persistence during bubbles.

Spillover Persistence and Average ΔCoSP are estimated in 5-year rolling windows, where the last year is (1-4) t or (5) $t+4$. 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. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro controls are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility; firm controls are size, leverage, dividends, and market-to-book ratio; bank controls are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets. All controls are for year $t-1$. Column (4) includes only 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 fraction of its standard deviations when the independent variable changes 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:		All		Ban & Bro	All
Boom$_t$	-3.550***	-3.217**	-2.231**	-2.226**	-2.627**
	(0.001)	(0.014)	(0.010)	(0.027)	(0.014)
Bust$_t$	-0.333		1.416	1.307	-1.735*
	(0.793)		(0.102)	(0.573)	(0.065)
Bubble$_t$		-0.333			
		(0.793)			
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No
Macro controls	Yes	Yes	Yes	Yes	Yes
Additional macro controls	No	No	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Bank controls	No	No	No	Yes	No
Boom & bust length	Yes	Yes	Yes	Yes	No
ΔCoVaR$_t$	No	No	Yes	Yes	No
Scaled coefficients					
Boom	-.5	-.45	-.31	-.31	-.39
Bust	-.05		.2	.18	-.25
No. of obs.	8,733	8,733	6,484	1,191	6,128
R^2	0.287	0.287	0.441	0.657	0.295
R^2 within	0.085	0.085	0.034	0.075	0.084

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

Spillover Persistence and Average ΔCoSP are estimated in 5-year 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 with no burst. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro controls are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility; firm controls are size, leverage, and market-to-book ratio; bank controls are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets. All controls are for year $t-1$. Column (4) includes only 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$_t$		
Sample:	Within Bubble	All		Ban & Bro
Boom × Burst Distance$_t$	-1.341*	-2.105***	-2.094***	-3.234***
	(0.069)	(0.001)	(0.002)	(0.000)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Macro controls	Yes	Yes	Yes	Yes
Additional macro controls	No	Yes	Yes	Yes
Firm controls	No	Yes	Yes	Yes
Bank controls	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$_t$	No	No	Yes	Yes
No. of obs.	1,235	5,308	5,295	1,022
R^2	0.473	0.368	0.386	0.625
R^2 within	0.140	0.165	0.191	0.535

Table 10. Risk-taking sample: descriptive statistics.

Based on firm-year observations in baseline regressions (1), (3), (4), and (6) in Table 11 for dividends, leverage, leverage (Ban & Bro), and CDS (Ban & Bro), respectively. "Ban & Bro" refers to the sample of firms included in BankFocus. Variable descriptions are provided in Table B.1.

	N	Mean	Median	SD	Min	Max
Spillover Persistence ($\bar{\tau}$, in days)	1,486	19.18	21.03	6.57	0.00	31.97
Average ΔCoSP ($\bar{\psi}$, in ppt)	1,486	4.18	3.31	3.23	0.00	10.94
Dividends	8,026	1.15	0.41	2.11	0.01	16.67
Leverage (Ban & Bro)	1,486	14.13	8.76	14.22	0.67	90.52
CDS (Ban & Bro)	608	0.23	0.00	0.67	0.00	3.85

Table 11. Spillover Persistence and risk-taking.

Dependent variables are cash dividends paid scaled by total assets, leverage, and CDS derivatives notional (CDS) in firm-year t. Average ΔCoSP and Spillover Persistence are estimated in 5-year windows, where the last year is $t-1$. Firm characteristics are size, leverage (except in columns (3-4)), market-to-book ratio, and cash flow as a share of total assets 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 controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises at $t-1$. All firm and bank characteristics are de-meaned. The omitted firm type in columns (2), (4), and (6) is (commercial) banks. Columns (2-6) include only 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:	Dividends$_t$		Leverage$_t$		CDS$_t$	
Sample:	All			Ban & Bro		
Spillover Persistence$_{t-1}$	-0.006*	0.001	-0.132**	-0.111*	-0.008*	-0.016**
	(0.087)	(0.819)	(0.026)	(0.074)	(0.079)	(0.015)
Average ΔCoSP$_{t-1}$	0.008	0.005	-0.005	-0.123	0.040	0.037
	(0.552)	(0.576)	(0.984)	(0.608)	(0.109)	(0.133)
Spillover Persistence$_{t-1}$ × Size$_{t-1}$		-0.002**		0.017		0.011***
		(0.044)		(0.398)		(0.004)
Spillover Persistence$_{t-1}$ × Leverage$_{t-1}$		0.000				-0.000
		(0.961)				(0.203)
Spillover Persistence$_{t-1}$ × Market-to-Book$_{t-1}$		-0.001		0.004		-0.017*
		(0.772)		(0.912)		(0.060)
Spillover Persistence$_{t-1}$ × Cash flow$_{t-1}$		0.011		-3.025**		-0.441
		(0.902)		(0.022)		(0.254)
Spillover Persistence$_{t-1}$ × Liquidity ratio$_{t-1}$		0.016**		0.106		0.031
		(0.049)		(0.302)		(0.188)
Spillover Persistence$_{t-1}$ × Demand deposits$_{t-1}$		-0.000		-0.366		0.024
		(0.948)		(0.153)		(0.263)
Spillover Persistence$_{t-1}$ × Time deposits$_{t-1}$		0.022*		0.145		0.039
		(0.068)		(0.693)		(0.182)
Spillover Persistence$_{t-1}$ × Loans$_{t-1}$		0.013		0.215		0.058
		(0.198)		(0.272)		(0.174)
Spillover Persistence$_{t-1}$ × Impaired loans$_{t-1}$		0.015		-7.209***		-1.806***
		(0.756)		(0.002)		(0.004)
Spillover Persistence$_{t-1}$ × Intangible assets$_{t-1}$		0.181		0.597		-0.084
		(0.288)		(0.529)		(0.582)
Spillover Persistence$_{t-1}$ × Broker-dealer		0.020		0.020		0.069*
		(0.197)		(0.865)		(0.077)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Bank characteristics	No	Yes	Yes	Yes	Yes	Yes
No. of obs.	8,026	1,457	1,486	1,486	608	608
R^2	0.772	0.675	0.837	0.842	0.861	0.883
R^2 within	0.002	0.085	0.092	0.121	0.181	0.309

Table 12. Spillover Persistence during and after crises.

Spillover Persistence is estimated in 5-year windows, were the final year is (1-2) t , (3-4) $t+1$, and (5) $t+2$. Macro controls 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 de-meaned. Columns (2-5) include only 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)
Dependent variable:	Spillover Persistence$_t$		Spillover Persistence$_{t+1}$		Spillover Persistence$_{t+2}$
Sample:	All	Ban & Bro			
Crisis$_t$	2.685***	4.320***	4.394***	4.248***	4.512***
	(0.009)	(0.009)	(0.002)	(0.000)	(0.004)
Crisis$_t$ × Size$_{t-1}$				-0.057	
				(0.854)	
Crisis$_t$ × Leverage$_{t-1}$				-0.026	
				(0.648)	
Crisis$_t$ × Market-to-Book$_{t-1}$				1.817*	
				(0.053)	
Crisis$_t$ × Cash flow$_{t-1}$				-2.136	
				(0.921)	
Crisis$_t$ × Liquidity ratio$_{t-1}$				0.153	
				(0.744)	
Crisis$_t$ × Demand deposits$_{t-1}$				-4.701	
				(0.133)	
Crisis$_t$ × Time deposits$_{t-1}$				-0.229	
				(0.962)	
Crisis$_t$ × Loans$_{t-1}$				5.436**	
				(0.041)	
Crisis$_t$ × Impaired loans$_{t-1}$				-97.501***	
				(0.004)	
Crisis$_t$ × Intangible assets$_{t-1}$				-4.719	
				(0.729)	
Crisis$_t$ × Broker-dealer				-1.704	
				(0.225)	
Firm FE	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes
Bank characteristics	No	Yes	Yes	Yes	Yes
No. of obs.	7,672	1,498	1,403	1,403	1,267
R^2	0.280	0.351	0.413	0.426	0.447
R^2 within	0.062	0.195	0.242	0.260	0.276

Table 13. Fire sales sample: descriptive statistics.

Firm-level observations for the monthly change in Spillover Persistence and Average ΔCoSP with respect to the banking system between August 22, 2005, and September 22, 2005. US P&C insurers are labeled as exposed if their ratio of premiums written in Louisiana and Mississippi in 2004 relative to that in all US states is among the 25% largest across all US P&C insurers.

	N	Mean	Median	SD	Min	Max
10 exposed US P&C insurers, 16 countries						
Δ_t Spillover Persistence ($\Delta_t \bar{\tau}_i$, in days)	64	0.78	0.34	2.88	-7.72	11.97
Δ_t Average ΔCoSP ($\Delta_t \bar{\psi}_i$, in ppt)	64	-0.05	0.00	0.63	-2.21	2.15

Table 14. Effect of hurricane Katrina on Spillover Persistence.
This table presents the results of triple difference-in-differences regressions of the effect of hurricane Katrina (August 23, 2005) on exposed US P&C (property & casualty) insurers. Following Girardi et al. (2020), Exposed = 1 if an insurer's ratio of premiums in Louisiana and Mississippi relative to that in all US states is in the upper quartile among US insurers. $\Delta_t \bar{\tau}$ and $\Delta_t \bar{\psi}$ are the monthly change in Spillover Persistence and Average ΔCoSP for the banking system from end-dates (1-3,5-6) August 22, 2005, to September 22, 2005, and (4) June 22, 2005, to July 22, 2005, estimated for (1-4) 18-months estimation window with 20-day maximum time lag, (5) 25-day maximum time lag, (6) 20-months estimation window with 25-day maximum time lag. The sample excludes insurers located outside of Northern America and Europe, and excludes reinsurers. Firms with SIC $\in [6300, 6400]\backslash\{6311\}$ (i.e., insurance carriers excluding agents, brokers, and life insurers) are classified as P&C insurers. Standard errors are clustered at country level. ***, **, * indicate significance at the 1%, 5% and 10% levels respectively. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			Δ_t Spillover Persistence ($\Delta_t \bar{\tau}$)			
Sample:		Baseline		Placebo	$\tau^{\max} = 25$	20M estimation
Exposed	0.836**	0.978***	0.861**	-1.133***	1.944***	0.913***
	(0.047)	(0.000)	(0.024)	(0.000)	(0.001)	(0.000)
$\Delta_t \bar{\psi}$			0.710			
			(0.375)			
Country FE	No	Yes	Yes	Yes	Yes	Yes
P&C FE	No	Yes	Yes	Yes	Yes	Yes
No. of obs.	64	58	58	68	55	52
R^2	0.011	0.348	0.365	0.294	0.222	0.238
R^2 within	0.011	0.018	0.043	0.038	0.037	0.012

Online Appendix

A Properties and estimation of CoSP

A.1 Estimation of CoSP

Denote by $D_t^I = \mathbb{1}_{\{r_t^I \leq VaR^I(q)\}}$ and $D_t^S = \mathbb{1}_{\{r_t^S \leq VaR^S(q)\}}$ binary random variables that signal the occurrence of a large loss of firm I and the system S, respectively, where the stationary distribution of $(r_t^x)_t$ satisfies $\mathbb{P}(r_t^s \leq VaR^x(q)) = q$ 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

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

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

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

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

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

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

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

where $Bin(n,p)$ is the Binomial distribution and the Value-at-Risk estimate is the nq^x-th (or

$[nq^x]+1$)-th) order statistic of r^x if nq^x is an integer (if it is not). I assume that $Y_1, Y_2, ..., Y_{\tau^{max}}$ are independently distributed, where $\tau^{max} < n - \tau$. Then, the log-likelihood function for observations $y_1, y_2, ...$ is given by

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

and the score functions as

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

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

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

I motivate the estimation framework in two ways: First, I additionally compute the standard nonparametric estimator for $r_{IS}(\tau)$, which implies that

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

is an estimator for $\Delta\psi(\tau)$. Note that $\widehat{\Delta\psi}(\tau)+q$ also equals the OLS estimator for the linear model[47]

$$\mathbb{1}_{\left\{r_{t+\tau}^S \leq \widehat{VaR}^S\right\}} = \psi \mathbb{1}_{\left\{r_t^I \leq \widehat{VaR}^I\right\}} + \varepsilon_t$$

if $q \cdot (n-\tau)$ is an integer. Otherwise, the equivalence holds asymptotically.

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 $\Delta\psi(\tau)$. Thus, even if time series properties deviate from the distributional assumptions made above for parametric estimation, the resulting estimates are appropriate.[48]

[47] The OLS estimate is $\frac{\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{r_t^I \leq \widehat{VaR}^I,\, r_{t+\tau}^S \leq \widehat{VaR}^S\right\}}}{\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{r_t^I \leq \widehat{VaR}^I\right\}}}$ and for integer $q \cdot (n-\tau)$ it is $\sum_{t=1}^{n-\tau} \mathbb{1}_{\left\{r_t^I \leq \widehat{VaR}^I\right\}} = q \cdot (n-\tau)$.

[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 distribution of $\delta_{i,t}$ shows that the median deviation is -0.03 percentage points, with the 5% and 95% percentile being -0.65 and 0.07 percentage points. The distribution of $\delta_{i,t}$ is also very stable over time. Thus, the parametric estimation framework does not induce a systematic bias compared to the nonparametric estimate.

Second, I motivate the parametric form for $\Delta\text{CoSP}(\tau)$ using an autoregressive model for large losses in the financial system, where a large loss of the firm persistently increases 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:

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

where $a, b, c > 0$, and let D_t^I and D_τ^I be independently distributed for all $t \neq \tau$. Since $\mathbb{E}[D_t^I] = q$, it is

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

The conditional probability of the stationary distribution is,

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

Iteration yields

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

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

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

and

$$\mathbb{P}(D^S_{t+\tau} = 1 \mid D^I_t = 1) = e^{\tau \log(c)} \underbrace{\left(e^{\log(b)-\log(c)} - e^{\log(\frac{bq}{1-c})-\log(c)} + \left(q - \frac{a}{1-c}\right)\right)}_{=:\gamma} + \frac{bq+a}{1-c} \tag{17}$$

$$= e^{\tau \log(c) + \log(\gamma)} + q, \tag{18}$$

where in the last step I use Equation (10), which implies that

$$\frac{bq+a}{1-c} = q\frac{b+1-b-c}{1-c} = q\frac{1-c}{1-c} = q. \tag{19}$$

Therefore, $\mathbb{P}(D^S_{t+\tau} = 1 \mid D^I_t = 1) = q + \Delta\psi(\tau) = q + e^{\alpha+\beta\tau}$ for $\alpha = \log(\gamma)$ and $\beta = \log(c)$. Importantly, note that $\beta = \log(c) < 0$ since the model is well-defined only for $c < 1$.

A.2 Estimation of Average Excess CoSP

I employ the estimated parametric form of $\Delta\text{CoSP}(\tau)$ for lags $\tau \geq 1$ to estimate Average Excess CoSP. For the sake of a small estimation error, I use a finite upper bound for the time lag, $\tau^{\max}$. Then, the estimator for Average Excess CoSP is given by

$$\bar{\psi} = \frac{1}{\tau^{\max}-1}\int_1^{\tau^{\max}} \Delta\text{CoSP}(\tau)\, d\tau. \tag{20}$$

First, note that

$$\int \Delta\text{CoSP}(\tau)\, d\tau = \int e^{\alpha+\beta\tau}\, d\tau = \frac{1}{\beta}e^{\alpha+\beta\tau}, \tag{21}$$

thus,

$$\int_1^{\tau^{\max}} e^{\alpha+\beta\tau}\, d\tau = \frac{1}{\beta}\left(e^{\alpha+\beta\tau^{\max}} - e^{\alpha+\beta}\right) \tag{22}$$

and

$$\overline{\psi} = \frac{1}{\tau^{\max}-1}\frac{1}{\beta}\left(e^{\alpha+\beta\tau^{\max}} - e^{\alpha+\beta}\right). \tag{23}$$

A.3 Estimation of Spillover Persistence

I employ the estimated parametric form of $\Delta\text{CoSP}(\tau)$ for lags $\tau \geq 1$ to estimate Spillover Persistence. For the sake of a small estimation error, I use a finite upper bound for the time lag, $\tau^{\max}$. Then, the estimator for Spillover Persistence is given by

$$\bar{\tau} = \frac{1}{\bar{\psi}(\tau^{\max} - 1)} \int_{1}^{\tau^{\max}} \tau \cdot \Delta\text{CoSP}(\tau)\, d\tau. \tag{24}$$

We have that

$$\int \tau \cdot \Delta\text{CoSP}(\tau)\, d\tau = \int \tau \cdot e^{\alpha+\beta\tau}\, d\tau = \left(\frac{\tau}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta\tau}, \tag{25}$$

thus,

$$\overline{\tau} = \frac{1}{\bar{\psi}(\tau^{\max} - 1)} \left(\left(\frac{\tau^{\max}}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta\tau^{\max}} - \left(\frac{1}{\beta} - \frac{1}{\beta^2}\right) e^{\alpha+\beta} \right). \tag{26}$$

B Empirical methodology and additional data descriptives

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

The correlation between a firm's and system's equity returns is biased upward if the system's index includes the firm. This endogeneity bias might also affect 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 we denote a firm I's unpadded and unadjusted price 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:

$$INDEX_t^{S|I} = INDEX_{t-1}^{S|I} \sum_{s \in S \setminus \{I\}} \frac{MC_{t-1}^s}{\sum_{j \in S \setminus \{I\}} MC_{t-1}^j} \frac{P_t^s N_t^s}{P_{t-1}^s N_{t-1}^s}, \tag{27}$$

where $INDEX_{t_0}^{S|I} = 1$ for some starting date t_0. The system's equity return is then computed as the index' log-return,[49]

$$r_t^S = r_t^{S|I} = \log\left(\frac{INDEX_t^{S|I}}{INDEX_{t-1}^{S|I}}\right) \tag{28}$$

and the firm's equity return is

$$r_t^I = \log\left(\frac{P_t^I N_t^I}{P_{t-1}^I N_{t-1}^I}\right). \tag{29}$$

The input to systemic risk measures for firm I and system S is then $(r_t^I, r_t^S)_{t=t_0,\ldots}$.

B.2 Data and descriptive statistics

B.2.1 Variable definitions.

Table B.1. Variable definitions and data sources. All macroeconomic variables are on daily frequency. All firm and bank characteristics are on yearly frequency and winsorized at 1%/99%.

Variable name	**Description**
Systemic risk measure inputs	
Unadjusted & unpadded equity price	Daily price of common equity. *Source*: Thomson Reuters Datastream
Number of outstanding shares	Daily number of outstanding shares of common equity. *Source*: Thomson Reuters Datastream
Market value	Daily market value in USD. *Source*: Thomson Reuters Datastream
Non-financial sector indices	Daily total return index of non-financial sector indices, described in Section 3. *Source*: Thomson Reuters Datastream
Risk measures	
ΔCoSP ($\Delta\psi(\tau)$)	Likelihood of system losses τ days after firm losses in excess of reference level $q = 0.05$.
$\Delta\psi(0)$	Likelihood of simultaneous systemic and firm losses in excess

[49] We use log-returns due to their desirable distributional properties.

	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 a 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 variables	
Inflation	Δlog(Consumer Price Index); annual rate, country-level. *Source*: BIS.
GDP growth	Δlog(real GDP); annual rate, country-level. *Source*: OECD.
Investment growth	Δlog(investment/GDP); annual rate, country-level. *Source*: OECD.
Credit growth	Δlog(credit/GDP); annual rate, country-level. *Source*: BIS.
Crisis	Indicator for the occurrence of banking crises. *Source*: Laeven and Valencia (2018).
Output loss	3-year cumulative deviation from GDP trend associated with banking crises. *Source*: Laeven and Valencia (2018).
log(interest rate)	log(10-year interest rate); annual average of weekly rate, continent-level. *Source*: see Table B.2.
3M yield change	Weekly change in 3-month government bond rates; average per year. *Source*: see Table B.2.
Term spread change of the yield curve	Weekly change in yield spread between 10-year and 3-month government bond rates; average per year. *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; average per year. *Source*: see Table B.2.
Market return	Weekly market return of system-specific MSCI indices; average per year. *Source*: see Table B.2.
Equity volatility	22-day rolling window market return of system-specific MSCI indices; average per year. *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.
Firm characteristics (*Source: Worldscope if not stated otherwise.*)	
Size	log(total assets)
Leverage	Total assets / market value
Market-to-book	Ratio of market value to book value of equity

Dividends	Total cash dividends paid relative to total assets
Cash flow	Sum of net income and non-cash charges or credits relative to total assets
SIFI	Indicator for whether firm is marked as globally systemically important bank (G-SIB) or insurer (G-SII) in a given year. *Source:* `https://www.fsb.org/`.
Bank characteristics (*Source: BankFocus if not stated otherwise*)	
Size	log(total assets)
Leverage	Total assets / market value *Source*: Bank Focus (Total assets) and Worldscope (Market value).
Demand deposits	Customer deposits that can be withdrawn immediately without notice or penalty, scaled by total assets
Time deposits	(Time + Savings deposits)/Total assets. Interest-bearing customer deposits with specified withdrawal date or conditionals
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 CDS notional / Total assets

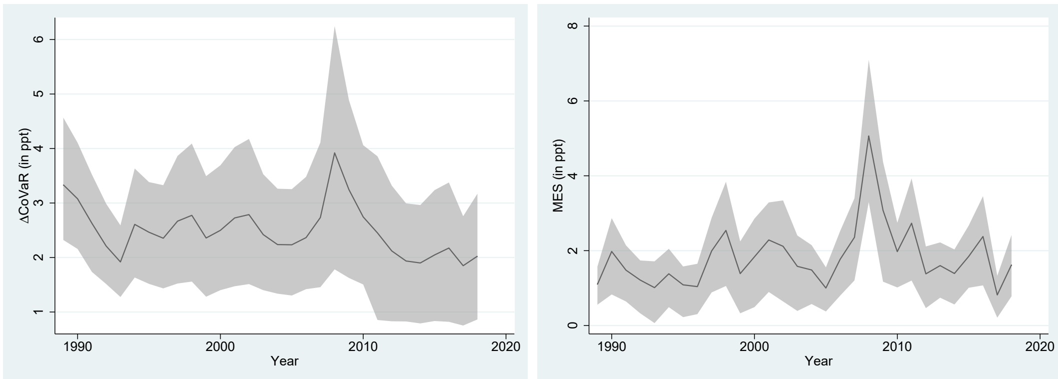
Table B.2. Macroeconomic state variables and data sources.

The table depicts the state variables used in the multi-country setting in this paper 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.

Figure B.1. Contemporaneous systemic risk measures: Evolution over time.
Figures depict the annual mean and interquantile range across firms of systemic risk measures with respect to the financial system over time. All measures are estimated based on equity market returns.



(a) ΔCoVaR (b) MES

Table B.3. Correlation of systemic risk measures.
This table depicts the correlation coefficient between systemic risk measures with respect to the financial system based on firm-year level observations from 1985 to 2018.

	Average ΔCoSP	Spillover Persistence	ΔCoVaR	MES
Average ΔCoSP	1			
Spillover Persistence	0.507***	1		
ΔCoVaR	0.304***	0.0869***	1	
MES	0.427***	0.0884***	0.489***	1

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

Table B.4. Decomposition of variation in Spillover Persistence.
The table depicts the standard deviation of residuals and 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) Baseline	(2) Firm FE	(3) Year FE	(4) Year× Continent FE	(5) Year × Continent & Firm FE
SD(Residuals)	7.36	6.48	6.84	6.49	5.65
R^2		0.22	0.14	0.22	0.41

B.2.3 Firm characteristics. I consider several firm-level variables that have been shown to be relevant for systemic risk, namely firm size (the logarithm of total assets), the ratio of market to book value, leverage (the ratio of total assets to the market value of equity), dividends and cash flow (both relative to total assets). Annual data for these variables are from Thomson Reuters Worldscope. I consider all firms for which I have estimated systemic risk measures, which results in a sample of firm-level data including (in total) 1,220 firms and ranging from 1984 to 2018. I winsorize observations for each variable at the 1% and 99% levels.

The median firm has total assets of roughly 6.4 billion USD, while firm size varies greatly (Table B.5). The median firm's market valuation is slightly larger than its book equity (by 23%), while there are many firms with much lower as well as much larger equity valuation in the sample. The median firm's leverage is 5.6, again with wide variation.

Table B.5. Firm-level characteristics: descriptive statistics
Based on firm-year observations after matching with the sample of systemic risk measures. *Source*: Bank Focus, own calculations.

	N	Mean	Median	SD	Min	Max
Total Assets (bn USD)	24,030	62.42	6.39	177.92	0.00	1,189.49
Market-to-Book	23,846	1.69	1.23	1.66	-1.13	11.60
Leverage	21,710	11.50	5.58	16.93	0.20	109.93
Dividends	19,506	1.35	0.45	2.40	0.01	16.67
Cash flow	19,194	0.04	0.02	0.06	-0.08	0.34
SIFI	6,824	0.04	0.00	0.18	0.00	1.00
Total Assets (banks; bn USD)	5,552	165.79	33.05	385.82	0.21	2,233.17
Leverage (banks)	5,305	15.55	10.25	15.79	0.67	90.52
Time Deposits (banks)	4,352	0.26	0.25	0.17	0.00	0.69
Demand Deposits (banks)	4,359	0.21	0.17	0.16	0.00	0.73
Loans (banks)	5,139	0.56	0.60	0.20	0.02	0.92
Impaired Loans (banks)	4,865	0.02	0.01	0.03	0.00	0.23
Intangible Assets (banks)	5,156	0.02	0.01	0.04	0.00	0.26
Liquidity Ratio (banks)	4,864	0.90	0.34	2.93	0.03	26.18
CDS (banks)	1,016	0.19	0.00	0.61	0.00	3.85

Additionally, I zoom in on the role of banks (including broker-dealers). For this purpose, I retrieve detailed bank-level data from 1990 to 2018 for all banks featured in both Moody's Analytics Bank Focus 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.[50] For additional analyses on bank risk-taking, I also retrieve data on banks' CDS exposure, which is the

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

CDS notional as a share of total assets. To ensure consistency in accounting, I use total assets from Bank Focus as a scaling factor for all bank-related variables and also re-calculate my measures for size and leverage for banks using Bank Focus in all regressions that are only using the sample of firms included in Bank Focus. I winsorize all variables at the 1% and 99% levels.

The median bank/broker-dealer in this sample has total assets of roughly 33 billion USD and a leverage of 10.3. It is thus substantially larger and more highly levered than the median firm in the broader sample that also covers non-banks. There is a wide range in the liquidity ratio. The median bank offers more time deposits (25% of total assets) than demand deposits (17% of total assets), while more than half of its assets are loans (60%). The amount of impaired loans and intangible assets are both relatively small (roughly 1% of total assets), but with wide variation.

B.2.4 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 10-year government bond yield (at region level). Table B.6 provides the summary statistics.

Table B.6. Macroeconomic characteristics: Descriptive statistics
The table depicts descriptive statistics for macroeconomic characteristics based on country-year observations from 1984 to 2018. *Sources*: OECD, BIS, St. Louis FRED, Thomson Reuters Datastream, Laeven and Valencia (2018), own calculations.

	N	Mean	Median	SD	Min	Max
Inflation (in ppt)	1,459	5.85	2.58	16.19	-0.13	278.72
Credit growth (in ppt)	1,166	2.04	1.72	6.13	-28.04	57.22
GDP growth (in ppt)	1,216	5.35	5.15	3.98	-25.08	31.12
Investment growth (in ppt)	1,214	-0.14	0.28	8.12	-132.01	77.68
log(interest rate)	1,299	1.37	1.67	1.01	-2.81	2.63
Crisis	1,210	0.12	0.00	0.32	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 yields, weekly changes in the slope of the yield curve (10-year and 3-month government bond yield spread), the TED spread (3-month interbank and government bond yield spread), weekly changes in credit spreads (between Moody's

Baa-rated bonds and the 10-year government bond yield), 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).[51] I winsorize at 1% and 99% and find wide variation in all 6 macroeconomic variables, as Table B.7 shows.

Table B.7. Additional region-level macro characteristics: Descriptive statistics
The table depicts descriptive statistics for macroeconomic characteristics based on continent-year observations (3-month yield change, term spread change, TED spread, credit spread change (all previous in bps), market return, and equity volatility) from 1985 to 2018. Geographical areas are Europe, North America, Asia, Japan, and Australia for each of which Table B.2 describes the data sources for macroeconomic variables. *Sources*: St. Louis FRED, Thomson Reuters Datastream, own calculations.

	N	Mean	Median	SD	Min	Max
3M yield change (in bps)	108	-0.36	-0.04	2.24	-10.73	6.95
Term spread change (in bps)	108	-0.07	-0.28	2.52	-7.47	14.93
TED spread (in bps)	97	30.93	20.50	33.42	-35.78	154.67
Credit spread change (in bps)	152	0.10	-0.06	2.06	-7.27	6.69
Market return (in ppt)	163	0.15	0.22	0.43	-1.41	1.24
Equity volatility (in ppt)	163	1.06	0.98	0.42	0.32	2.91

[51] 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 in the Online Appendix.

C Additional empirical results and robustness

C.1 Crises

Table C.1. Predicting crises: robustness.

Spillover Persistence and Average ΔCoSP are estimated in 5-year windows, where the last year is t and corresponds to macroeconomic control variables. 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. Variable definitions are provided in Table B.1. Standard errors are clustered at year, firm, and year-country levels. 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)	(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$_t$	-0.002*	-0.002**	-0.002***	-0.002***	-0.001**	-0.037**	-0.007*
	(0.073)	(0.016)	(0.001)	(0.005)	(0.024)	(0.039)	(0.073)
Average ΔCoSP$_t$	0.028***	0.028***	0.023***	0.028***	0.021***	0.716***	0.140**
	(0.002)	(0.000)	(0.001)	(0.000)	(0.004)	(0.006)	(0.017)
ΔCoVaR$_t$	0.013	-0.005			-0.019**	-0.406	-0.126*
	(0.341)	(0.677)			(0.012)	(0.126)	(0.059)
Boom$_t$			-0.044				
			(0.541)				
Bust$_t$			-0.130**				
			(0.038)				
MES$_t$				0.000			
				(0.990)			
Crisis$_t$					0.418***		
					(0.009)		
Output loss$_t$						0.530***	
						(0.001)	
Fiscal cost$_t$							0.585***
							(0.001)
Macro controls	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
Scaled coefficients							
Spillover Persistence$_t$	-.01	-.01	-.01	-.01	-.01	-.27	-.05
Average ΔCoSP$_t$	.08	.08	.07	.08	.06	2.11	.41
ΔCoVaR$_t$	.02	-.01			-.03	-.65	-.2
MES$_t$				0			
No. of obs.	8,268	8,268	7,522	8,889	8,879	8,877	8,879
R^2	0.638	0.713	0.769	0.745	0.797	0.795	0.747
R^2 within	0.295	0.306	0.338	0.285	0.432	0.544	0.482

C.2 Bubbles

Table C.2. Robustness: Spillover Persistence during bubbles, controlling for lagged Spillover Persistence.

Spillover Persistence and Average ΔCoSP are estimated in 5-year rolling windows, where the last year is (1-4) t or (5) $t+4$. 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. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro controls are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility; firm controls are size, leverage, dividends, and market-to-book ratio; bank controls are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets. All controls are for year $t-1$. Column (3) includes only 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 fraction of its standard deviations when the independent variable changes 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:	All		Ban & Bro	All
Boom$_t$	-2.884***	-1.553**	-1.363***	-2.382***
	(0.001)	(0.031)	(0.005)	(0.002)
Bust$_t$	-1.719	0.423	0.881	-0.183
	(0.231)	(0.585)	(0.548)	(0.779)
1-year lagged dep. var.	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
Macro controls	Yes	Yes	Yes	Yes
Additional macro controls	No	Yes	Yes	Yes
Firm controls	No	Yes	No	Yes
Bank controls	No	No	Yes	No
Boom & bust length	Yes	Yes	Yes	No
ΔCoVaR$_t$	No	Yes	Yes	No
Scaled coefficients				
Boom	-.4	-.22	-.19	-.35
Bust	-.24	.06	.12	-.03
No. of obs.	7,585	5,758	1,103	5,767
R^2	0.456	0.555	0.723	0.460
R^2 within	0.303	0.215	0.223	0.316

Table C.3. Robustness: Spillover Persistence and distance to the bubble burst, controlling for lagged Spillover Persistence.

Spillover Persistence and Average ΔCoSP are estimated in 5-year 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 with no burst. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and banking crises; additional macro controls are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility; firm controls are size, leverage, and market-to-book ratio; bank controls are liquidity ratio, and demand deposits, time deposits, loans, impaired loans, and intangible assets as a share of total assets. All controls are for year $t-1$. Column (4) includes only 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$_t$			
Sample:	Within Bubble	All		Ban & Bro
Boom × Burst Distance$_t$	-1.558**	-1.619***	-1.607***	-2.753***
	(0.030)	(0.000)	(0.001)	(0.000)
1-year lagged dep. var.	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Macro controls	Yes	Yes	Yes	Yes
Additional macro controls	No	Yes	Yes	Yes
Firm controls	No	Yes	Yes	Yes
Bank controls	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$_t$	No	No	Yes	Yes
No. of obs.	1,060	4,650	4,640	936
R^2	0.498	0.500	0.509	0.682
R^2 within	0.172	0.337	0.350	0.620

C.3 Amplification during crises

Table C.4. Robustness: Spillover Persistence during and after crises, controlling for lagged Spillover Persistence.

Spillover Persistence is estimated in 5-year windows, were the final year is (1-2) t , (3-4) $t+1$, and (5) $t+2$. Macro controls 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 de-meaned. Columns (2-5) include only 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$_t$	Spillover Persistence$_{t+1}$		Spillover Persistence$_{t+2}$
Sample:	All	Ban & Bro		
Crisis$_t$	1.610*	2.767**	2.671***	2.160*
	(0.072)	(0.034)	(0.007)	(0.092)
Crisis$_t$ × Size$_{t-1}$			0.226	
			(0.262)	
Crisis$_t$ × Leverage$_{t-1}$			-0.049	
			(0.279)	
Crisis$_t$ × Market-to-Book$_{t-1}$			2.124***	
			(0.006)	
Crisis$_t$ × Cash flow$_{t-1}$			-15.237	
			(0.446)	
Crisis$_t$ × Liquidity ratio$_{t-1}$			-0.173	
			(0.676)	
Crisis$_t$ × Demand deposits$_{t-1}$			-3.176	
			(0.222)	
Crisis$_t$ × Time deposits$_{t-1}$			0.484	
			(0.894)	
Crisis$_t$ × Loans$_{t-1}$			6.189***	
			(0.001)	
Crisis$_t$ × Impaired loans$_{t-1}$			-92.874***	
			(0.004)	
Crisis$_t$ × Intangible assets$_{t-1}$			15.332	
			(0.217)	
Crisis$_t$ × Broker-dealer			-0.994	
			(0.527)	
1-year lagged dep. var.	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Bank controls	No	Yes	Yes	Yes
No. of obs.	6,839	1,307	1,307	1,211
R^2	0.439	0.518	0.535	0.537
R^2 within	0.282	0.396	0.417	0.418

C.4 Liquidity and auto-serial correlation

Firm specific daily turnover by value (VA) and volume (VO) comes from Thomson Reuters Datastream. 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))

$$ILLIQ_t = \frac{1}{n_t}\sum_{i=1}^{n_t}\frac{|r_{t,i}|}{VA_{t,i}}, \tag{30}$$

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. For both, turnover by volume and $ILLIQ_t$, I use the same 5-year time periods used to estimate Spillover Persistence. To calculate the turnover by volume of a system, I use the average daily turnover volume per firm. The Amihud measure for a system is similarly based on the system's (value-weighted) return and average daily turnover by value. Finally, I account for outliers by winsorizing at 1% and 99%, and take yearly averages of both measures.

Table C.5. CoSP and financial market liquidity.
Average ΔCoSP and Spillover Persistence are estimated in 5-year windows, firm (and system) turnover corresponds 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 level. ***, **, * 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)	0.101	0.063			0.203***	0.255***		
	(0.114)	(0.709)			(0.000)	(0.000)		
log(System turnover)	0.200	0.267			0.034	-0.028		
	(0.121)	(0.497)			(0.554)	(0.826)		
Firm ILLIQ			-0.000***	-0.000**			-0.000*	-0.000*
			(0.003)	(0.037)			(0.082)	(0.077)
System ILLIQ			-0.309	-0.498***			0.050	0.175
			(0.401)	(0.003)			(0.865)	(0.257)
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	13,499	13,397	7,866	7,792	13,499	13,397	7,866	7,792
R^2	0.004	0.351	0.005	0.413	0.037	0.718	0.001	0.703
R^2 within	0.004	0.000	0.005	0.004	0.037	0.010	0.001	0.002

To examine the impact of auto-serial correlation in equity prices on CoSP-measures, I estimate the autocorrelation function of the system's index return for each estimation window. Then, I regress CoSP-measures on the average auto-serial correlation coefficient across lags 1 to 10 days. Table C.6 reports the estimates.

Table C.6. CoSP and auto-serial correlation in the system.

Average ΔCoSP and Spillover Persistence are estimated in 5-year windows. $ACF_{1:10}$ is the system's autocorrelation, which corresponds to the average (across lags) auto-serial correlation 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	
$ACF_{1:10}$	-65.833***	13.285	-63.154***	-12.252
	(0.000)	(0.675)	(0.000)	(0.212)
Time FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
No. of obs.	13,697	13,595	13,697	13,595
R^2	0.020	0.347	0.128	0.712
R^2 within	0.020	0.000	0.128	0.002

Finally, I examine the effect of predictable variation in the system's equity returns on my results. If an omitted variable today causes both the system and firm to suffer losses today and in the future, removing predictable variation from the system's returns takes away its effect on Spillover Persistence. For this purpose, I first estimate an AR(1) model for the system's index return loss and then estimate CoSP and CoSP-measures based on the system's AR(1)-residuals and the firm's actual equity return loss, a process called "pre-whitening". Table C.7 reports the estimates for baseline regressions using pre-whitened Average ΔCoSP and Spillover Persistence. I find that all baseline results remain to hold.

Table C.7. Robustness: Baseline results with pre-whitened Spillover Persistence.
Pre-whited CoSP is computed based on a firm's equity return loss and the AR(1)-residuals of the system's equity return loss. In (1-7) Spillover Persistence and Average Δ CoSP are estimated in 5-year rolling windows, where the last year in the estimation window is (1-2, 5-7) t and (3-4) $t-1$. In (8) $\Delta_t$pre-wtd $\bar{\tau}$ is the change in pre-whitened Spillover Persistence from end-dates August 22, 2005, to September 22, 2005, estimated for 18-month rolling windows. The definition of bubble indicators, crises, and hurricane exposure is as in the baseline regressions. Macro controls are inflation, GDP growth, investment growth, log(interest rate), credit growth, and (only in (3-7)) banking crises. Additional macro controls are short-term yield change, term spread change, TED spread, credit spread change, equity market average return and volatility. Firm controls are size, leverage (except for (4)), market-to-book ratio, and (3-4) cash flow or (6-7) dividends. Variable definitions are provided in Table B.1. Standard errors are clustered at (1-2) firm, year, and country-year level, (3-7) firm and country-year level, and (8) country level . ***, **, * 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		Risk-taking		Bubbles		Fire sales
Dep. variable:	Crisis$_{t+1}$		Output loss$_{t+1}$	Leverage$_t$		Pre-wtd Spillover Persistence$_t$		$\Delta_t$pre-wtd $\bar{\tau}$
Sample:	Firms	Countries	Firms & Crisis$_{t+1}=1$	Ban & Bro		All		Insurers
Pre-wtd $\bar{\tau}_t$	-0.001*	-0.022**	-0.008**					
	(0.058)	(0.043)	(0.047)					
Pre-wtd $\bar{\psi}_t$	0.027***	0.055	0.053**					
	(0.001)	(0.222)	(0.019)					
Pre-wtd $\bar{\tau}_{t-1}$				-0.102**				
				(0.036)				
Pre-wtd $\bar{\psi}_{t-1}$				0.066				
				(0.693)				
ΔCoVaR$_t$								
Boom$_t$					-3.422***	-2.062**	4.923*	
					(0.002)	(0.021)	(0.093)	
Bust$_t$					0.112	2.536	2.558	
					(0.920)	(0.281)	(0.395)	
Boom $\times$ Burst Distance$_t$							-3.551***	
							(0.000)	
Exposed								0.915***
								(0.003)
ΔCoVaR$_t$						-0.068	-0.776*	
						(0.823)	(0.083)	
Firm FE	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Country FE	No	Yes	No	No	No	No	No	Yes
Year FE	Yes	No	No	Yes	No	Yes	No	No
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Add. macro controls	Yes	Yes	Yes	No	No	Yes	Yes	No
Firm controls	No	No	No	Yes	No	Yes	Yes	No
Bank controls	No	No	No	Yes	No	Yes	Yes	No
Boom & bust length	No	No	No	No	Yes	Yes	No	No
Boom & bust-years	No	No	No	No	No	No	Yes	No
P&C FE	No	No	No	No	No	No	No	Yes
No. of obs.	8,912	157	1,461	1,498	8,750	1,192	1,025	56
R^2	0.746	0.380	1.000	0.831	0.288	0.649	0.601	0.292
R^2 within	0.287	0.357	0.640	0.102	0.086	0.065	0.510	0.012