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Survivorship Bias in Systemic Risk Estimation

By *Alexandros Skouralis*

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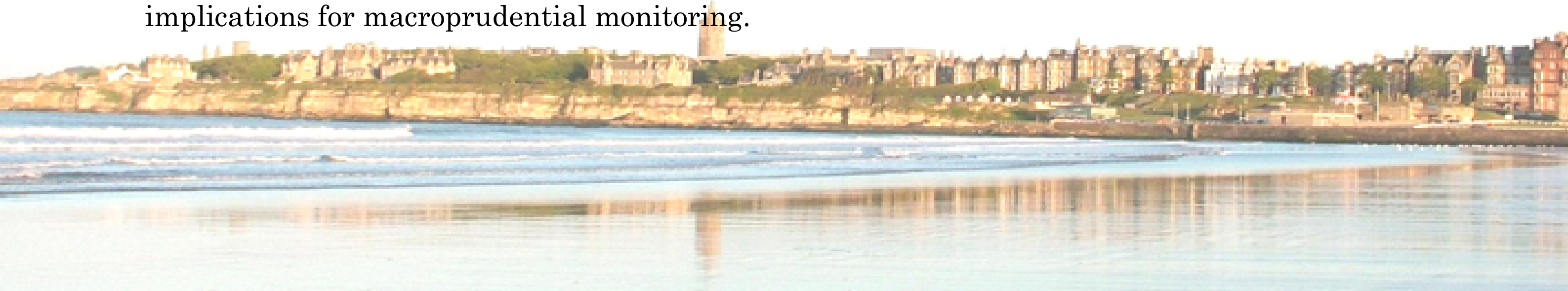
WP Nº 26-016

2nd Quarter 2026



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February 20, 2026

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Keywords: *Systemic risk; Survivorship bias; Sample Selection Bias; Delisted Financial Institutions; Macroprudential Policy; Financial Stability*

JEL classifications: G01; G20; G21; G28; G32

Acknowledgments: I am grateful to João Rafael Cunha and Giovanni Urga for their detailed and constructive feedback. I also thank all participants of the 6th Conference on Contemporary Issues in Banking at the University of St Andrews for helpful comments and discussions.

Data Availability: The data underlying this article are acquired under licence by Refinitiv Datastream and are available through institutional subscriptions. The ownership rights remain with the respective data provider.

1. Introduction

The concept of systemic risk has risen to the forefront of macroprudential analysis following the global financial crisis (GFC) of 2007-2009, which revealed how interconnectedness, maturity mismatches, and liquidity spirals can propagate idiosyncratic shocks into major systemic events (Brunnermeier, 2009; Allen and Carletti, 2013; Acemoglu et al., 2015). In the aftermath of the GFC, systemic risk became central to financial regulation, prompting the development of forward-looking measures designed to monitor institutions whose distress could trigger broader instability and to guide timely macroprudential interventions during crisis periods (Zhang et al., 2015; Liang, 2013; Acharya et al., 2025). Prominent firm-level measures, including ΔCoVaR (Adrian and Brunnermeier, 2016), MES (Acharya et al., 2017), and SRISK (Brownlees and Engle, 2017), are now widely used to assess institutions' contributions to, and exposures to, aggregate financial instability and to inform macroprudential monitoring.

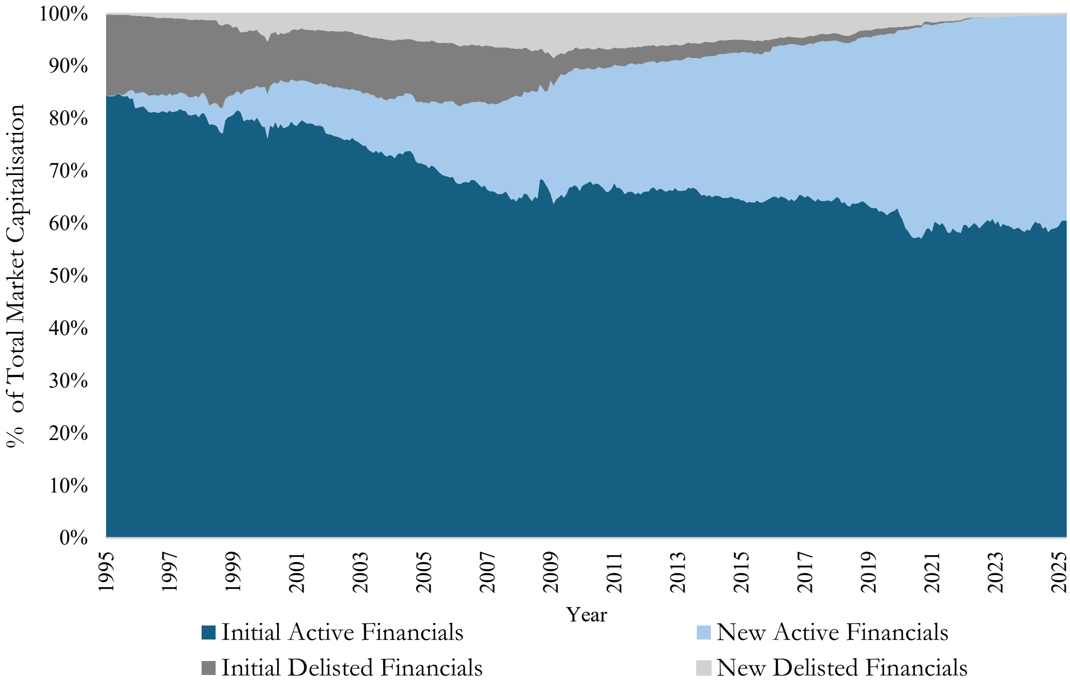
Despite these advances, systemic risk remains a complex and multidimensional concept that is difficult to define, let alone measure accurately and it is often recognised more clearly ex post than ex ante (Billio et al., 2012; Benoit et al., 2017; Berger and Sedunov, 2024). Moreover, existing measurement approaches remain vulnerable to data limitations that can systematically distort empirical inference (Ellis et al., 2022; Leong, 2025) and to mechanical features of their construction that can generate misleading signals (Löffler and Raupach, 2018). This paper provides the first, to the best of our knowledge, empirical investigation of the effect of survivorship bias in systemic risk estimation.[1] Survivorship bias represents a significant but underexplored challenge in systemic risk measurement since the vast majority of policy and academic studies often rely exclusively on surviving financial institutions, implicitly omitting institutions that exited the market and thereby introducing systematic biases into both firm-level risk estimates and country-level aggregates.

Our analysis covers 1995–2025, a period characterised by substantial turnover in the financial sector, and shows that survivorship is a quantitatively important feature of financial system data. Figure 1 illustrates this evolution in the U.S. market, showing that firms active at the beginning of the sample account for only about 60% of total market capitalisation by the end. At the outset, roughly 16% of system-wide market capitalisation is attributable to institutions that are subsequently delisted, and this share rises in the run-up to the GFC, with about 8% linked to new entrants that later exit. Delisted institutions record systematically lower returns, with average returns among surviving firms being approximately four to five times larger. These patterns

[1] A few previous studies (Armanious, 2024; Skouralis, 2023; Varotto and Zhao, 2018; Zhang et al., 2015; Weiß and Mühlnickel, 2014) acknowledge the issue and note the importance of including delisted firms in their analysis, but do not provide any further investigation.

indicate that entry and exit are pervasive and that excluding delisted institutions can distort systemic risk estimates in both magnitude and direction.

FIGURE 1: Sample decomposition of active and delisted financial institutions



Note: This Figure presents the composition of financial institutions in the US sample over the period 1995-2025. It illustrates the evolving relative shares of different groups, distinguishing between the initial cohort of firms active in 1990, subsequently classified as either surviving (active) or delisted, and institutions that entered the sample thereafter. Active firms are defined as those still listed at the end of the sample period (May 2025), while delisted firms are those that exited due to failures or through mergers, acquisitions, or privatization.

Using both a large U.S. sample and a comprehensive global panel of financial institutions, we find that systemic risk estimates based solely on active institutions are, on average, higher than those obtained from samples that incorporate delisted firms. At the country level, survivor-only estimates overstate aggregate ΔCoVaR by approximately 13 basis points, corresponding to about 5% of measured systemic risk. This magnitude is non-trivial given the widespread use of market-based systemic risk measures in macroprudential surveillance and stress testing. Importantly, the bias is not constant over time. It increases markedly during periods of financial stress, exceeding 8% during the GFC, and declines in more tranquil periods. These dynamics indicate that survivorship bias is partly cyclical, increasing during crises when exit intensifies, and partly structural, reflecting the benchmark construction of systemic risk measures.

The effect can be decomposed into two distinct channels. The first is a weighting effect (WE) stemming from the benchmark-dependent nature of systemic risk measures. Because systemic risk is measured relative to a system portfolio, the exit of institutions mechanically reallocates benchmark weights toward surviving firms, thereby raising their measured systemic contributions even when their underlying risk exposures are unchanged. Quantitatively, the weighting effect increases the active-only systemic risk index by about 6 basis points, or 2.2% relative to the average active-only systemic risk estimate, and accounts for roughly 43% of total survivorship bias. This component is persistent and remains positive even in tranquil periods and after major delisting episodes, reflecting ongoing consolidation and benchmark reweighting in financial systems.

The second channel is an omission effect (OE) consistent with the traditional notion of survivorship bias. Including delisted institutions lowers average systemic risk because exiting firms are typically smaller, less interconnected, and less exposed to systemic tail events. We estimate that, globally, delisted institutions exhibit, on average, about 28% lower systemic risk than surviving firms. This pattern reflects both a "too-small-to-save" mechanism (Grammatikos and Papanikolaou, 2018; Barth and Wihlborg, 2016) and the fact that many exiting institutions are not present during major systemic episodes such as the GFC or the COVID-19 shock (sample period bias). The omission effect accounts for roughly 57% of total survivorship bias and is particularly pronounced in market-oriented systems. Conceptually, this mechanism is related to reverse survivorship bias (Linnainmaa, 2013), as early-exiting firms appear less systemic partly because their exposure to tail events is limited.

To interpret these mechanisms, the paper develops a Monte Carlo framework that isolates the roles of exiting-firm characteristics. The results indicate that the weighting effect (WE) is driven mainly by the size of exiting firms and, to a lesser extent, by their interconnectedness. The exit of large institutions mechanically reshapes benchmark weights and reallocates measured systemic contributions toward survivors. Exit timing also matters as institutions that remain longer carry greater cumulative weight, so their disappearance induces a larger reweighting and shift in measured systemic importance. OE is also driven by size and exit timing. Smaller and earlier-exiting institutions are less exposed to systemic tail events, so including them lowers country-average systemic risk estimates. The simulations show that survivorship bias does not have a fixed sign. Although it is positive in most configurations, its direction depends on the joint distribution of size and interconnectedness. In particular, when large and highly correlated institutions exit, survivor-only samples can understate systemic risk. Overall, the simulations clarify the conditions under which survivorship bias is most severe and provide a structural interpretation of the empirical findings.

Our empirical results reveal substantial cross-country heterogeneity in both the magnitude and composition of survivorship bias. The bias tends to be larger in thinner and more volatile markets, where tail-risk measures are more sensitive to changes in the composition of the financial system.

It is also more pronounced in financial systems with higher institutional turnover and in more market-based financial structures, where systemic risk measures rely more heavily on market valuations rather than balance-sheet aggregates (Beck and Levine, 2002; Bats and Houben, 2020). Several emerging and non-OECD economies exhibit sizeable distortions, but economically meaningful biases are also present in advanced economies, including parts of the Euro Area. These findings indicate that survivorship bias is not merely a development-related phenomenon but reflects cross-country differences in financial structure, market volatility, and exit dynamics.

Finally, the results are robust across a wide range of specifications. They hold when using alternative systemic risk measures such as SRISK, where survivorship bias arises primarily through the omission channel and remains economically meaningful, particularly during crises. The findings are also robust to alternative sample selection criteria, including different minimum size thresholds and alternative time windows. In addition, augmenting the dataset with manually collected data on failed institutions and cross-checking against FDIC records and Compustat confirms that the documented patterns are not driven by database coverage bias.

Overall, the findings indicate that institutional size and exposure to systemic events jointly shape measured systemic risk. Survivor-only datasets tend to overstate the importance of long-lived institutions while understating risks associated with early-exiting firms and new entrants. Because the magnitude of survivorship bias depends on market structure, crisis timing, and exit dynamics, systemic risk measures are not directly comparable across countries or over time when survivorship is ignored. These results have implications for the identification of systemically important institutions and the calibration of stress tests, and they highlight the importance of accounting for survivorship bias in the macroprudential use of systemic risk measures.

This paper builds on the literature on survivorship bias, which has long been recognised as a source of distortion in empirical finance, affecting asset pricing, performance evaluation, and risk measurement Early work by Brown et al. (1992) shows that excluding failed or discontinued mutual funds leads to inflated risk-adjusted returns and spurious evidence of managerial skill, with implications not only for average performance, but also for higher-order moments and cross-moments of returns. Subsequent studies document the pervasiveness of these effects. For example, Carhart et al. (2002) demonstrate that survivorship bias leads to overstated mean returns and false evidence of persistence in fund performance, an effect that grows with sample length[2], while Rohleder et al. (2011) find that it can substantially inflate risk-adjusted returns and even

[2] Elton et al. (1996) and Carpenter and Lynch (1999) highlight how mergers and closures disproportionately remove poorly performing funds from samples, introducing attrition bias that exaggerates performance persistence.

reverse the sign of Jensen's alpha. A conceptually important extension of this literature is provided by Linnainmaa (2013), who introduces the notion of reverse survivorship bias. Unlike traditional survivorship bias, which arises from excluding failed entities, reverse survivorship bias persists even in survivorship-bias-free datasets. The key mechanism is that exit is correlated with adverse realisations as estimates based on finite histories of defunct entities reflect not only true underperformance but also idiosyncratic negative shocks that precipitate exit. As a result, performance measures may be systematically biased even when all available data are used. This insight is particularly relevant in settings where exposure to tail events is uneven across institutions.

Related concerns arise beyond the mutual fund context. In equity markets, Shumway (1997) shows that omitting delisting returns biases average stock returns upward, while Jorion and Goetzmann (1999) document overstated long-run equity premia when failed markets are excluded from international samples. Bessembinder (2018) further shows that most individual stocks underperform Treasury bills over their lifetimes and that aggregate wealth creation is driven by a small fraction of extreme winners, underscoring how survivorship can generate misleading inferences about risk and return. Finally, survivorship bias has also been documented in other asset classes, including hedge funds (Fung and Hsieh, 2000), fixed-income markets (Altman, 1989), and cryptocurrencies (Ammann et al., 2022).

Despite this extensive evidence, the implications of survivorship bias for systemic risk measurement remain largely unexplored. This gap is non-trivial because systemic risk measures rely explicitly on tail co-movements, benchmark construction, and exposure to rare stress events, precisely the settings in which selective exit is most likely to matter. As a result, firm exit can distort both firm-level contributions and aggregate systemic risk measures in ways that differ from standard performance settings. The remainder of the paper is organised as follows. Section 2 describes the data and estimation methodology. Section 3 defines survivorship bias conceptually and through simulation and presents the empirical analysis. Section 4 discusses policy implications and Section 5 concludes.

2. Methodology

2.1 Data

Our dataset comprises a global panel of publicly listed financial institutions from Refinitiv Datastream over the period 1995-2025. The sample includes commercial banks, investment banks and brokers, asset managers, life and non-life insurers, finance and credit service firms, and real estate investment trusts (REITs). To focus on systemically relevant firms and ensure reliable market-based measures, we restrict the sample to institutions listed on primary exchanges and with total assets above USD 1 billion.[3] The final sample contains more than 2,500 institutions across 32 countries. We use weekly stock prices and market capitalisation to construct market-based systemic risk measures. All series are expressed in U.S. dollars using Datastream's currency conversions to ensure cross-country comparability. The dataset spans multiple global and regional crisis episodes, providing substantial variation in both firm characteristics and macro-financial conditions. The U.S. and China together account for nearly half of total market capitalisation (38% and 11%, respectively). Across sectors, banks represent the largest share of the sample in number (41%) and market capitalisation (49%), followed by insurers and investment firms. Delistings occur across all countries and sectors and display substantial heterogeneity, making sample attrition quantitatively important for systemic risk measurement.[4]

2.2 *Measuring systemic risk*

We measure systemic risk using the Conditional Value-at-Risk (CoVaR) framework of Adrian and Brunnermeier (2016), which quantifies an institution's contribution to system-wide tail risk. CoVaR extends the traditional Value-at-Risk (VaR) by focusing on the distribution of financial system returns conditional on distress at a particular institution, thereby capturing spillovers from firm-level shocks to aggregate financial instability. Let R_t^i and R_t^s stand for the firm and financial system returns, respectively. Following Adrian and Brunnermeier (2016), the financial system (*s*) is based on a weighted portfolio comprising all financial institutions in our sample. The mathematical representation of $CoVaR_q^{s|i}$ of the financial system index (*s*) when a financial institution (*i*) is under distress (or equal to its VaR_q^i that stands for the unconditional q-quantile of institution i's return distribution) is presented in Equation (1):

$$P\,(R_t^s < CoVaR_q^{s|i} \mid R_t^i = VaR_q^i) = q \tag{1}$$

$$\Delta CoVaR^{s|i} = CoVaR_{q=0.05}^{s|i} - CoVaR_{q=0.5}^{s|i} \tag{2}$$

The marginal contribution of an institution to systemic risk is measured as the difference between the system's CoVaR conditional on the institution being in distress and the CoVaR conditional on it being in a normal state. This difference, denoted ΔCoVaR and defined in Equation (2), captures the incremental tail risk imposed on the system when the institution moves from normal conditions to distress.

[3] This threshold follows a similar approach to Engle et al. (2015), who impose a comparable size filter (1 billion euros) in their analysis of systemic risk in European financial institutions.
[4] Detailed sample composition statistics are reported in Appendix Tables A1 and A2.

Following standard convention, we express all risk measures in positive terms, so that higher ΔCoVaR values indicate greater systemic importance. The CoVaR estimation is based on the quantile-regression framework of Koenker and Bassett (1978). Quantile regression allows the conditional quantiles of system returns to depend on firm returns without imposing distributional assumptions on the error term. Specifically, we run a quantile regression of system returns R_t^s on firm returns R_t^i. For each institution *i*, we calculate its VaR as the unconditional 5th percentile of its return distribution and by using the estimated coefficients from Equation (3), we calculate the system's CoVaR conditional on institution *i*'s distress:

$$R_t^s = \alpha_q^{s|i} + \beta_q^{s|i}\, R_t^i + \varepsilon_{q,t}, \qquad q \in \{0.05, 0.50\} \tag{3}$$

$$\mathrm{Co}VaR_q^{s|i} = VaR_q^{s|R^i = VaR_t^i} = \hat{\alpha}_q^{s|i} + \hat{\beta}_q^{s|i}\; VaR_q^i \tag{4}$$

This expression yields the conditional VaR of the system ($\mathrm{Co}VaR_{q=0.05}^{s|i}$), evaluated at the distress threshold of institution *i*. We also estimate the system's conditional return when the institution is in a normal state using the median (50th percentile) regression. The marginal contribution of institution *i* to systemic risk, $\Delta \mathrm{Co}VaR_q^{s|i}$ is then defined as the difference between the CoVaR at the 5th and 50th percentiles, as presented in Equation (5):

$$\Delta CoVaR^{s|i} = CoVaR_{q=0.05}^{s|i} - CoVaR_{q=0.5}^{s|i} = \hat{\beta}_q^{s|i}\; (VaR_{q=0.05}^i - VaR_{q=0.5}^i) \tag{5}$$

ΔCoVaR is particularly well suited to our analysis because it relies solely on market return data and can therefore be implemented consistently across a wide range of financial institutions and jurisdictions, facilitating cross-country and cross-sector comparisons (López-Espinosa et al., 2012; Dungey et al., 2022). In addition, its reliance on quantile regression focuses directly on the joint tail behaviour of institutions and the financial system, making it robust to extreme market movements and less sensitive to outliers (Adrian and Brunnermeier, 2016). Finally, unlike capital- or leverage-based measures such as SRISK, ΔCoVaR does not directly rely on balance-sheet information, which can be infrequent, and subject to accounting discretion.

2.3 Time-varying ΔCoVaR and baseline estimates

The unconditional $\Delta CoVaR^{s|i}$ defined in Equation (5) provides a summary measure of an institution's contribution to systemic risk over the full sample period. Our objective, however, is to examine how survivorship bias evolves over time and to identify the periods in which it becomes most pronounced. Because unconditional ΔCoVaR is constant by construction, we estimate a time-varying version that allows systemic risk contributions to evolve with financial conditions. Following Adrian and Brunnermeier (2016) and the literature, we adopt a state variables-based quantile-regression framework in which tail dependence varies with observable market conditions. The dynamic estimation relies on the same quantile regression structure as the static specification but augments it with a vector of lagged state variables S_{t-1} that capture prevailing financial conditions. These variables are chosen to be highly liquid and forward-looking, allowing the measure to reflect the time-varying nature of systemic risk. Allowing tail dependence to evolve with market conditions yields a time series of institution-level systemic risk contributions, which is central to our analysis of survivorship bias across different phases of the financial cycle.

On the selection of state variables, we follow the established literature (Adrian and Brunnermeier, 2016; Anginer et al., 2014; Weiß and Mühlnickel, 2014; Bostandzic and Weiß, 2018; Kladakis et al., 2025) and employ a set of highly liquid, forward-looking indicators that capture prevailing financial conditions. For the U.S. analysis, the state variables include the daily change in the three-month Treasury yield, the term spread (10-year minus three-month Treasury yields), the Moody's Baa–Treasury credit spread, the TED spread, the monthly average of S&P 500 weekly returns, and the CBOE VIX index. These variables capture movements in interest rates, credit risk, funding liquidity, equity market performance, and aggregate uncertainty. All series are obtained from the St. Louis Fed database. The summary statistics are reported in Table 1.

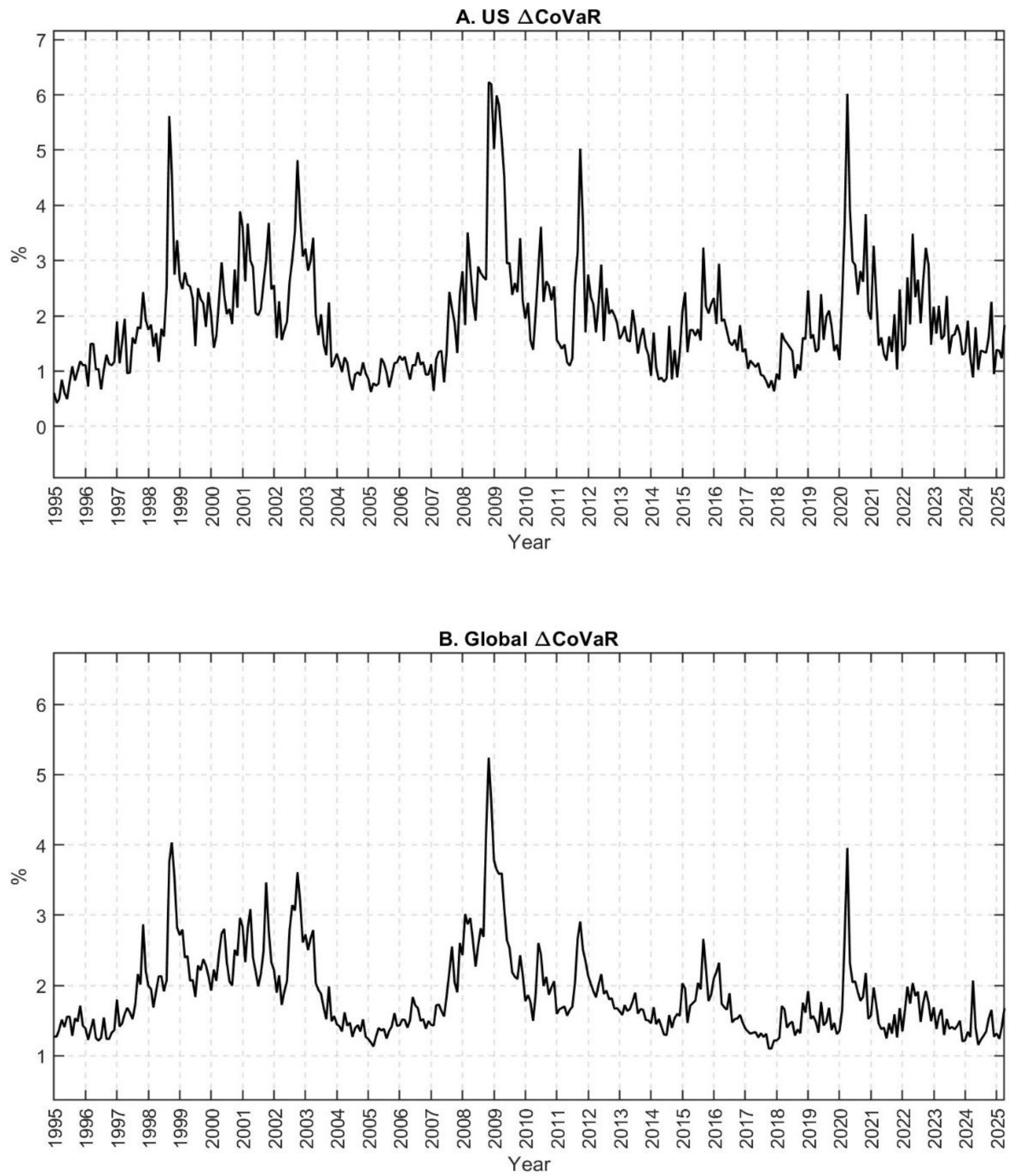
TABLE 1: US State variables summary statistics

	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
Change in 3M T-Bill	-0.0004	0.0425	-0.2500	0.2200	-0.4248	10.7271
Term Spread	0.3979	1.2547	-1.8800	3.7900	-0.1547	-0.5633
Credit Spread	2.3728	0.7390	1.3300	6.1000	1.6736	5.0953
TED Spread	0.3979	0.4877	-1.1300	5.2000	3.5788	29.8004
S&P 500 Returns	-0.0514	1.0728	-6.8010	5.4200	-0.2855	6.5536
VIX	20.0636	7.7100	9.5100	59.8900	1.6463	4.1676

Note: The Table presents the summary statistics for the six selected state variables and the period 1995-2025. Change in 3M T-Bill is the monthly change in the market yield on U.S. Treasury securities at three months. Term Spread is the yield difference between 10-year and 3-month U.S. Treasury securities. Credit Spread is the difference between Moody's seasoned Baa corporate bond yield and the 10-year U.S. Treasury yield. TED Spread is the difference between the three-month LIBOR (or SONIA) rate and the three-month secondary market Treasury bill rate. S&P 500 Returns are the monthly averages of weekly S&P 500 returns. VIX is the Chicago Board Options Exchange Volatility Index, a measure of expected equity market volatility. All variables are obtained from the Federal Reserve Bank of St. Louis (FRED).

To provide context for the subsequent bias analysis, Figure 2.A plots the market-capitalisation-weighted average ΔCoVaR for the eight U.S. systemically important banks, computed using a system index that includes only active institutions. The series exhibits pronounced spikes during episodes of financial stress, most notably in the early 2000s (dot-com bust), the GFC (2008–2009), and the COVID-19 shock in 2020 and lower values in more tranquil periods, consistent with the procyclical nature of systemic risk documented in the literature. However, while the U.S. provides a natural benchmark, institutional structures, regulatory regimes, and market characteristics differ substantially across countries.

FIGURE 2: Country-aggregate ΔCoVaR



Note: Figure A reports the market-capitalisation-weighted average ΔCoVaR for the eight U.S. systemically important banks (SIBs). Figure B presents the corresponding market-capitalisation-weighted average ΔCoVaR of active financial institutions for 32 countries, covering a broad set of financial institutions, including commercial banks, insurers, investment banks and brokers, finance and credit service providers, and real estate investment trusts (REITs). Estimates are based on the state-variables approach, with the system index constructed as a market-capitalisation-weighted average of active financial institutions over the period 1995–2025. Reported values correspond to 6-month moving-average.

To assess the external validity of the analysis, we extend the estimation to a global sample of 32 countries. The expanded sample increases the number of observations and allows us to exploit cross-country variation in financial systems and macro-financial conditions when examining systemic risk dynamics and survivorship bias. Country selection is dictated by data availability. Equity return data are sourced from Refinitiv Datastream, and we require each country to have at least three financial institutions with a minimum of three years of observations. For the international analysis, the set of state variables is restricted to those consistently available across countries, including domestic equity market returns and volatility, changes in short-term government bond yields, and term spreads between long- and short-term government rates.[5] In addition, we include U.S. funding and credit conditions, captured by the TED spread and the corporate credit spread, to proxy for global financial conditions, following common practice in the ΔCoVaR literature (López-Espinosa et al., 2012; Zhang et al., 2015). Figure 2.B reports the market-capitalisation-weighted global ΔCoVaR. Similarly to the U.S. estimates, the series exhibits pronounced time variation, with higher levels around widely documented episodes of global financial stress, such as the Asian crisis (1997-99), the early-2000s distress, the GFC (2008-09), and the pandemic shock in 2020, and lower levels in calmer periods. This pattern reinforces the view that systemic risk is inherently time-varying and supports our focus on how survivorship bias behaves over the financial cycle.

3. Survivorship bias in systemic risk estimation

The analysis so far relies on systemic risk estimates constructed from surviving institutions only. For benchmark-relative measures such as ΔCoVaR, this survivor-based approach can generate bias because firm entry and exit mechanically alter the composition and weighting of the system index. From this section onwards, delisted institutions are explicitly incorporated to quantify survivorship bias in firm-level and aggregate systemic risk measures.

3.1 Weighting effect (WE)

Equation (5) shows that an institution's ΔCoVaR depends on two components: the gap between the tail and median of its return distribution, and the quantile regression coefficient $\hat{\beta}_q^{(s|i)}$,

[5] A similar specification of state variables has been adopted by Kladakis and Skouralis (2025). In cases where the short-term government bond series exhibit persistent gaps or remain unchanged over extended periods, we substitute them with the German series for European countries and the US series for Latin American and other non-European countries. As a robustness check, which is not reported in the current version of the manuscript, we also estimate the results using only the periods for which the original series are available, and we observe no meaningful differences in our findings.

which captures the sensitivity of system returns to firm-level distress. Consequently, the construction of the system-wide index is a critical step in CoVaR estimation, as it defines the benchmark against which spillovers from individual institutions are measured. As emphasised by Löffler and Raupach (2018), ΔCoVaR is inherently benchmark-dependent, so changes in the benchmark's composition or weighting can affect both the level and ranking of systemic risk contributions even when firm-level return dynamics are unchanged. This benchmark sensitivity becomes particularly relevant when the system portfolio evolves mechanically due to firm exit. Excluding delisted institutions redistributes their market capitalisation across surviving firms, altering the historical return distribution of the system index and hence estimated tail spillovers from each survivor.

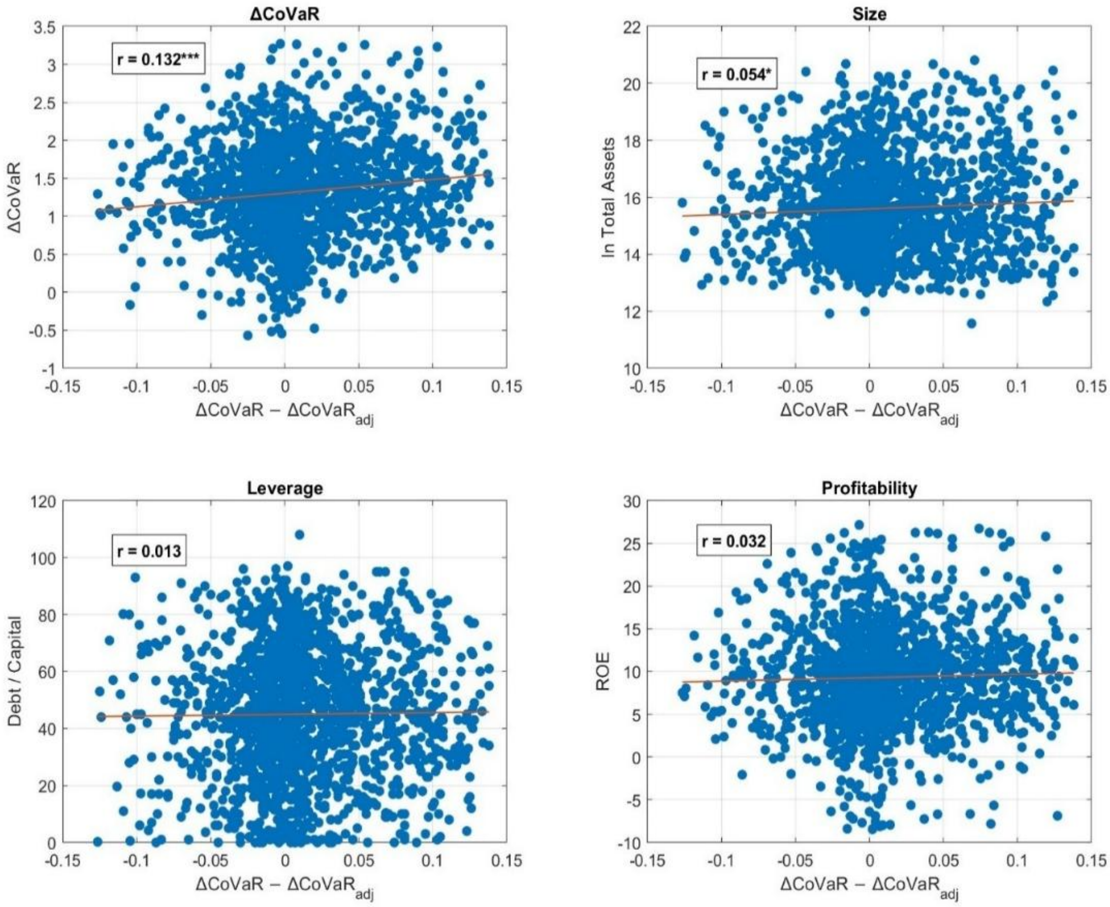
Our data shows that in the U.S. between 1995 and 2025, delisted institutions account for above 10% of system market capitalisation, and a survivor-only index delivers an average annual return about 0.8 percentage points higher than the full-sample index. The difference is most pronounced during the GFC and reflects the exclusion of underperforming firms prior to delisting. By mechanically improving the system index's return profile, survivorship inflates estimated spillover sensitivities $\hat{\beta}_q^{(s|i)}$, and biases ΔCoVaR upward for surviving firms. The weighting effect (WE) of firm i is measured by comparing the ΔCoVaR of active financial institutions under two benchmarks defined in Equation (6):

$$WE_{q,t}^{i} = \Delta CoVaR_{q,t}^{s|i} - \Delta CoVaR_{q,t}^{s^*|i} \tag{6}$$

$$country\, WE_{q,t} = A\Delta CoVaR_{q,t_{active}}^{s|i} - A\Delta CoVaR_{q,t\ active}^{s^*|i} \tag{7}$$

Where s is the system index composed solely of active institutions, and s^* is the system index that also includes delisted institutions. At the country level, we aggregate firm-level AΔCoVaR using market-capitalisation weights following Rodríguez-Moreno and Peña (2013) and Skouralis (2023). To measure the economic relevance of the weighting effect, we use unconditional ΔCoVaR estimates to isolate distortions driven solely by benchmark composition. Figure 3 shows that WE is positively and statistically significantly associated with firm size and baseline systemic risk estimates, implying that larger surviving institutions experience a greater upward shift in estimated systemic risk when evaluated against a survivor-only benchmark. By contrast, leverage and profitability are not statistically related to the magnitude of the bias. These patterns suggest that WE is driven by changes in the composition of the system benchmark rather than by cross-sectional balance-sheet characteristics.

FIGURE 3: Systemic risk survivorship bias and firm characteristics



Note: The Figure plots the relationship between the difference in unconditional/static systemic risk estimates, measured as $\Delta CoVaR_q^{s|i} - \Delta CoVaR_q^{s^*|i}$, and firm characteristics: ΔCoVaR, Size (ln Total Assets), Leverage (Debt / Capital), and Profitability (ROE). Each panel reports the Pearson correlation coefficient (r) between variables, with significance levels denoted by ∗p<0.05*, ∗∗p<0.01, and ∗∗∗p<0.001. Outliers are removed using the median absolute deviation method. The regression line in each plot is based on a simple OLS fit.

3.2 Omission Effect (OE)

We next consider the omission effect (OE), which captures survivorship bias in its traditional sense. Unlike the weighting effect, which operates through mechanical reweighting of the system benchmark, the OE reflects the informational loss arising from the exclusion of institutions that exit the sample. The OE therefore operates at the country level, capturing how the omission of delisted institutions alters measured aggregate systemic risk even when the benchmark is held fixed. Figure 4.A illustrates this mechanism by comparing the average systemic risk contributions of active and delisted institutions. The two groups exhibit a clear and economically meaningful difference. Active institutions exhibit a statistically significantly higher average ΔCoVaR of 1.84%, compared with 1.44% for delisted firms, as well as greater dispersion.[6] Interestingly, during the pre-GFC period the spread between the two indices is temporarily reduced and is even turned negative, as delisted institutions exhibited systemic risk levels comparable to those of surviving firms. In terms of size, delisted institutions, across all our examined countries, account for less than 10% of total market capitalisation on average, although their share rose to nearly 17% in the pre-GFC period.

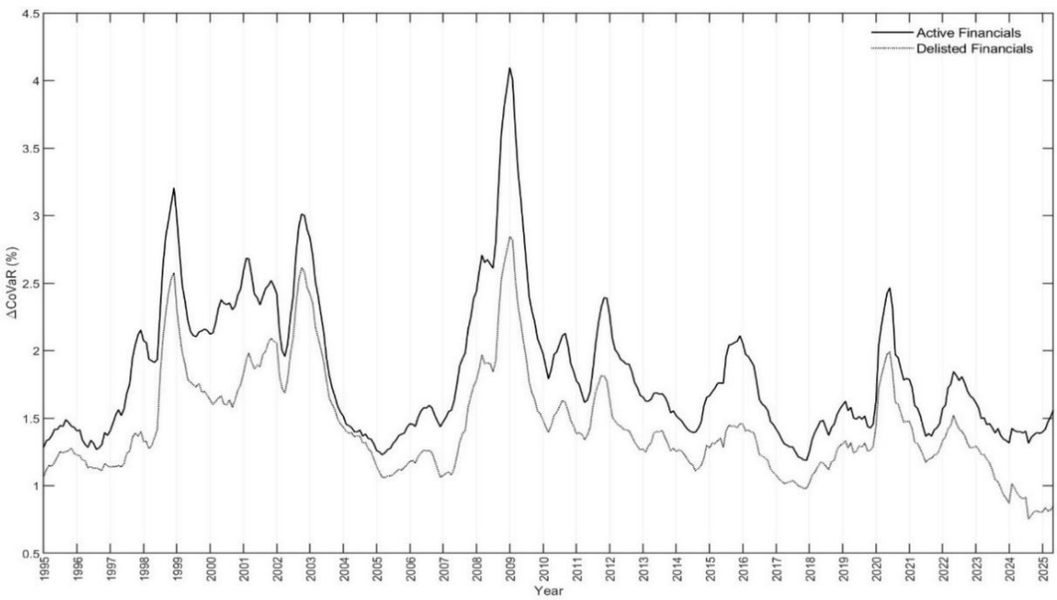
The relatively low measured systemic risk of delisted institutions reflects two features of the sample construction and exit dynamics. First, many of the delisted institutions were "too-small-to-save" implying that large, systemically important firms were more likely to receive government support and thus remain in the active sample. This reflects a selection bias in exit patterns, whereby delisted firms are disproportionately smaller and less systemic. Second, a number of delisted firms did not survive long enough to experience the major systemic crises of the sample period (e.g. GFC, Eurozone sovereign debt crisis, COVID-19 pandemic), which limited the extent to which their ΔCoVaR captured tail dependencies during episodes of systemic stress. This sample period bias mechanically lowers measured systemic risk for early-exiting firms.

Consistent with this mechanism, Figure 4.B examines the sensitivity of measured systemic risk to the choice of estimation window, holding the institutional universe fixed. Specifically, we compute the market-capitalisation-weighted average ΔCoVaR of the eight U.S. systemically important banks using alternative subsamples, without altering index composition. For example, when the estimation window excludes major crisis episodes (1995-2005), the average ΔCoVaR is about 1.69%, compared with 1.93% in the baseline specification that includes both the GFC and COVID-19 shock. The opposite result is observed in later subsamples. Over 2005-2025, average ΔCoVaR is 2% when estimated on the subperiod alone, but 1.9% when embedded in the full 1995–2025 window, while for 2015–2025 the estimate changes from 1.82% under the full-sample estimation to 1.97% when only post-2015 data are used. All reported differences are statistically significant at 5% confidence level and they indicate that crisis episodes leave a persistent imprint on tail dependence. As a result, institutions that exit prior to major crises may appear less systemically important not because they are intrinsically safer, but because their return histories are truncated before the realisation of extreme systemic shocks.

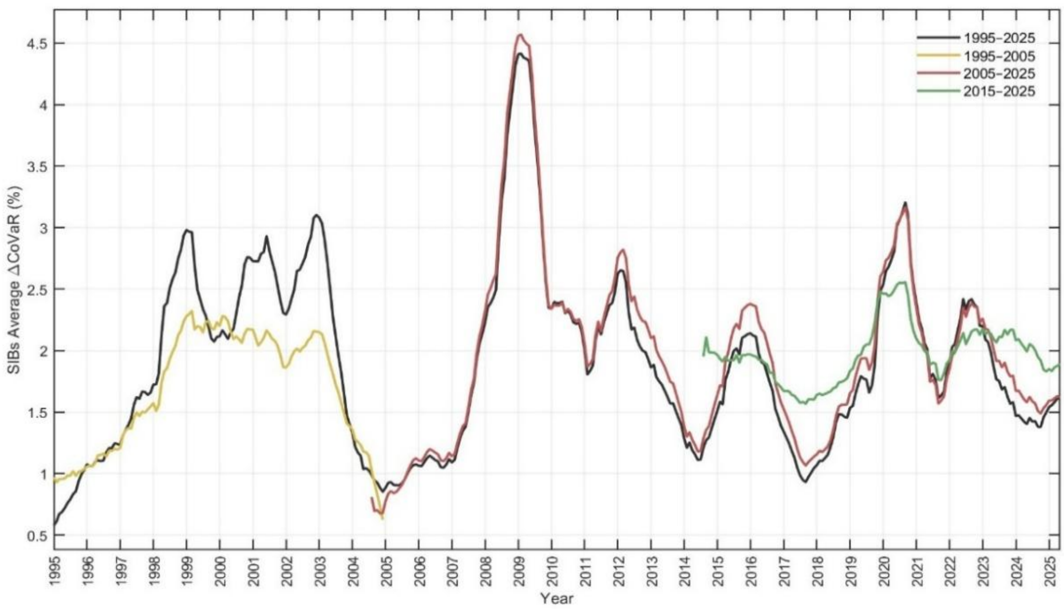
[6] We also compare the aggregate systemic risk index with and without delisted firms and the difference between the two indices is economically and statistically significant. The mean gap is 2.37 percentage points, with paired t-tests, Wilcoxon tests, and Newey-West-adjusted tests all rejecting equality at conventional levels.

FIGURE 4: Drivers of the Omission Effect (OE)

A. Systemic risk in active vs delisted financial institutions



B. Sample selection bias and systemic risk



Note: The Figure examines the omission effect in systemic risk measurement. Panel A presents the global market-capitalisation-weighted average ΔCoVaR for indices constructed from active-only and delisted-only institutions. The sample includes commercial banks, insurers, investment banks and brokers, finance and credit service providers, and REITs over 1995-2025. Panel B reports the market-capitalisation-weighted average ΔCoVaR of the eight U.S. global systemically important banks (G-SIBs) estimated over alternative sample windows. The full-sample estimate (1995–2025) is compared with estimates based on 1995-2005, 2005-2025, and 2015-2025 subsamples. All ΔCoVaR estimates are obtained using the state-variables approach, with the system index defined as the market-capitalisation-weighted average of active financial institutions. Differences across series reflect sample composition and estimation-window effects. All values are expressed in percentage terms and reported as 6-month moving averages.

To quantify the omission effect, country-level average ΔCoVaR estimates based on surviving institutions are compared with those computed using the full sample:

$$country\ OE_{q,t}^{i} = A\Delta CoVaR_{q,t}^{s^*|i}{}_{active} - A\Delta CoVaR_{q,t}^{s^*|i}{}_{all} \tag{8}$$

where both measures are estimated with respect to the same financial system index s^*, which includes all firms. Holding the benchmark fixed isolates the informational component of survivorship bias from the mechanical reweighting captured by the weighting effect. Although ΔCoVaR is not strictly additive, this comparison provides a useful approximation of the level and dynamics of survivorship bias in country-level systemic risk measures.

3.3 The drivers behind survivorship bias: A simulation exercise

This section develops a Monte Carlo simulation framework designed to isolate the mechanisms through which survivorship bias arises in market-based measures of systemic risk. The empirical decomposition introduced earlier shows that survivorship bias can be expressed as the sum of WE and OE. The simulation therefore focuses on three primitives that theory identifies as sufficient to generate these channels: institutional size, interconnectedness with the financial system, and exit timing. Rather than attempting to replicate specific historical delisting episodes, the exercise provides a controlled environment in which these primitives can be varied independently and jointly. This approach yields transparent comparative statics and clarifies the conditions under which survivorship bias leads to overstatement or understatement of systemic risk. The baseline universe is a closed system that consists of the eight U.S. global systemically important banks (G-SIBs), indexed by i, observed over periods t. For each bank and period, we observe equity returns $R_{i,t}$ and market capitalisations $MC_{i,t}$. The benchmark system return used in systemic risk estimation is the market-capitalisation-weighted return of the incumbents.

3.3.1 Synthetic institution

The simulation augments the baseline universe with a ninth, synthetic institution. The objective is to construct a return process representative of a large U.S. bank while retaining explicit control over its similarity to the financial sector. The return on the synthetic institution follows a parsimonious one-factor structure. The common component is proxied by the return on a broad index of U.S. financial institutions, including both active and delisted firms, denoted F_t, which captures sector-wide conditions and financial cycles.

The index return is standardised to zero mean and unit variance. The synthetic bank's return is defined as:

$$R_t^{synthetic} = \rho\, F_t + \sqrt{1-\rho^2}\, \eta_t \tag{9}$$

where $\rho \in [0,1]$ governs similarity to the financial sector and η_t is an idiosyncratic shock. Idiosyncratic shocks are drawn from a Student-t distribution[7], capturing the empirically documented heavy tails in bank-level equity returns while preserving finite variance. The resulting series is rescaled to match the average volatility of the eight incumbents. This volatility normalisation ensures that differences in measured systemic risk are driven by similarity and size rather than mechanical differences in unconditional variance. Because η_t is drawn independently of F_t, the parameter ρ provides a direct measure of co-movement with the financial sector. In this case, a single financial-sector factor is sufficient because the objective is not to fully replicate return dynamics, but to isolate how survivorship mechanically affects systemic risk measurement. With regards to the firm size, that is controlled independently through a parameter representing the synthetic bank's market-capitalisation share relative to the incumbent universe. Let $w \in (0,1)$ denote this size parameter. The synthetic bank's market capitalisation is set proportionally to the incumbents' aggregate capitalisation:

$$MC_t^{synthetic} = w \cdot \sum_{i=1}^{8} MC_{i,t} \tag{10}$$

This scaling ensures that the synthetic institution's size evolves proportionally with the incumbent universe while allowing its relative importance to be varied exogenously. Comparative statics with respect to size therefore isolate the mechanical role of benchmark weights without conflating them with shifts in the incumbent size distribution.

3.3.2 Exit process

Exit timing is modelled using a discrete-time hazard process whose probability increases in distress states. For a fixed tail probability q, define a distress indicator, where $Q_q\left(R^{synthetic}\right)$is the unconditional q-quantile of the synthetic bank's return distribution. The period-specific exit probability is given by Equation (12).

$$D_t = 1\{R_t^{synthetic} \leq Q_q(R^{synthetic})\} \tag{11}$$

[7] The default degrees of freedom are set to five. As a robustness exercise, we also construct the idiosyncratic component using an empirical residual pool rather than parametric Student-t draws. Specifically, we extract residual return series from a panel of non-systemic U.S. banks after removing a common component and standardising each series to unit variance. In each Monte Carlo draw, the idiosyncratic shock is sampled from this empirical pool. This approach preserves the cross-sectional distributional features and temporal dependence patterns observed in bank-level returns without imposing a parametric distribution. The main simulation results are quantitatively and qualitatively similar under this alternative specification and they can be found in Appendix, Table A4.

$$p_t = \min\{p_{\max}, p_0 + p_1 D_t\} \tag{12}$$

where p_0 is a baseline hazard, p_1 captures the incremental hazard in distress, and $p_{\max}$ caps the probability at 20%. Let survival through period t be:

$$S(t) = \prod_{s=1}^{t}(1 - p_s) \tag{13}$$

A single uniform draw $U \sim U(0,1)$ is taken for each simulation, and the exit time τ is defined as the first period satisfying $S(\tau) \leq U$. Setting $p_T = 1$ ensures a unique exit date in each simulation. For $t > \tau$, the synthetic institution is treated as delisted and removed from the observable universe. This structure captures the empirical regularity that attrition is more likely in stress periods while allowing exit timing to vary independently of institutional size and similarity to the financial sector.

3.3.3 Monte Carlo implementation and interpretation

For each parameter combination (ρ, w, p_0, p_1), the simulation is repeated over 500 Monte Carlo draws. Each draw produces a synthetic panel of returns, market capitalisations, and exit realisations from which systemic risk measures are computed. Each simulation draw proceeds in three steps. First, a new idiosyncratic shock path is generated and combined with the financial-sector factor to construct the synthetic institution's return series. Second, an exit time τ is simulated using the hazard specification. In the data, bank attrition arises through M&As, failures, or transitions to private ownership, and these events are concentrated in periods of financial stress. The hazard-based mechanism therefore provides a parsimonious representation of this state dependence. For $t > \tau$, the synthetic institution is treated as delisted and its returns and market capitalisation are removed from the observable universe. Third, system returns and benchmark weights are constructed under alternative sample compositions. In the incumbent-only environment, only the eight incumbents are present and the system return is based solely on this sample, denoted R_t^8. In the full environment, the synthetic institution is included prior to exit, so that:

$$R_t^s = wR_t^{synthetic} + (1 - w)R_t^8, \quad t \leq \tau, \tag{14}$$

with the system return reverting to R_t^8 after exit. In the mixed environment, the expanded benchmark is used but systemic risk is aggregated only across the eight incumbents. This structure mirrors the institutional setting of the empirical analysis while allowing size, similarity, and exit timing to vary independently. The simulations are therefore interpreted as disciplined counterfactuals that isolate mechanisms present in the data rather than as purely numerical exercises. Firm-level systemic risk is estimated using the ΔCoVaR measure of Adrian and Brunnermeier (2016). For each institution, the conditional q-quantile of the system return is obtained from the quantile regression:

$$Q_q(R_t^{sys} \mid R_{i,t}, X_t) = \alpha_i + \beta_i R_{i,t} + \gamma_i' Statevars_t \tag{15}$$

where $Statevars_t$ denotes the (U.S.) state variables. ΔCoVaR is defined as the change in the system's left-tail quantile when the institution moves from its median state to a distress state. Firm-level measures are aggregated using market-capitalisation weights and time-averaged. The weighting effect captures mechanical benchmark reweighting, while the omission effect reflects the removal of exiting institutions; the total effect is defined as the sum of the two. Both effects are computed in accordance with Equations (7) and (8).

3.3.4 The role of size and connectedness

The Monte Carlo results provide a structured view of how the exclusion of exited institutions affects measured systemic risk and how this effect varies with institutional size, similarity to the financial sector, and exit timing. A first and robust finding is that institutional size is a central determinant of survivorship bias. Across similarity levels, the weighting effect increases monotonically with the size parameter. When the synthetic institution represents a negligible share of system capitalisation, its exit has little influence on benchmark composition and limited implications for systemic risk measurement. As its relative size increases, its removal reallocates benchmark weights toward surviving banks and raises their measured contributions to the system index. Figure 5 shows a clear upward gradient along the size dimension. This pattern indicates that survivorship bias arises not only from selection but also from the aggregation scheme used to construct systemic risk measures. The disappearance of a large institution mechanically alters the weighting structure underlying the system index and can inflate the apparent importance of surviving institutions in active-only samples.

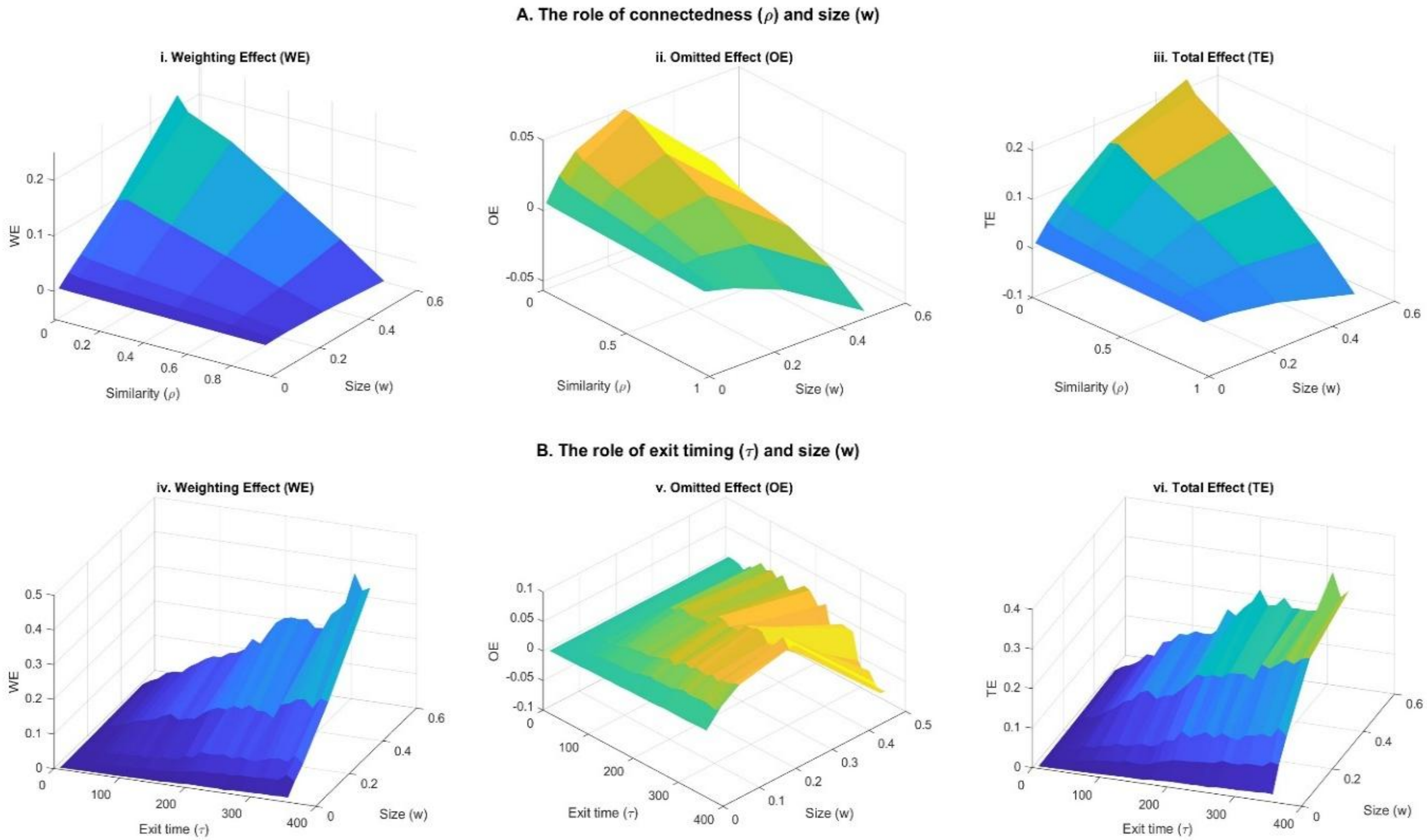
Similarity to the financial sector (connectedness) introduces a distinct channel operating through the omission component. When similarity is low or moderate, the exiting institution carries exposures only partially aligned with the system factor. Excluding such an institution removes tail risk that is not fully shared by other banks, leading the active-only sample to attribute relatively more systemic risk to survivors and generating a positive omission effect. As similarity increases, the synthetic institution loads more strongly on the system factor and becomes more tightly linked to aggregate tail events. Including such an institution in the full sample raises measured systemic risk because it contributes directly to system tail outcomes. When it is omitted, the active-only measure no longer reflects this exposure, and measured systemic risk can decline relative to the full sample. In this region, OE becomes negative, particularly when the exiting institution is also large.

A similar mechanism also explains the negative WE observed at very high levels of connectedness ($\varrho \gtrsim 0.9$). When an institution is both highly connected and sizeable, its returns closely track system-wide movements. In such cases, its presence in the benchmark does not merely add independent tail risk but co-determines the benchmark itself. Removing it can therefore lower the estimated tail sensitivity of surviving institutions relative to the system index, generating negative WE. The total survivorship bias reflects the interaction of these forces. For most parameter combinations, the total effect is positive, indicating that active-only samples tend to overstate systemic risk because benchmark reweighting dominates. The simulations nevertheless reveal economically relevant regions in which the total effect becomes small or negative. These cases arise mainly when institutions are both large and highly correlated with the financial sector. In such settings, removing a strongly systemic institution can offset or outweigh mechanical reweighting, so that active-only samples understate systemic risk. The possibility of sign reversal shows that survivorship bias does not have a fixed direction as its sign depends on the joint distribution of institutional size and the degree of co-movement with the system.

3.3.5 The role of exit timing

Exit timing adds a further dimension to these results. Figure 5.B conditions the decomposition of survivorship bias on the timing of exit and shows that the bias depends not only on institutional characteristics but also on when attrition occurs relative to the realisation of tail risk. First, WE varies systematically with exit timing. Early exit shortens the period over which the institution influences benchmark weights, so the induced reallocation toward surviving banks is limited. When exit is delayed, the institution carries non-trivial weight for longer, and its disappearance generates a larger shift in benchmark weights toward remaining banks. The upward slope of the WE surface along the exit-time dimension reflects this accumulation mechanism. Second, OE depends critically on exposure to stress periods. For early exits, OE is typically positive because the institution leaves before many tail events occur. As exit is delayed, the institution remains present during more stress episodes and contributes to system tail outcomes in the full simulation. When such an institution is subsequently removed from the active-only benchmark, those joint tail realisations are no longer reflected, often producing a negative OE. This pattern is most pronounced for small and medium-sized institutions, for which omission primarily affects tail-event representation rather than benchmark weights.

FIGURE 5: Simulation exercise results



Note: The figure reports median survivorship bias effects from Monte Carlo simulations. Survivorship bias is defined as systemic risk measured using only active institutions minus systemic risk measured using the full sample including exited institutions. Positive values therefore indicate overstatement of systemic risk in active-only samples. Systemic risk is measured using ΔCoVaR and aggregated with market-capitalisation weights. The weighting effect (WE) captures benchmark reweighting among surviving institutions. The omission effect (OE) captures the direct contribution of the exiting institution. The total effect (TE) equals WE plus OE. Panel A shows results across combinations of financial-sector connectedness (ϱ) and relative size (w). Panel B shows results by exit timing (τ) and size for a representative level of connectedness. Exit follows a state-dependent hazard that increases in distress periods. The synthetic institution's volatility and scale are calibrated to large U.S. banks. Results are based on 500 Monte Carlo draws per parameter combination. Similar patterns obtain using an empirical residual pool instead of parametric shocks.

The negative region therefore indicates that excluding a bank that has co-moved with the system in tail states can lower measured systemic risk in the active-only sample. Economically, negative OE reflects the loss of systemic content rather than diversification gains. Overall, WE dominates in most regions, so the total effect generally increases with later exit, particularly for larger institutions. OE can nonetheless partially offset this pattern when exit follows periods of stress. Survivorship bias is therefore path dependent as its magnitude depends not only on which institutions exit, but also on their duration in the sample and their exposure to system-wide stress episodes.

3.4 Empirical results

We next turn to the empirical analysis to assess the quantitative relevance of these mechanisms. Using a comprehensive panel of active and delisted financial institutions, we measure the magnitude, time variation, and cross-country heterogeneity of survivorship bias in systemic risk.

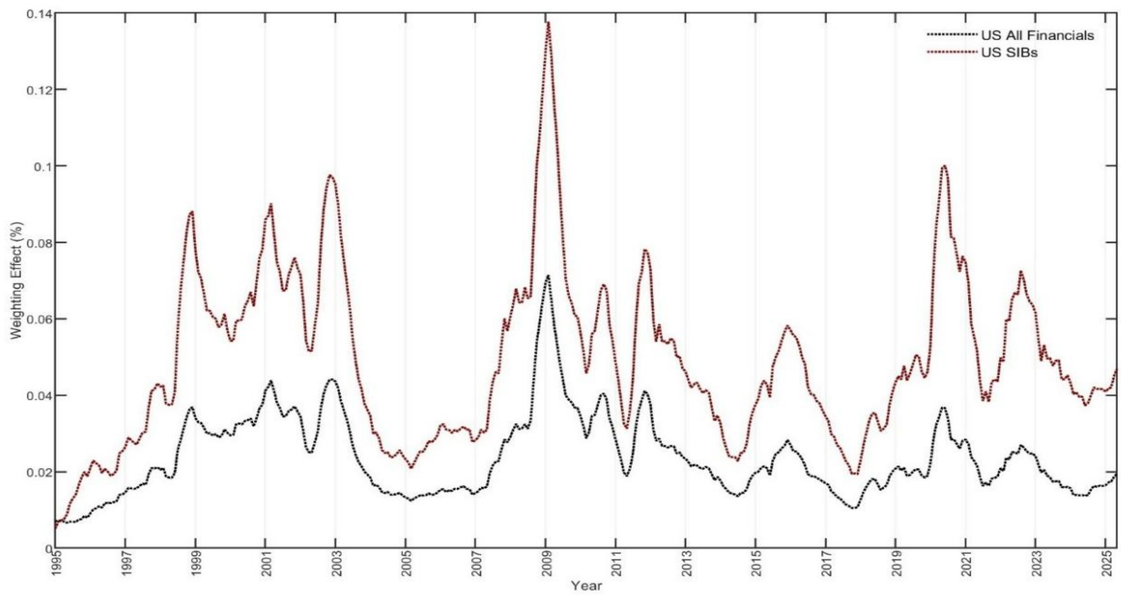
3.4.1 U.S. sample

Following the simulation results, we begin with the U.S. and Figure 6 that illustrates the WE estimates, defined as the difference between market-capitalisation-weighted average systemic risk computed using a system index that includes only active firms, and one that includes both active and delisted institutions. The red line corresponds to the eight U.S. G-SIBs, while the black line reports the same measure for the full universe of U.S.-listed financial institutions. On average, the weighting effect amounts to approximately 4.9 basis points (2.5%) for the G-SIBs and 2.4 basis points (1.5%) for all U.S. financial firms. Thus, survivorship bias inflates measured systemic risk for systemically important institutions by roughly twice as much as for the broader financial sector. This indicates that survivorship bias inflates measured systemic risk for large, systemically important institutions by nearly twice as much as for the market as a whole. This pattern is consistent with the mechanism highlighted earlier that, by construction, WE is more pronounced for larger institutions whose relative market capitalisation increases mechanically when smaller and less systemically important firms exit the sample.

Figure 7.A combines WE and OE to quantify total survivorship bias. Both channels contribute materially, but their relative importance varies over the financial cycle. On average, OE (dashed line) accounts for roughly 60% of total bias, while WE (dotted line) explains the remainder. During major crisis episodes, OE becomes the dominant component. Excluding distressed firms disproportionately removes institutions with lower measured ΔCoVaR, which mechanically raises the benchmark against which surviving firms are evaluated. By contrast, WE is more stable over

time, reflecting the ongoing reallocation of market capitalisation toward surviving institutions as weaker firms exit. Although smaller in magnitude, WE also exhibits procyclical variation, with noticeable increases during stress periods when the market share of the largest and most interconnected institutions rises.

FIGURE 6: Weighting Effect: US SIBs vs. US all financials



Note: The Figure plots the difference between $\Delta CoVaR_q^{s|i}$ and its counterpart adjusted for delisted institutions ($\Delta CoVaR_q^{s^*|i}$) for the eight US systemically important banks (SIBs, red line) and for all US listed financial institutions (black line) from 1995 to 2025. The estimation is based on the state variables approach. Values are expressed in percentage points. Positive values indicate an upward bias in systemic risk estimates when only surviving institutions are considered. Reported values correspond to 6-month moving-average.

On average, survivorship bias in the U.S. amounts to about 6.2 basis points, or 3.9% in relative terms. The effect peaks during the GFC, exceeding 25 basis points (around 8%), before declining toward the end of the sample as the omission channel weakens in more tranquil periods. While OE explains most cyclical variation in total bias, the persistence of WE, even outside crisis periods, indicates that survivorship bias is not solely crisis-driven. Instead, it reflects a structural feature of survivor-only samples that can systematically distort systemic risk measurement over the business cycle.

3.4.2 Global sample

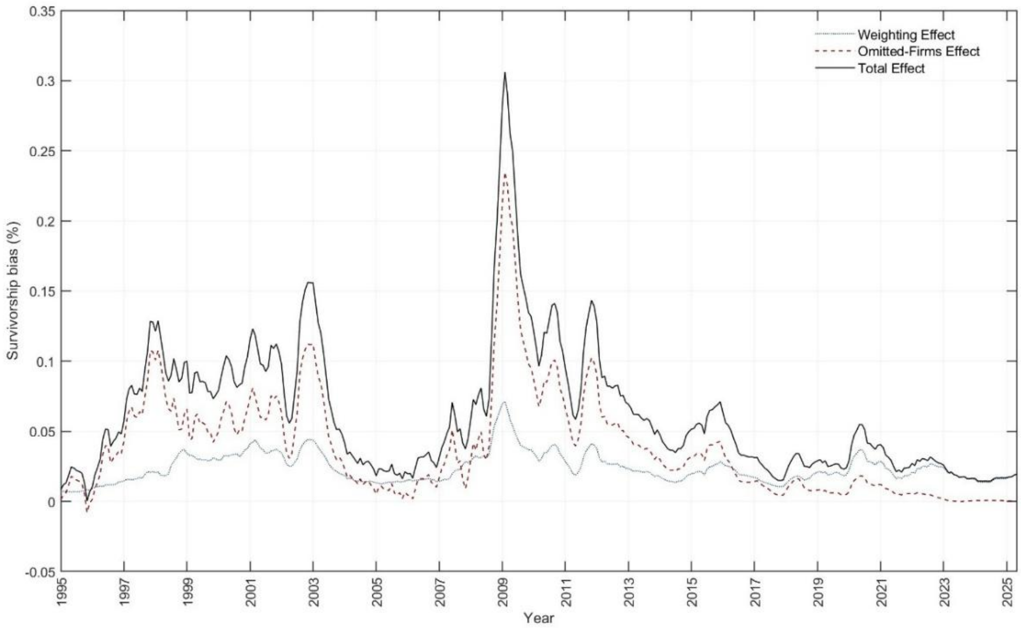
We now turn to the global sample of 32 countries. Figure 7.B presents the global time-series decomposition of survivorship bias and two systematic patterns emerge. First, WE is relatively persistent over time and remains positive even outside crisis periods, indicating that the mechanical reallocation of market capitalisation toward surviving firms systematically affects the distribution of system returns. This persistence is consistent with the benchmark dependence of ΔCoVaR and with gradual consolidation and exit dynamics in financial sectors. Second, OE is strongly state-dependent and rises sharply during the GFC and, to a lesser extent, during the COVID-19 pandemic period, before gradually converging toward zero as the population of delisted institutions stabilises toward the end of the sample. Averaged over the full period, survivorship bias amounts to approximately 13 basis points, or 5% in relative terms. During the GFC, however, the effect exceeds 30 basis points, corresponding to around 8.7% of aggregate systemic risk.

Table 2 reports sub-period averages. Even in the early dot-com period, systemic risk is meaningfully overstated, with a total effect of 10 basis points, corresponding to 5.6% of average ΔCoVaR. In the pre-GFC expansion (2002-2006), when aggregate systemic risk is lower, survivorship bias declines to 8 basis points (4.3%) and is driven primarily by the weighting effect. During the GFC, survivorship bias reaches its peak at 16 basis points, accounting for 6.5% of measured systemic risk, with the omission effect exceeding the weighting effect. A similar configuration emerges during the Eurozone sovereign debt crisis. Finally, in the post-crisis and COVID period (2015-2025), both systemic risk and survivorship bias decline, with total bias averaging 5 basis points (2.5% in relative terms) and the omission effect becoming small. All reported differences are statistically significant at the 1% level based on Newey-West heteroskedasticity and autocorrelation consistent tests. These patterns indicate that survivorship bias has both a cyclical component, linked to crisis-induced exits, and a structural component, linked to ongoing benchmark reweighting.

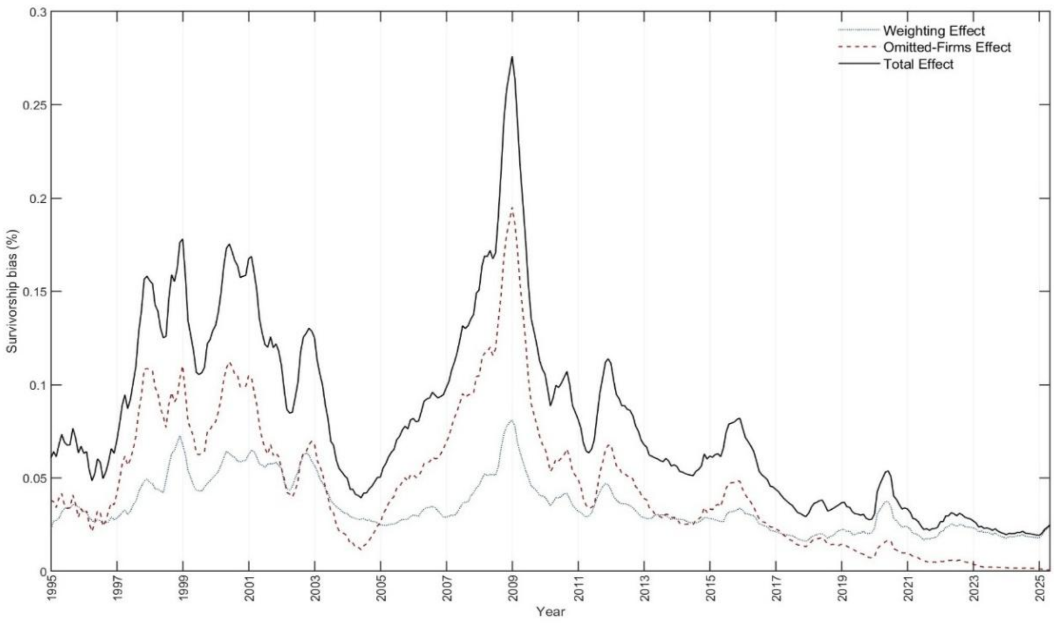
Country-level results reveal substantial heterogeneity in survivorship bias. Total survivorship bias is positive in the majority of countries and often represents a non-trivial fraction of country-average ΔCoVaR. The effect is generally stronger in non-OECD and emerging market systems, where several countries display particularly large biases. For example, Brazil and Argentina exhibit total effects exceeding 15% when expressed relative to country-level systemic risk. These magnitudes are consistent with thinner markets, higher turnover, and greater financial concentration, all of which amplify the impact of exit on index composition. Exit intensity itself plays a central role as countries with a higher share of delisted institutions exhibit systematically larger weighting and omission effects, consistent with more frequent reallocation of benchmark weights and greater informational loss from missing distressed firms. However, this relationship is not uniform. Some emerging markets display modest biases, while several advanced economies also exhibit meaningful distortions, including Greece, Germany, and France within the Euro Area.

FIGURE 7: Weighting vs Omission effects

A. U.S. Sample



B. Global sample



Note: The Figure decomposes survivorship bias in systemic risk for the U.S. (Panel A) and a global sample (Panel B) into two components: the omission effect (OE, dashed line) and the weighting effect (WE, dotted line). WE is defined as the difference between the average systemic risk of active institutions computed with respect to a system index based only on active firms ($\Delta \mathrm{CoVaR}_q^{s|i}$) and one that also includes delisted firms ($\Delta \mathrm{CoVaR}_q^{s^*|i}$). OE measures the bias arising from excluding delisted institutions and is calculated as the difference between the average systemic risk of active firms and that of the combined active-and-delisted sample. Positive values indicate that the active-only index exceeds the full-sample index, implying positive survivorship bias. ΔCoVaR estimates are obtained using the state-variables approach over 1995-2025. The global sample covers 32 countries. Both samples include a broad set of financial institutions, including commercial banks, insurers, investment banks and brokers, finance and credit service providers, and REITs. Reported values are 12-month moving averages.

TABLE 2: Sub-period analysis of ΔCoVaR and survivorship bias decomposition

Average Systemic risk (%):	$\Delta CoVaR_q^{s\|i}$	$\Delta CoVaR_{q,active\ only}^{s^*\|i}$	$\Delta CoVaR_{q,all}^{s^*\|i}$
Early/dot-com	2.05%	2.00%	1.94%
Pre-GFC	1.78%	1.74%	1.70%
GFC	2.54%	2.49%	2.37%
Eurozone crisis	2.18%	2.14%	2.07%
Post-crisis/COVID	1.61%	1.58%	1.57%
Bias decomposition:	Weighting Effect (WE)	Omission Effect (OE)	Total Effect (TE)
Survivorship bias effect (%)			
Early/dot-com	0.05%	0.07%	0.12%
Pre-GFC	0.04%	0.04%	0.08%
GFC	0.05%	0.12%	0.16%
Eurozone crisis	0.04%	0.07%	0.11%
Post-crisis/COVID	0.02%	0.02%	0.04%
Survivorship bias effect as % of systemic risk (active-only)			
Early/dot-com	2.23%	3.40%	5.63%
Pre-GFC	2.02%	2.32%	4.34%
GFC	1.92%	4.56%	6.48%
Eurozone crisis	1.87%	3.11%	4.98%
Post-crisis/COVID	1.47%	1.02%	2.49%

Note: The Table reports average systemic risk, measured by ΔCoVaR, across alternative periods of our sample of 32 countries over the period 1995-2025. $\Delta CoVaR_q^{s|i}$ denotes the aggregate computed using surviving listed institutions, with respect to an active-only institutions (s); $\Delta CoVaR_{q,active\ only}^{s^*|i}$ includes delisted firms in the construction of the market index (s^*) but not in the estimation of the average value; and $\Delta CoVaR_{q,all}^{s^*|i}$ includes both active and delisted institutions in both sample and system index (s^*) estimation . Sub-periods are defined as follows: Early/dot-com (1995-2001), Pre-GFC (2002-2006), GFC (2007-2011), Eurozone crisis (2012-2014), and Post-crisis/COVID (2015-2025m4). The lower panel decomposes survivorship bias into the Weighting Effect (WE), arising from the reallocation of market weights toward surviving institutions ($\Delta CoVaR_q^{s^*|i} - \Delta CoVaR_q^{s|i}$), and the Omission Effect (OE), capturing the impact of excluding delisted institutions from the sample ($\Delta CoVaR_q^{s^*|i}$ (all) - $\Delta CoVaR_q^{s^*|i}$ (active)). The Total Effect (TE) equals the sum of WE and OE. All reported differences are statistically significant at the 1% level based on Newey-West heteroskedasticity and autocorrelation consistent tests.

This pattern indicates that development status alone does not determine the magnitude of survivorship bias. Instead, country-level systemic risk and market volatility appear to be key conditioning factors. Regions with higher volatility, such as Latin America and parts of the Euro Area and emerging Europe, display larger survivorship distortions. This is consistent with ΔCoVaR being a tail-risk measure and higher volatility increases the sensitivity of joint tail outcomes to changes in sample composition. Conversely, large and diversified financial systems tend to exhibit more moderate biases, as greater cross-sectional dispersion dilutes the mechanical impact of individual exits and reduces sensitivity to sample composition. Nonetheless, even in deep and diversified markets, survivorship distortions remain economically meaningful. Overall, survivorship bias is therefore not confined to a particular development category but reflects a combination of exit dynamics, volatility, and market structure. Cross-country group comparisons are presented in Table 3, with detailed country-level results reported in Appendix Table A5.

Financial structure also provides a useful lens to interpret the cross-country heterogeneity in survivorship bias. In bank-centric systems, financial intermediation is concentrated in a relatively small number of large institutions whose balance sheets play a central role in credit provision. When exits occur in such systems, the redistribution of market shares and risk exposures among surviving intermediaries can mechanically amplify measured systemic risk. As a result, both WE and OE can be stronger when systemic risk is concentrated in a narrow set of intermediaries. In more market-oriented systems, financing is distributed across a wider range of institutions and market instruments. This broader risk-sharing base reduces the sensitivity of aggregate risk measures to the exit of individual firms, since the system index is less dependent on any single intermediary.

Consistent with this intuition, the estimates indicate that survivorship distortions are, on average, smaller in market-centric systems than in bank-centric ones, although the differences are not uniform across countries. These patterns align with the general view that the structure of financial intermediation influences how shocks propagate and how risk is distributed across the system. Interestingly, a small number of countries display near-zero or negative weighting effects. A negative WE implies that including delisted firms increases measured tail dependence. In such cases, excluding them reduces system-wide tail risk and causes survivor-based measures to understate systemic vulnerability. Mechanically, as discussed in the simulation exercise, negative WE arises when exiting firms exhibit strong tail co-movement (ϱ>0.9) with the system. Removing such institutions reduces the left-tail thickness of system returns and lowers estimated spillover sensitivities. This pattern is observed in East Asia countries, where there are large concentrated financial systems and exits involve relatively systemic institutions, such as large mergers or restructurings. In addition, the characteristics of delisted institutions are also critical for understanding sign reversals. When exits predominantly remove marginal institutions, survivorship bias is positive, however when exits remove systemically important institutions, the bias can turn negative. Switzerland provides a clear illustration that results in a negative effect in the developed European (but not EA or emerging) economies sample average. In that case, the exit of Credit Suisse removes an institution that experienced all major systemic events in the sample, reducing measured co-movement among surviving firms.

TABLE 3: Cross-country analysis and survivorship bias decomposition

	WE /ΔCoVaR	OE /ΔCoVaR	TE /ΔCoVaR	Avg ΔCoVaR	% of Delisted	Market Volatility
Country classification:						
OECD	1.84%	2.73%	4.57%	2.21%	8.00%	1.89%
Non-OECD	3.52%	3.55%	7.07%	2.16%	10.61%	2.22%
Developed	1.21%	2.59%	3.80%	2.44%	8.43%	1.88%
Emerging	3.96%	3.44%	7.41%	1.75%	8.59%	2.08%
Exit Intensity						
High exit intensity	2.85%	4.21%	7.07%	2.56%	15.17%	2.10%
Low Exit intensity	1.74%	2.08%	3.82%	1.98%	4.48%	1.86%
Market Volatility						
High	6.35%	5.57%	11.93%	4.51%	11.52%	3.74%
Moderate	3.06%	3.76%	6.82%	2.15%	9.85%	2.34%
Low	1.29%	2.24%	3.53%	1.90%	7.64%	1.58%
Financial Structure						
Bank-centric system	0.44%	2.14%	2.58%	8.46%	0.04%	1.77%
Market-centric system	3.73%	3.96%	7.69%	9.38%	0.02%	2.18%
Regions:						
East Asia	-0.70%	1.56%	0.86%	1.76%	6.29%	1.72%
Emerging Europe (EE)	4.40%	3.77%	8.17%	1.73%	6.19%	2.39%
Euro Area (EA)	2.68%	3.60%	6.28%	3.05%	8.16%	2.25%
Europe (not EA, EE)	-0.83%	0.83%	0.01%	1.98%	9.52%	1.53%
Latin America	6.09%	4.38%	10.47%	1.91%	8.44%	1.94%
North America	1.11%	2.23%	3.34%	1.35%	7.08%	1.41%

Note: The Table reports equally weighted cross-country averages. The classification of countries as developed or emerging follows the BIS definition. Exit intensity and market volatility are defined using sample-based thresholds. A country is classified as high exit intensity if the market capitalisation share of delisted firms exceeds 10% (12 of 32 countries), and low exit intensity otherwise. Market volatility is measured as the average volatility of the domestic financial-sector index. Countries with average volatility below 2% are classified as low volatility, those above 3% as high volatility (10 of 32 countries), and the remainder as moderate volatility. Financial structure classifications follow Beck and Levine (2002). Market-centric systems include the US, UK, Canada, Japan, Australia, South Korea, Switzerland, Israel, Hong Kong, Sweden, the Netherlands, and Ireland. Bank-centric systems include Germany, France, Italy, Spain, Greece, Austria, Slovakia, and Poland. All remaining countries are treated as financially mixed systems and are not included in the analysis. Regional groupings are defined as follows: East Asia (China, Hong Kong, Japan, South Korea); Emerging Europe (Slovakia, Poland, Turkey); Euro Area (Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Greece, Ireland, Finland); Non-EA/Non-EE Europe (Sweden, Norway, UK, Switzerland, Israel); Latin America (Argentina, Brazil, Colombia, Chile, Peru); and North America (US, Canada, Mexico).

3.5 Alternative Measure of Systemic Risk: SRISK

This section examines the effect of survivorship bias on an alternative measure of systemic risk, SRISK, by Acharya et al. (2012) and Brownlees and Engle (2017). The purpose is to assess whether the survivorship bias documented using ΔCoVaR also arises when systemic risk is measured in terms of expected capital shortfalls rather than tail dependence with a system benchmark. The comparison highlights important commonalities, but also meaningful differences in how survivorship bias emerges depending on the construction of the systemic risk measure. SRISK is designed to capture the expected capital shortfall of a financial institution in the event of a severe market downturn. It combines information on equity, liabilities, and downside exposure to market-wide stress. The underlying intuition is that systemic crises are most damaging when large, highly levered institutions suffer equity losses that leave them unable to meet prudential capital requirements. SRISK quantifies the amount of additional equity capital an institution would require to restore solvency under such conditions. For a financial institution i at time t, $SRISK_{i,t}$ is defined as:

$$SRISK_{i,t} = \max\{0, k \times (D_{i,t} + E_{i,t}) - (1 - LRMES_{i,t}) \times E_{i,t}\} \tag{16}$$

where $E_{i,t}$ denotes the market capital, $D_{i,t}$ is the total liabilities, k the prudential capital ratio (8%), and $LRMES_{i,t}$ is the long-run marginal expected shortfall. the term $k \times (D_{i,t} + E_{i,t})$ corresponds to the minimum required equity buffer under regulation, while $(1 - LRMES_{i,t}) \times E_{i,t}$ is the equity value that would remain after a systemic downturn. SRISK therefore measures the capital shortfall that would emerge in such a crisis. The long-run marginal expected shortfall (LRMES) is itself based on the marginal expected shortfall (MES) framework of Acharya et al. (2012, 2017), which measures a firm's expected equity loss conditional on a market-wide downturn. LRMES extends MES to a longer horizon by mapping short-run tail exposure into an expected cumulative equity loss under a fixed market decline scenario, typically a 40% drop over six months. As a result, SRISK inherits key properties of MES, including its focus on downside exposure and its sensitivity to the timing of tail events. This link is central for understanding survivorship bias in SRISK as institutions that exit before or early in major stress episodes exhibit limited observed MES and therefore low LRMES, even if they would have been vulnerable had they remained in the sample.

Unlike ΔCoVaR and MES, SRISK is additive across institutions. However, to maintain comparability with the earlier analysis and to avoid mechanically inflating aggregate risk through the inclusion of marginal institutions, we construct a market-capitalisation-weighted country-level

SRISK index rather than relying on simple aggregation. This ensures that the aggregate measure reflects the relative importance of institutions within the financial system. SRISK is most naturally suited to banks, where liabilities, equity, and capital adequacy ratios have a clear regulatory interpretation. It can nevertheless be applied, with appropriate caution, to other financial institutions such as insurers and asset managers, in which case it should be interpreted as a leverage-adjusted measure of downside exposure rather than as a precise regulatory capital shortfall. In our analysis, we include all financial institutions with total assets above USD 1 billion and exclude firms with zero SRISK, which provide no information for country-level aggregation.

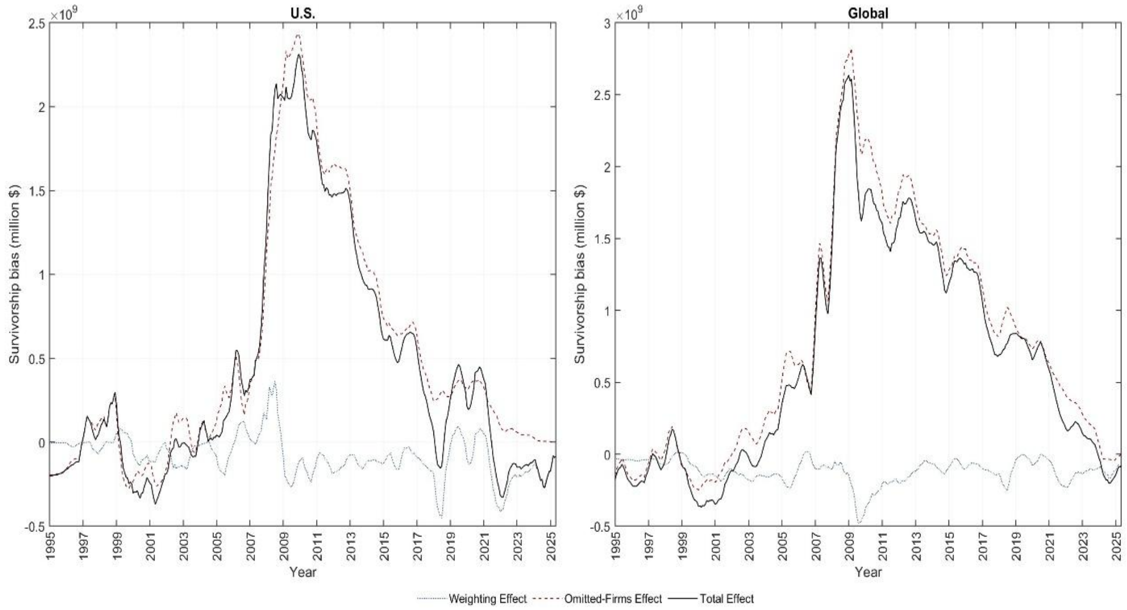
Figure 8 presents the results for the U.S. and the global sample of 32 countries. Consistent with the construction of SRISK, the weighting effect (WE) is economically insignificant.[8] Changes in index composition have little impact on estimated SRISK because the system index affects SRISK only indirectly through the estimation of LRMES, which is driven primarily by firm-level exposure to extreme market declines rather than by relative benchmark weights. As a result, survivorship bias in SRISK arises almost exclusively through the OE. On average, OE increases measured SRISK by 2.95%, with substantial variation over time. Due to the muted WE, the survivorship bias effect is modest during the start of the examined tranquil periods, but rises sharply during episodes of financial stress, including the dot-com collapse, the global financial crisis, and the Eurozone sovereign debt crisis. These spikes reflect the fact that institutions that delist tend to be smaller, less levered, and to exit before or early in major stress episodes.

Consequently, they contribute relatively little to measured SRISK conditional on observed histories. Excluding them concentrates capital shortfalls among large, surviving institutions, mechanically inflating the country-level SRISK index. At its peak, the omission effect raises measured SRISK by more than 9% relative to the global sample-period average. The evidence from ΔCoVaR and SRISK shows that survivorship bias is a pervasive feature of systemic risk measurement, but that its magnitude and transmission channel depend critically on the construction of the metric. ΔCoVaR is the most sensitive, as its benchmark-driven nature exposes it to both weighting and omission effects, particularly when delistings occur during crises. SRISK,

[8] WE is consistently small, but in some cases also negative. The negative sign is expected because LRMES and MES measure the systemic exposure of an institution rather than its marginal systemic importance, as in ΔCoVaR. As a result, the estimated exposure of an institution to market-wide variation can weaken when the market benchmark is expanded to include delisted institutions. Delisted firms often exhibit lower or less synchronized co-movement with the surviving core of the system, so their inclusion alters the distribution of market returns and reduces the measured tail sensitivity of surviving institutions. This attenuation in estimated exposure mechanically translates into a negative WE. Quantitatively, for the U.S. sample, the MES-based WE is economically small, averaging about −0.09% in relative terms, whereas the total survivorship effect is estimated at 1.8%.

by contrast, is affected almost entirely through the omission channel and its bias remains small in tranquil periods, but increases sharply during systemic stress.

FIGURE 8: Alternative measures of systemic risk



Note: The Figure presents the effect of survivorship bias in SRISK and its decomposition into two components: the omission effect (OE, dashed line) and the weighting effect (WE, dotted line). The left-hand side Figure is based on a large U.S. sample of financial institutions and the right-hand side uses data from a large sample of 32 countries. SRISK is expressed in million of USD and its estimation is based on Market Capitalisation, Total Liabilities (Debt) and stock market data. In both cases the stock market index is the weighted sample average. WE is estimated as the difference between the average systemic risk of all active institutions with respect to a market index including only active firms (and with respect to a market index including both active and delisted firms). OE captures the bias from excluding delisted institutions and is calculated as the difference between the average systemic risk of active firms and that of the combined active-and-delisted sample. Positive values indicate that the active-only index exceeds the full-sample index, implying a positive survivorship bias. Reported values correspond to 12-month moving-average.

3.6 Accounting for Database Coverage Bias

A central concern in empirical finance is survivorship bias arising from the systematic exclusion of delisted or failed firms from commercial databases. Shumway and Warther (1999) show that ignoring delisting returns generates economically meaningful distortions in asset-pricing tests, while Davis (1996) demonstrates that augmenting the Compustat-CRSP universe with delisted firms substantially weakens the apparent predictive power of firm fundamentals. These concerns are particularly relevant in the context of this study. To mitigate potential survivorship bias arising from incomplete database coverage, the dataset construction extends beyond standard Refinitiv Datastream data. The analysis is re-estimated for the U.S. subsample using records of failed and resolved institutions from the Federal Deposit Insurance Corporation (FDIC). These records are cross-checked against Compustat, and missing institutions are manually added when sufficiently reliable return histories can be reconstructed.

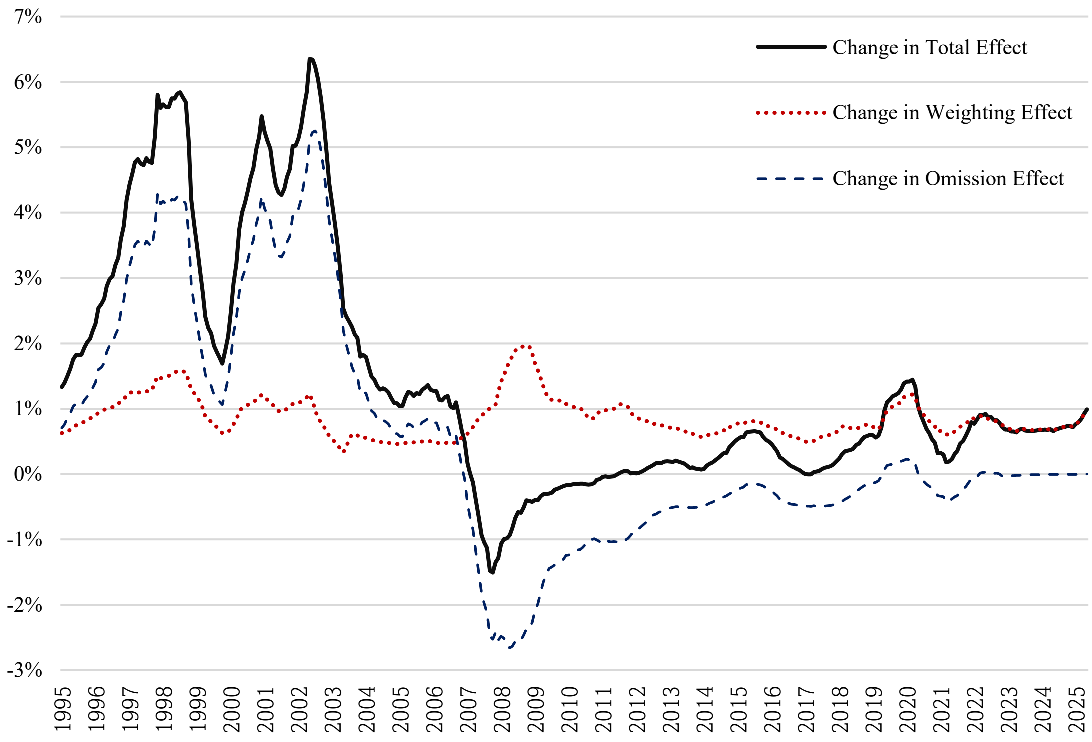
The final dataset includes 37 additional large firms across banking, investment banking, insurance, real estate finance, and specialty credit sectors that held total assets exceeding USD 1 billion at any point between 1995 and 2025. Several economically important institutions absent from Datastream, such as Lehman Brothers, Bear Stearns, Washington Mutual, First Republic Bank, and Signature Bank, are thus incorporated. Institutions with fewer than three years of continuous return data are excluded to ensure reliable estimation of tail-risk measures. This procedure substantially reduces database-driven survivorship bias and ensures that the analysis captures both surviving and exited institutions that were systemically relevant during the sample period. On average, these additional institutions account for approximately 2% of total U.S. financial-sector market capitalisation, with their share exceeding 5% in the pre-GFC period. Their time-varying importance indicates that potential database omissions are not uniformly distributed over time and are more pronounced ahead of major stress episodes.

Re-estimating survivorship bias using the augmented dataset further confirms our baseline findings. For the U.S. sample, the average total effect (TE) increases from 62 to 76 basis points in ΔCoVaR terms, corresponding to a rise from 3.9% to 4.8% relative to the active-only average ΔCoVaR. The increase is associated with a consistently increased weighting effect (WE), which rises, on average, from 1.5% to 2%. The omission effect (OE) also increases from 2.4% to 2.7%, but exhibits significant volatility and negative changes during the GFC and in the post-crisis period.

Figure 9 better illustrates that these differences are not uniform over time and instead reflect systematic variation across financial cycles. The Figure presents the change in WE, OE and total survivorship bias effect from the inclusion of the additional firms with all values presented in percentages. In the pre-GFC period, both OE and subsequently TE are noticeably higher in the augmented sample. This reflects the disappearance of relatively small/medium-size and less systemically exposed firms ahead of the crisis. These institutions either carried low systemic risk or appear less systemic because their histories do not include major tail events. Their exclusion from survivor-only samples therefore generates a positive OE, which in turn raises the overall survivorship bias. During this phase, WE also remains positive, reinforcing the upward bias.

At the onset of the GFC, the inclusion of the additional firms appears to have a negative effect on the total survivorship bias, driven primarily by a sharp decline in OE. The overall bias is reduced by 15 basis points, but still remains positive. This period coincides with the peak systemic risk of several large U.S. institutions, such as Lehman Brothers, Bear Stearns, and Washington Mutual, followed by their exit. When these institutions are included, measured system-wide tail risk rises relative to the survivor-only benchmark, producing a negative OE. However, TE does not fall as much as OE alone would imply because the effect is mitigated by the increased WE. Finally, in the post-GFC period, the inclusion of the additional firms results in an increase in the overall effect, but its composition changes. The contribution of OE becomes smaller and at times negative, while WE becomes the dominant component of TE. This indicates that survivorship bias increasingly reflects differences between surviving and delisted firms rather than the truncation of tail-event exposure. Including large distressed institutions initially raises measured systemic risk, but this effect gradually dissipates as the sample moves away from crisis conditions. Consistent with our previous findings, by 2020 OE converges toward zero, while WE remains persistently positive, implying that survivorship bias in tranquil periods is primarily driven by benchmark reweighting rather than by omitted tail exposures. Overall, the augmented dataset refines the time profile of survivorship bias without altering the central conclusion that survivorship bias is a structural feature of systemic risk measurement rather than a database artefact.

FIGURE 9: Survivorship bias decomposition: Baseline vs Augmented U.S. sample



Note: The Figure presents the survivorship bias (total effect, TE) and its decomposition into the weighting effect (WE) and omission effect (OE) for the U.S. sample after incorporating additional institutions identified from FDIC and Compustat. Survivorship bias is defined as the difference between the active-only index and the full-sample index that includes delisted institutions and positive values therefore indicate an overstatement of systemic risk in survivor-only samples. In this figure, a larger positive difference after augmentation indicates that including the additional firms strengthens the estimated survivorship bias. The analysis is based on ΔCoVaR estimates obtained using the state-variables approach over the period 1995-2025. Reported values are shown as 6-month moving averages.

3.7 *Sensitivity Analysis*

To assess the robustness of our findings, we conduct a series of sensitivity analyses. First, we re-estimate all specifications using equal weights instead of market-capitalisation weights. The results remain qualitatively unchanged and are larger in magnitude, reflecting the greater relative importance of delisted firms under equal weighting. Second, we apply alternative firm-size inclusion thresholds in place of the USD 1 billion baseline, using cut-offs of USD 1 million, USD 100 million, USD 5 billion, and USD 50 billion. The results remain consistent, and in line with our main findings, the magnitude of survivorship bias increases with firm size. Third, we consider alternative sample periods by shifting the starting year to 2000, 2005, and 2010. The qualitative patterns persist across these subsamples. Fourth, we vary the risk-threshold quantile used in the estimation of systemic risk measures, setting it to 0.10 instead of the baseline 0.05 and the results remain broadly unchanged. Finally, the results hold when we restrict the sample to banking institutions only. All results are reported in Appendix Table A6. Overall, the qualitative patterns of the results are preserved, indicating that the documented survivorship bias is not driven by modelling assumptions.

4 Practical and Policy Dimensions of Survivorship Bias

Our findings indicate that survivorship bias introduces a systematic measurement distortion into empirical assessments of systemic risk. When estimation relies on survivor-only datasets, measured tail dependence can be mechanically altered, systemic importance can be redistributed across institutions, and cross-country comparisons can become unreliable. Accordingly, the core challenge is not simply to reconstruct historical samples ex post, but to develop measurement frameworks that remain internally consistent as institutions enter and exit the system.

The accuracy of systemic risk measurement matters because these metrics are routinely used as inputs into macroprudential monitoring frameworks that target systemically important institutions. Empirical evidence shows that regulatory designation and heightened supervisory scrutiny of O-SIIs and G-SIBs are associated with changes in lending behaviour and balance-sheet adjustment (Behn et al., 2016), and may contribute to risk reallocation across the financial system without necessarily reducing aggregate risk (Bräuning and Fillat, 2025; Favara et al., 2021; Jiménez et al., 2017). In this setting, distortions in the measurement of systemic risk do not operate in isolation, but they can shape how supervisory attention is allocated across institutions and sectors. The results of this paper therefore have direct relevance for the interpretation of systemic risk indicators used in macroprudential surveillance and for the evaluation of policy interventions. Based on these findings, the paper offers several practical implications for supervisory design and risk monitoring.

A first implication concerns the treatment of firm exit in supervisory data architecture. Standard index construction mechanically reallocates market capitalisation toward surviving institutions following delistings, amplifying the WE documented in this paper. One way to mitigate this distortion is through the use of continuity indices that preserve the weights of delisted institutions from the point of exit onward, thereby preventing artificial increases in the measured systemic importance of surviving firms. In the context of M&As, exposures absorbed by acquiring institutions should be tracked explicitly over a transition horizon, rather than disappearing from system-wide benchmarks at the moment of delisting. This distinction is crucial for interpreting changes in aggregate systemic risk, which may otherwise reflect consolidation-induced reweighting rather than genuine changes in underlying fragility.

A second implication is that survivorship adjustments should be made transparent and operational within supervisory reporting frameworks. When survivorship bias is left unaddressed, systemic risk measures may place disproportionate weight on long-lived incumbents, contributing to misclassification of systemic importance and uneven capital burdens across surviving institutions (Naubert and Tesar, 2019; Andrieș et al., 2020). Stress-testing exercises can therefore benefit from reporting results based on both survivor-only and survivorship-adjusted benchmarks, with discrepancies between the two serving as diagnostic indicators of consolidation-driven mismeasurement. More generally, system-level risk indices should be accompanied by summary statistics that quantify weighting and omission effects, particularly during crisis periods.

A third implication relates to the design of systemic risk measures. Estimating benchmark-dependent measures such as ΔCoVaR or MES relative to broad market indices (e.g. S&P 500 or FTSE100). Market indices that include delisted institutions provide a more stable benchmark and weaken the sensitivity of tail dependence estimates to changes in sample composition. At the same time, no single systemic risk metric is immune to survivorship bias. Benchmark-based measures are primarily exposed to reweighting effects, while balance-sheet-sensitive measures, such as SRISK, are affected mainly through selective omission. Therefore, the joint use of multiple systemic risk indicators is essential. Divergences across measures provide information about the dominant channel through which survivorship bias operates at a given point in time and should be interpreted as diagnostic rather than as inconsistency. Frozen-composition benchmarks and equal-weighted placebo indices can also offer simple robustness checks that can be implemented routinely and reported alongside baseline estimates.

Finally, the results also call for caution in the interpretation of systemic risk estimates for newly listed or recently established financial institutions. As we show in the sample selection bias analysis, financial institutions that enter the market after major systemic crises have not been exposed to comparable tail events and therefore tend to appear less systemically risky in market-based measures. This pattern reflects limited crisis exposure rather than intrinsic resilience. In other words, supervisory assessments should therefore avoid interpreting low measured systemic risk for new entrants as evidence of limited systemic relevance, particularly in post-crisis periods.

5 Conclusions

Using a global panel of approximately 2,500 financial institutions across 32 countries from 1995 to 2025, we show that excluding delisted institutions systematically biases market-based measures of systemic risk. At the country level, survivor-only samples overstate systemic risk, measured by the market-capitalisation-weighted average ΔCoVaR, by around 13 basis points, or 5% on average. This bias operates through two distinct but complementary channels. First, a firm-level WE, whereby exits mechanically reallocate benchmark weights toward surviving institutions, inflating their measured systemic footprint. Second, a country-level OE, reflecting the exclusion of institutions that are smaller, less interconnected, and often absent during major systemic stress episodes. Because of this sample period bias, our estimates indicate that exiting firms exhibit, on average, approximately 27 percent lower systemic risk than currently active institutions. The relative importance of the two channels is state-dependent and heterogeneous across countries, and time periods with survivorship bias intensifying during crisis periods and exceeding 8% during the 2008-2009 GFC period.

The analysis further shows that survivorship bias is not confined to ΔCoVaR. While benchmark-driven WE is largely absent by construction in SRISK, OE remains quantitatively important, particularly during crisis periods, as institutions that exit prior to or early in systemic downturns exhibit mechanically low measured capital shortfalls. Overall, these findings imply that systemic risk measures based exclusively on surviving institutions can misstate the build-up and distribution of vulnerabilities, undermining cross-country and cross-sector comparability and complicating the interpretation of stress tests and systemic institution designations. Accounting explicitly for survivorship, through benchmark choice, sample construction, and transparent diagnostics, is therefore central to the credible use of market-based systemic risk measures in macroprudential analysis.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564-608. https://doi.org/10.1257/aer.20130456

Acharya, V. V., Brunnermeier, M. K., & Pierret, D. (2025). Systemic risk measures: From the panic of 1907 to the banking stress of 2023. *Annual Review of Financial Economics*, *17*. https://doi.org/10.1146/annurev-financial-112823-015828

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, *30*(1), 2-47. https://doi.org/10.1093/rfs/hhw088

Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, *102*(3), 59-64. https://doi.org/10.1257/aer.102.3.59

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705. https://doi.org/10.1257/aer.20120555

Allen, F., & Carletti, E. (2013). What is systemic risk?. *Journal of Money, Credit and Banking*, *45*(s1), 121-127. https://doi.org/10.1111/jmcb.12038

Altman, E. I. (1989). Measuring corporate bond mortality and performance. *The Journal of Finance*, *44*(4), 909-922. https://doi.org/10.1111/j.1540-6261.1989.tb02630.x

Ammann, M., Burdorf, T., Liebi, L., & Stöckl, S. (2022). Survivorship and delisting bias in cryptocurrency markets. *Available at SSRN:* http://dx.doi.org/10.2139/ssrn.4287573

Andrieş, A. M., Nistor, S., Ongena, S., & Sprincean, N. (2020). On becoming an O-SII ("other systemically important institution"). *Journal of Banking & Finance*, *111*, 105723. https://doi.org/10.1016/j.jbankfin.2019.105723

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk?. *Journal of Financial Intermediation*, *23*(1), 1-26. https://doi.org/10.1016/j.jfi.2013.11.001

Armanious, A. (2024). Too-systemic-to-fail: Empirical comparison of systemic risk measures in the Eurozone financial system. *Journal of Financial Stability*, *73*, 101273. https://doi.org/10.1016/j.jfs.2024.101273

Barth, J. R., & Wihlborg, C. (2016). Too big to fail and too big to save: dilemmas for banking reform. *National Institute Economic Review*, *235*, R27-R39. https://doi.org/10.1177/002795011623500113

Bats, J. V., & Houben, A. C. (2020). Bank-based versus market-based financing: Implications for systemic risk. *Journal of Banking & Finance*, *114*, 105776. https://doi.org/10.1016/j.jbankfin.2020.105776

Beck, T., & Levine, R. (2002). Industry growth and capital allocation:: does having a market- or bank-based system matter?. *Journal of financial economics*, *64*(2), 147-180. https://doi.org/10.1016/S0304-405X(02)00074-0

Behn, M., Haselmann, R., & Wachtel, P. (2016). Procyclical capital regulation and lending. *The Journal of Finance*, *71*(2), 919-956. https://doi.org/10.1111/jofi.12368

Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. *Review of Finance*, *21*(1), 109-152. https://doi.org/10.1093/rof/rfw026

Berger, A. N., & Sedunov, J. (2024). The Life Cycle of Systemic Risk and Crises. *Journal of Money, Credit and Banking*, *56*(8), 1923-1961. https://doi.org/10.1111/jmcb.13231

Bessembinder, H. (2018). Do stocks outperform treasury bills?. *Journal of Financial Economics*, *129*(3), 440-457. https://doi.org/10.1016/j.jfineco.2018.06.004

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535-559. https://doi.org/10.1016/j.jfineco.2011.12.010

Bostandzic, D., & Weiß, G. N. (2018). Why do some banks contribute more to global systemic risk?. *Journal of Financial Intermediation*, *35*, 17-40. https://doi.org/10.1016/j.jfi.2018.03.003

Bräuning, F., & Fillat, J. L. (2025). The Impact of Regulatory Stress Tests on Banks' Portfolio Similarity and Implications for Systemic Risk. *Journal of Money, Credit and Banking*, *57*(6), 1387-1419. https://doi.org/10.1111/jmcb.13239

Brown, S. J., Goetzmann, W., Ibbotson, R. G., & Ross, S. A. (1992). Survivorship bias in performance studies. *The Review of Financial Studies*, *5*(4), 553-580. https://doi.org/10.1093/rfs/5.4.553

Brownlees, C., & Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, *30*(1), 48-79. https://doi.org/10.1093/rfs/hhw060

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, *23*(1), 77-100. https://doi.org/10.1257/jep.23.1.77

Carhart, M. M., Carpenter, J. N., Lynch, A. W., & Musto, D. K. (2002). Mutual fund survivorship. *The Review of Financial Studies*, *15*(5), 1439-1463. https://doi.org/10.1093/rfs/15.5.1439

Carpenter, J. N., & Lynch, A. W. (1999). Survivorship bias and attrition effects in measures of performance persistence. *Journal of Financial Economics*, *54*(3), 337-374. https://doi.org/10.1016/S0304-405X(99)00040-9

Davis, J. L. (1996). The cross-section of stock returns and survivorship bias: Evidence from delisted stocks. *The Quarterly Review of Economics and Finance*, *36*(3), 365-375. https://doi.org/10.1016/S1062-9769(96)90021-6

Dungey, M., Flavin, T., O'Connor, T., & Wosser, M. (2022). Non-financial corporations and systemic risk. *Journal of Corporate Finance*, *72*, 102129. https://doi.org/10.1016/j.jcorpfin.2021.102129

Ellis, S., Sharma, S., & Brzeszczyński, J. (2022). Systemic risk measures and regulatory challenges. *Journal of Financial Stability*, *61*, 100960.https://doi.org/10.1016/j.jfs.2021.100960

Elton, E. J., Gruber, M. J., & Blake, C. R. (1996). Survivor bias and mutual fund performance. *The Review of Financial Studies*, *9*(4), 1097-1120. https://doi.org/10.1093/rfs/9.4.1097

Engle, R., Jondeau, E., & Rockinger, M. (2015). Systemic risk in Europe. *Review of Finance*, *19*(1), 145-190. https://doi.org/10.1093/rof/rfu012

Favara, G., Ivanov, I., & Rezende, M. (2021). GSIB surcharges and bank lending: Evidence from US corporate loan data. *Journal of Financial Economics*, *142*(3), 1426-1443. https://doi.org/10.1016/j.jfineco.2021.06.026

Fung, W., & Hsieh, D. A. (2000). Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases. *Journal of Financial and Quantitative analysis*, *35*(3), 291-307. https://doi.org/10.2307/2676205

Grammatikos, T., & Papanikolaou, N. I. (2018). "Too-Small-To-Survive" versus "Too-Big-To-Fail" banks: The two sides of the same coin. *Financial markets, institutions & instruments*, *27*(3), 89-121. https://doi.org/10.1111/fmii.12094

Jiménez, G., Ongena, S., Peydró, J. L., & Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*, *125*(6), 2126-2177. https://doi.org/10.1086/694289

Jorion, P., & Goetzmann, W. N. (1999). Global stock markets in the twentieth century. *The Journal of Finance*, *54*(3), 953-980. https://doi.org/10.1111/0022-1082.00133

Kladakis, G., & Skouralis, A. (2025). Press freedom and systemic risk. *Journal of Business Finance & Accounting*, 52 (3), 1535-1556. https://doi.org/10.1111/jbfa.12855

Kladakis, G., Lux, N., & Skouralis, A. (2025). Exploring the non-linear dynamics between Commercial Real Estate and systemic risk. *Journal of Empirical Finance*, *82*, 101607. https://doi.org/10.1016/j.jempfin.2025.101607

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33-50. https://doi.org/10.2307/1912528

Leong, S. H. (2025). Consistent Backtesting Systemic Risk Measures. *Journal of Financial and Quantitative Analysis*, 1-53. https://doi.org/10.1017/S0022109025102421

Liang, N. (2013). Systemic risk monitoring and financial stability. *Journal of Money, Credit and Banking*, *45*(s1), 129-135. https://doi.org/10.1111/jmcb.12039

Linnainmaa, J. T. (2013). Reverse survivorship bias. *The Journal of Finance*, *68*(3), 789-813. https://doi.org/10.1111/jofi.12030

Löffler, G., & Raupach, P. (2018). Pitfalls in the use of systemic risk measures. *Journal of Financial and Quantitative Analysis*, *53*(1), 269-298. https://doi.org/10.1017/S0022109017001041

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking & Finance*, *36*(12), 3150-3162. https://doi.org/10.1016/j.jbankfin.2012.04.020

Naubert, C., & Tesar, L. L. (2019). The value of systemic unimportance: The case of MetLife. *Review of Finance*, *23*(6), 1069-1078. https://doi.org/10.1093/rof/rfy037

Rodríguez-Moreno, M., & Peña, J. I. (2013). Systemic risk measures: The simpler the better?. *Journal of Banking & Finance*, *37*(6), 1817-1831. https://doi.org/10.1016/j.jbankfin.2012.07.010

Rohleder, M., Scholz, H., & Wilkens, M. (2011). Survivorship bias and mutual fund performance: Relevance, significance, and methodical differences. *Review of Finance*, *15*(2), 441-474. https://doi.org/10.1093/rof/rfq023

Shumway, T. (1997). The delisting bias in CRSP data. *The Journal of Finance*, *52*(1), 327-340. https://doi.org/10.1111/j.1540-6261.1997.tb03818.x

Shumway, T., & Warther, V. A. (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *The Journal of Finance*, *54*(6), 2361-2379. https://doi.org/10.1111/0022-1082.00192

Skouralis, A. (2023). The role of systemic risk spillovers in the transmission of Euro Area monetary policy. *Open Economies Review*, *34*(5), 1079-1106. https://doi.org/10.1007/s11079-022-09707-0

Varotto, S., & Zhao, L. (2018). Systemic risk and bank size. *Journal of International Money and finance*, *82*, 45-70. https://doi.org/10.1016/j.jimonfin.2017.12.002

Weiß, G. N., & Mühlnickel, J. (2014). Why do some insurers become systemically relevant?. *Journal of Financial Stability*, *13*, 95-117. https://doi.org/10.1016/j.jfs.2014.05.001

Zhang, Q., Vallascas, F., Keasey, K., & Cai, C. X. (2015). Are market-based measures of global systemic importance of financial institutions useful to regulators and supervisors?. *Journal of Money, Credit and Banking*, *47*(7), 1403-1442. https://doi.org/10.1111/jmcb.12249

Appendix

TABLE A1: Sector summary statistics

	Active	Delisted	Sector share (No of firms)	Sector share (Market Cap)
Banks	684	350	41.28%	48.77%
Insurance	213	100	12.50%	20.34%
Investment banks	388	131	20.72%	18.01%
Finance & credit services	108	38	5.83%	2.57%
Real Estate	385	103	19.48%	10.29%
Undefined	0	5	0.20%	0.02%
Total	1778	727	100%	100%

Note: The Table reports the sectoral composition of the sample by number of firms and by market capitalisation. The sample comprises 2,505 financial institutions from 32 countries, with figures reported separately for active and delisted firms. Sector shares are presented as percentages of the total number of firms and of the aggregate market capitalisation, with all monetary values converted to US dollars.

TABLE A2: Country summary statistics

Country	Total Number of firms	Market Cap share	Delisted (% of MCap)	Market Returns (%)	Market St.Dev. (%)
Argentina	9	0.09%	18.67%	0.45%	3.36%
Australia	108	4.34%	12.24%	0.10%	1.25%
Austria	10	0.33%	0.52%	0.08%	1.71%
Belgium	24	0.96%	10.11%	0.01%	1.67%
Brazil	24	0.72%	14.21%	0.04%	2.25%
Canada	93	4.77%	1.27%	0.14%	1.17%
Chile	23	0.50%	6.51%	0.10%	1.07%
China	135	10.92%	1.38%	0.12%	1.84%
Colombia	15	0.27%	0.91%	0.07%	1.32%
Finland	8	0.58%	2.67%	0.16%	1.68%
France	80	3.35%	10.91%	0.04%	1.83%
Germany	93	5.28%	9.65%	0.04%	1.72%
Greece	17	0.31%	13.99%	-0.36%	4.10%
Hong Kong	66	1.97%	4.97%	0.07%	1.72%
Ireland	7	0.36%	1.90%	-0.25%	3.76%
Israel	35	0.34%	3.31%	0.13%	1.55%
Italy	55	2.17%	10.53%	0.02%	1.88%
Japan	228	6.49%	10.94%	-0.06%	1.57%
Mexico	33	0.50%	9.85%	0.18%	1.68%
Netherlands	19	1.18%	5.33%	0.03%	2.20%
Nigeria	17	0.10%	22.53%	0.05%	2.45%
Norway	35	0.40%	2.78%	0.13%	1.60%
Peru	13	0.20%	1.91%	0.09%	1.72%
Poland	22	0.53%	9.34%	0.14%	2.01%
Slovakia	5	0.02%	4.12%	0.12%	2.23%
South Korea	76	1.16%	8.32%	-0.02%	2.27%
Spain	34	2.14%	15.98%	0.10%	1.98%
Sweden	25	1.08%	2.03%	0.14%	1.50%
Switzerland	47	3.39%	31.75%	0.05%	1.50%
Turkey	44	0.71%	5.10%	0.41%	2.94%
UK	107	6.60%	7.72%	0.02%	1.51%
US	998	38.25%	10.13%	0.10%	1.37%
Total/ Average	2505	100%	8.49%	0.08%	1.95%

Note: The Table reports the country composition of the sample by number of firms and by market capitalisation. The sample covers 2,505 financial institutions across 32 countries. For each country, the total share of global market capitalisation is shown, along with the proportion of market value accounted for by active and delisted firms. All market capitalisation figures are converted to US dollars to ensure comparability. Market returns and standard deviation refer to the country financial system index that is estimated as a market capitalisation-weighted average of all active financial institutions listed in the primary stock market of each country.

TABLE A3: Monte Carlo simulation results

ϱ	w	WE (%)	OE (%)	TE (%)	P (TE>0)	Exit timing
0	0.01	0.40%	0.44%	0.84%	0.97	164.75
0	0.05	2.19%	2.06%	4.25%	0.99	169.37
0	0.10	4.18%	3.37%	7.56%	0.99	154.11
0	0.25	10.12%	5.02%	15.14%	1.00	150.34
0	0.50	22.58%	-0.84%	21.74%	1.00	168.60
0.05	0.01	0.33%	0.38%	0.70%	0.97	151.40
0.05	0.05	1.80%	1.69%	3.50%	0.98	149.60
0.05	0.10	3.71%	2.97%	6.68%	0.99	149.39
0.05	0.25	10.68%	4.99%	15.67%	0.99	168.04
0.05	0.50	20.02%	-0.61%	19.41%	1.00	156.42
0.25	0.01	0.30%	0.29%	0.59%	0.97	157.89
0.25	0.05	1.51%	1.34%	2.85%	0.98	155.57
0.25	0.10	2.84%	2.21%	5.05%	0.99	149.21
0.25	0.25	8.15%	3.41%	11.56%	0.99	159.13
0.25	0.50	16.73%	-1.78%	14.95%	0.99	162.85
0.50	0.01	0.20%	0.19%	0.40%	0.94	155.72
0.50	0.05	1.03%	0.91%	1.93%	0.97	159.63
0.50	0.10	1.97%	1.49%	3.46%	0.99	156.49
0.50	0.25	5.21%	1.99%	7.20%	0.97	158.32
0.50	0.50	10.49%	-2.43%	8.06%	0.96	154.23
0.75	0.01	0.10%	0.08%	0.18%	0.88	155.87
0.75	0.05	0.55%	0.34%	0.89%	0.92	161.28
0.75	0.10	0.95%	0.49%	1.44%	0.90	160.05
0.75	0.25	2.10%	0.05%	2.16%	0.87	158.74
0.75	0.50	4.36%	-3.79%	0.57%	0.64	151.39
0.95	0.01	0.02%	-0.04%	-0.02%	0.50	144.07
0.95	0.05	0.09%	-0.29%	-0.20%	0.42	158.93
0.95	0.10	0.10%	-0.58%	-0.48%	0.44	160.54
0.95	0.25	-0.17%	-1.99%	-2.16%	0.28	156.11
0.95	0.50	-1.10%	-5.68%	-6.77%	0.17	160.92

Note: This Table reports Monte Carlo simulation results across combinations of similarity to the financial sector (ϱ) and relative size (w). WE, OE, and TE denote the average weighting effect, omission effect, and total survivorship bias across simulation draws. Survivorship bias is defined as systemic risk measured using the active-only sample minus systemic risk measured using the full sample including exited institutions, so positive values indicate overstatement in survivor-only samples. In each simulation, a synthetic institution is added with returns generated from a one-factor structure that combines a financial-sector factor and an idiosyncratic shock drawn from a Student-t distribution. Exit timing is determined by a distress-dependent hazard process. P(TE>0) reports the fraction of simulations in which the total effect is positive. Exit timing denotes the median simulated exit time of the synthetic institution. Each cell is based on 500 Monte Carlo draws.

TABLE A3: Monte Carlo simulation results robustness

ϱ	w	WE (%)	OE (%)	TE (%)	P (TE>0)	Exit timing
0	0.01	0.23%	0.43%	0.66%	0.98	155.34
0	0.05	1.78%	2.10%	3.88%	1.00	158.74
0	0.10	3.80%	3.58%	7.38%	0.99	155.96
0	0.25	10.42%	6.07%	16.49%	1.00	160.32
0	0.50	20.31%	1.20%	21.51%	1.00	149.07
0.05	0.01	0.22%	0.41%	0.63%	0.96	153.94
0.05	0.05	1.60%	1.86%	3.46%	0.98	148.74
0.05	0.10	3.78%	3.58%	7.36%	1.00	166.30
0.05	0.25	10.14%	5.62%	15.76%	1.00	162.26
0.05	0.50	19.66%	1.53%	21.19%	1.00	151.22
0.25	0.01	0.16%	0.33%	0.49%	0.98	157.66
0.25	0.05	1.30%	1.57%	2.87%	0.99	167.03
0.25	0.10	2.78%	2.67%	5.45%	0.99	150.34
0.25	0.25	7.45%	4.26%	11.71%	1.00	156.47
0.25	0.50	15.91%	0.50%	16.41%	1.00	159.49
0.50	0.01	0.07%	0.24%	0.31%	0.94	162.60
0.50	0.05	0.74%	1.04%	1.79%	0.98	157.66
0.50	0.10	1.56%	1.79%	3.35%	0.98	153.47
0.50	0.25	4.68%	2.83%	7.51%	0.99	152.17
0.50	0.50	9.59%	-0.27%	9.32%	0.98	155.67
0.75	0.01	0.00%	0.11%	0.11%	0.78	162.49
0.75	0.05	0.29%	0.55%	0.84%	0.94	162.17
0.75	0.10	0.62%	0.83%	1.45%	0.93	155.93
0.75	0.25	1.71%	1.09%	2.81%	0.90	157.12
0.75	0.50	3.56%	-1.26%	2.30%	0.77	153.36
0.95	0.01	-0.02%	-0.05%	-0.07%	0.46	152.85
0.95	0.05	-0.08%	-0.28%	-0.36%	0.39	163.84
0.95	0.10	-0.07%	-0.58%	-0.65%	0.39	152.44
0.95	0.25	-0.35%	-2.00%	-2.35%	0.36	158.52
0.95	0.50	-1.32%	-5.39%	-6.71%	0.21	159.73

Note: This Table reports Monte Carlo simulation results across combinations of similarity to the financial sector (ϱ) and relative size (w). WE, OE, and TE denote the average weighting effect, omission effect, and total survivorship bias across simulation draws. Survivorship bias is defined as systemic risk measured using the active-only sample minus systemic risk measured using the full sample including exited institutions, so positive values indicate overstatement in survivor-only samples. In each simulation, a synthetic institution is added with returns generated from a one-factor structure that combines a financial-sector factor and an idiosyncratic shock drawn from the empirical donor return pool. Exit timing is determined by a distress-dependent hazard process. P(TE>0) reports the fraction of simulations in which the total effect is positive. Exit timing denotes the median simulated exit time of the synthetic institution. Each cell is based on 500 Monte Carlo draws.

TABLE A5: Cross-country comparison results

Country	Weighting Effect (WE)	Omission Effect (OE)	Total Effect (TE)	WE /ΔCoVaR	OE /ΔCoVaR	TE /ΔCoVaR
Argentina	0.41%	0.24%	0.65%	11.3%	6.6%	17.9%
Australia	0.07%	0.10%	0.17%	3.9%	5.2%	9.1%
Austria	0.01%	0.01%	0.02%	0.5%	0.4%	0.9%
Belgium	0.02%	0.13%	0.14%	0.8%	6.1%	6.9%
Brazil	0.27%	0.27%	0.54%	10.3%	10.4%	20.7%
Canada	0.01%	0.01%	0.02%	0.4%	0.7%	1.1%
Chile	0.04%	0.03%	0.07%	4.0%	2.9%	6.9%
China	-0.01%	0.01%	0.00%	-0.6%	0.6%	0.1%
Colombia	0.00%	0.00%	0.01%	0.3%	0.3%	0.6%
Finland	0.06%	0.03%	0.09%	2.3%	1.2%	3.5%
France	0.09%	0.10%	0.19%	3.5%	4.0%	7.5%
Germany	0.17%	0.14%	0.31%	6.5%	5.3%	11.8%
Greece	0.18%	0.45%	0.63%	3.6%	8.7%	12.3%
Hong Kong	-0.07%	0.03%	-0.04%	-3.5%	1.6%	-2.0%
Ireland	0.20%	0.06%	0.27%	4.2%	1.4%	5.6%
Israel	0.04%	0.03%	0.07%	1.8%	1.4%	3.2%
Italy	0.06%	0.06%	0.13%	2.3%	2.2%	4.5%
Japan	0.04%	0.05%	0.09%	2.1%	3.0%	5.1%
Mexico	0.01%	0.03%	0.05%	1.5%	3.6%	5.0%
Netherlands	0.02%	0.09%	0.11%	0.5%	2.8%	3.3%
Nigeria	-0.02%	0.01%	-0.01%	-0.9%	0.4%	-0.5%
Norway	-0.03%	0.02%	-0.02%	-1.7%	0.8%	-0.8%
Peru	0.05%	0.02%	0.07%	4.6%	1.7%	6.2%
Poland	0.04%	0.08%	0.13%	2.0%	3.7%	5.7%
Slovakia	0.06%	0.02%	0.08%	8.9%	3.5%	12.4%
South Korea	-0.03%	0.03%	0.00%	-1.6%	1.4%	-0.2%
Spain	0.07%	0.11%	0.18%	2.6%	3.9%	6.5%
Sweden	0.00%	0.02%	0.02%	0.1%	0.8%	0.9%
Switzerland	-0.13%	-0.05%	-0.18%	-6.6%	-2.4%	-9.0%
Turkey	0.05%	0.10%	0.15%	2.3%	4.1%	6.5%
UK	0.03%	0.05%	0.08%	2.3%	3.4%	5.8%
US	0.02%	0.04%	0.06%	1.5%	2.4%	3.9%

Note: The Table reports the cross-country decomposition of survivorship bias in ΔCoVaR over 1995–2025. ΔCoVaR is estimated on weekly returns using the state-variables approach, with the system proxy defined as a market capitalisation-weighted portfolio of listed financial institutions. The Weighting Effect (WE) is the change in ΔCoVaR induced by the reallocation of benchmark weights when delisted institutions are excluded; the Omission Effect (OE) captures the additional change arising from the exclusion of the delisted institutions themselves. The last three columns present the ratio by scaling each effect by the country's baseline ΔCoVaR measured on the active-only sample. Positive values indicate that excluding delisted firms results in an increase in measured systemic risk, whereas negative values indicate the opposite.

TABLE A6: Sensitivity analysis

Survivorship bias:	WE/ΔCoVaR	OE/ΔCoVaR	TE/ΔCoVaR
Baseline Model:	1.48%	2.39%	3.87%
Threshold limit			
>1 million	1.37%	2.18%	3.55%
>100 millions	1.35%	2.18%	3.53%
>5 billions	3.42%	4.86%	8.27%
>50 billions	4.94%	4.02%	8.96%
Sample periods			
2000-2025	1.82%	2.69%	4.51%
2005-2025	3.03%	3.17%	6.20%
2010-2025	1.00%	3.36%	4.35%
Equal weights	9.37%	14.46%	23.83%
Bank only	1.74%	0.78%	2.52%
Tail threshold (q = 10%)	1.86%	2.41%	4.27%

Note: This table reports sensitivity analyses of survivorship bias in systemic risk estimation for the U.S.. WE, OE, and TE denote the weighting effect, omission effect, and total survivorship bias, respectively, expressed as percentages relative to baseline systemic risk. Survivorship bias is defined as systemic risk measured using the active-only sample minus systemic risk measured using the full sample including exited institutions and positive values therefore indicate that survivor-only samples overstate systemic risk. The table reports alternative firm-size inclusion thresholds (in USD), alternative sample periods, equal-weighted aggregation instead of market-capitalisation weights, a higher tail threshold (q = 0.10), and a restriction to banks only. The baseline specification corresponds to market-capitalisation weights, a USD 1 billion size threshold, and a tail threshold of q = 0.05 over the period 1995-2025.

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