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Abstract

How do interdependent economic shocks impact the financial system and reverberate within it? To model the financial system, we start with a two-sector microstructural model of the financial system that includes banks and insurers. We develop a stress testing methodology that stochastically computes economic profits and losses at banks and insurers following correlated corporate default shocks. Taking into account the feedback and amplification of the initial shock though the financial system, we quantify its impact on firms' capital positions. This methodology is applied to a very rich panel data set of UK banks and insurers. Our approach enables us to distil the contribution of initial economic shocks and the feedback and amplification mechanisms to extreme tail events. Overall, we find that, since the Covid pandemic (2020–21), the UK financial system has experienced an improvement in both profit expectations and tail losses. Comparing sectoral losses in an extreme stress scenario, we find that insurers are more affected than banks by economic credit and traded risk losses, while fire sale losses affect banks more than insurers.

Key words: Credit risk portfolio, systemic risk, financial contagion, financial network, system-wide stress testing.

JEL classification: D85, G21, G32, L14.

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1. Introduction

Input-output linkages among non-financial corporations affect the productive structure of our economic system, similarly to the way contractual relationships among financial institutions determine the microstructure of the financial system. The two systems are tightly woven together as the financial sector provides funding to the real economy via loans and allocates capital in the form of debt and equity securities. Ultimately, macro-financial linkages matter for business cycle fluctuations and financial stability (Gabaix 2011, Acemoglu et al. 2012, Acemoglu et al. 2015).

Our work aims at modelling one side of this macro-financial nexus, namely how correlated corporate default shocks impact the financial system. Then, we model how these shocks propagate within the financial system via solvency and fire-sales contagion. To achieve this, we develop a state-of-the-art microstructural stress testing methodology that aims to lay the foundations for modelling and assessing solvency risks in a system-wide setting.

To model the wider financial system, we start with a two-sector microstructural model of the financial system that includes banks and insurers. There have been many such models of the banking sector, but very few modelling the interactions across sectors (Roncoroni et al. 2021, Battiston et al. 2017), especially capturing the interplay with the insurance sector. The insurance sector can be of systemic importance to the wider financial system, as it is one of the main investors in financial assets. The Global Financial Crisis indeed revealed that insurers can be a source of contagion (Weiß and Mühlnickel, 2014; Acharya et al. 2009). Therefore, the assessment of risks for the insurance sector through stress testing and its interaction with the banking sector is very important from a financial stability perspective, especially through the lens of fire-sale dynamics.

To compute economic losses, we use a stochastic approach to stress test design (Montagna et al. 2021, Sydow et al. 2024 and Elsinger et al. 2006), which includes estimating economic credit and traded risk losses via a Gaussian copula model capturing the dependence structure of counterparty defaults across sectors and countries (Glasserman, 2004 and Glasserman and Li, 2005), as well as firms' gross realized profits so as to model firms' net profit and loss (P&L) distributions over time. Once we derived the net profit and loss for each firm, we deterministically compute feedback and amplifications mechanisms as a function of the P&L shock and quantify its impact on firms' capital positions. The feedback and amplification mechanisms we include are fire-sale spillover and solvency contagion. Our approach enables us to distil the contribution of initial economic shocks and the feedback and amplification

mechanisms to extreme tail events, tracking four contagion channels: economic credit and traded risk losses, economic profits, fire sales losses and solvency contagion losses.
To empirically test and calibrate the methodology, we construct the most comprehensive granular exposures dataset of the UK financial system covering loan and security exposures of banks and insurers, capturing roughly £4.6 trillion of assets. Our dataset also has a time series dimension and spans from 2019 to 2023.

Overall, we find that, since the Covid-19 Pandemic (2020-21), the UK financial system has experienced an improvement in both profit expectations and tail losses. Throughout the paper, we compute tail losses using the Conditional Capital at Risk (CCaR) metric, which is the average tail loss conditional on the outcomes in the 90^{th}, 95^{th} and 99^{th} percentile (CCaR90, CCaR95 and CCaR99 respectively) or, in other words, an extreme stress event that would occur with 1% probability (so at the 99^{th} percentile). A CCaR99 scenario may lead to a £133 billion loss in the UK financial system on average in our sample.

Next, we isolate the contribution of UK banks and insurers to these tail losses. Banks contribute more to tail losses (80% of total CCaR99 losses) than insurers, consistent with banks' larger share in the exposure network (81%). Digging deeper, the picture becomes more nuanced across sectors. It is important to note that the contribution of different contagion channels to tail losses differs across sectors as well as across percentiles of the profit and loss distribution. Specifically, in the CCaR99 scenario, we find that insurers are more affected than banks by economic credit and traded risk losses, respectively 68% and 60%, while economic profits in both sectors play a less relevant contribution. Moreover, fire-sale losses affect banks (33%) more than insurers (25%), although banks only hold 23% of their assets as securities, while insurers' portfolio composition is made up exclusively of securities. The low relative contribution of fire-sales to insurers' tail risk is due to the limited passthrough of asset shocks to their capital.

The analysis also illustrates that feedback and amplification mechanisms - primarily fire-sales spillovers - materially increase the likelihood of experiencing extreme stress events as well as their severity. We showcase that the profit channel is materially less important than the economic credit loss channel, respectively explaining 5% and 62% of total variation respectively in the CCaR99 scenario. This result corroborates findings in the existing literature on the significance of correlated exposures in determining systemic financial externalities (Elsinger et al. 2006; Acharya, 2009; Billio et al. 2012; Patro et al., 2013; and Glasserman and Young, 2015).

Moreover, we show that using a homogeneous price impact function without either security-specific selling pressures or market selling pressure may lead to overestimate losses for low stress events, consistently with the findings provided in Fukker et al. (2022). Nonetheless, we show that for medium (90^{th}), severe (95^{th}) and extreme stress events (99^{th}) a homogeneous price impact function leads us to materially underestimate fire-sale losses in the range of -9% to -50%. Moreover, also related to the modelling of fire-sale dynamics, we provide evidence on the impact of a pecking order strategy (selling liquid assets first) versus a pro-rata approach. Consistently with Caccioli et al. (2024), we find that on average a pro-rata approach does overestimate fire sales losses compared to a pecking-order strategy. In this respect, we find a non-linear fire sales impact between the two strategies, which gets wider the lower the severity of the stress event the system experiences, respectively ranging from a factor of 7 times to 20 times. This result corroborates findings by Jiang et al. (2017) and Schaanning (2016) that a pro-rata approach is more suitable for periods of stress (tail outcomes), whereas a pecking order strategy bring much larger benefits given a medium-low stress environment.

Our framework showcases that systemic events may be triggered via idiosyncratic shocks to firms' counterparties and that financial amplification mechanisms exacerbate materially the outcome both in terms of severity and loss correlation between the two sectors.[1] The contribution of the drivers to the realized severity differs across percentile of the profit and loss distribution as well as across sectors and on a firm-basis, highlighting that a probabilistic approach combined with firm heterogeneity and multiple risk channels is necessary to disentangle the role of interconnectedness and financial contagion in triggering market disruptions in modern financial systems.

The remainder of the paper is organized as follows. Section 2 details the methodology, including the modelling of the P&L distribution and the feedback and amplification mechanisms. Section 3 covers the data and calibration of the methodology. Section 4 showcases our results in terms of severity and probability of tail events using as proxy expected losses (Capital at Risk estimates) as well as expected shortfalls – expected tail losses conditional to various degree of severity. In the end, Section 5 provides a sensitivity analysis shedding light on key assumptions affecting our results. Last section concludes and discusses main findings of the paper.

[1] Limitations relate to the exclusion of liquidity contagion and solvency-liquidity interactions which may further amplify the results here documented, and the lack of the investment fund sector which plays an important role in the determination of the fire-sale price dynamics as shown by Sydow et al. 2024.

1.1 Literature Review

Gabaix (2011) has showed how concentration risk in the economic system such as shocks to large non-financial corporations may lead to remarkable fluctuations in economic activity - the granular origins of aggregate fluctuations. Moreover, Acemoglu et al. (2012) showed how interconnectedness in economic activity such as a high level of interdependency in the intersectoral input-output firms' linkages - network origins - may explain aggregate fluctuations in output. These results are extremely relevant in light of the Covid-19 pandemic, which has caused bottleneck problems in the global supply chain. These network features - concentration risk and interconnectedness - also play an important role within the financial system determining fluctuations in the level of systemic risk.

Our paper is related to several studies on the role played by interconnectedness and concentration risk in modern financial systems, and how they might exacerbate systemic risk externalities. This paper extends the granular mapping of the UK banking sector of Covi et al. (2022) to include UK insurers and thus represents a step forward in painting a very detailed picture of the UK financial system[2]. Moreover, our dataset has also a time series dimension, which allows to track and compare losses over time. This is a key contribution to the literature, as it is very rare that microstructural contagion models can be run over multiple time periods.

Next, our work contributes to the stress testing and system-wide systemic risk literature, since we develop a multi-sector model comprising banks and insurers. There have been many network models of the banking sector[3] and more recently multi-sector network models of the financial system[4] (Aikman et al. (2019), Halaj (2018), Mirza et al. (2020), Farmer et al. (2020), Bookstaber et al. (2018)), but only one of banks and insurers jointly (Caccioli et al. 2024). Of the multi-sector models, the closest to ours is Sydow et al. (2024) since we also rely on a stochastic approach to scenario design thereby endogenously determining the full distribution of potential P&L shocks. Their paper shows how the integration of endogenous reactions (asset liquidation) of investment funds and the related security exposure network into a microstructural banking model can amplify banks' losses further via indirect fire-sale contagion. In the same way, we provide evidence that the UK insurance sector also tends to amplify UK banks' losses via indirect fire-sale price-mediated equity contagion proportionally to the insurers' share of total security holdings and materially under medium/severe stress conditions - 90th/95th percentile. Furthermore, we find that under extreme stress conditions (99th

[2] French et al. (2015) provide a good overview of the UK insurance sector.
[3] See Huser (2015) for a review of the financial network literature.
[4] See Aikman et al (2023) for a survey of the literature on macro-prudential stress testing models.

percentile) UK banks and insurers' loss correlation decreased due to a low degree of correlated credit risk losses, implying smaller fire-sale spillovers across the two sectors. In the end, consistent with findings by Billio et al. (2012) and Chen et al. (2012) we find evidence that banks' fire-sale spillovers affect insurers' solvency position more materially than vice versa.

The third contribution is at a methodological level. Indeed, we model feedback and amplification mechanisms as a function of the P&L shocks endogenously derived according to exposure/obligor-specific information instead of relying on a set of exogeneous shocks which are not anchored to current economic and financial conditions. To achieve this, we build upon Covi et al (2022) and combine different reaction functions for the different sectors: banks may be forced to deleverage (Khandani and Lo, 2011; Cont and Wagalath, 2016; Coen et al. 2019) to restore their targeted leverage ratio; non-life insurers may liquidate assets to restore their targeted solvency ratio (Ellul et al., 2011; Caccioli et al., 2024); life insurers may deleverage to meet potential investor redemptions (Coval and Stafford, 2007; Baranova et al. 2019). In the end, when a firm ends up breaching its minimum regulatory capital requirements, and thus becomes insolvent, it transmits losses via direct financial exposures in the bank-insurance network (Eisenberg and Noe, 2001; Upper 2011; Bardoscia et al. 2019). Indirect financial exposures via overlapping portfolios constitute a well-recognised source of risk, providing a channel for financial contagion induced by the market price impact of asset deleveraging. We rely on the novel method developed by Fukker et al. (2022) to calibrate the market price impact on a security basis from historical daily traded volumes and price returns. Caccioli et al (2024) find that performing a stress simulation that does not account for common asset holdings across multiple sectors can severely underestimate the fire sale losses in the financial system. Leveraging upon this methodological framework, we shed light on the sensitivity of the results to key fire-sale modelling assumptions such as homogeneous versus heterogenous price-impact functions, firms' selling strategies (pro-rata versus HQLA pecking order), as well as the role of insurers' asset-liability adjustments.

Finally, our paper builds upon the existing literature using a stochastic approach to portfolio credit risk modelling (Glasserman, 2004; Montagna et al. 2021; and Sydow et al., 2024) and augment it with a profit channel so as to derive a full P&L distribution for the UK financial system. This modelling innovation allows us to benchmark the expected (mean) model outcomes in terms of balance sheet variables and regulatory ratios against actual quarter-firm specific values. Moreover, it also allows us to smooth initial losses so as to place the severity of the initial shocks into a more realistic perspective.

2. Methodology

The methodology aims to derive a profit and loss distribution augmented with feedback and amplification mechanisms for both banks and insurers exploiting loan and security-level portfolio information on a quarterly frequency. To do so, we derive a two-step sequential procedure in which *as first step* we calculate via Monte Carlo simulations the loss distribution on direct economic exposures by sampling counterparty default events (Elsinger et al. 2006). Next, we match consistently across simulations and by firm supervisory data on gross realized profits to the estimated economic credit and traded risk losses so as to derive a firm-specific net profit and loss distribution. *As second step*, conditional to the realization of each P&L simulation, we quantify deterministically the potential feedback and amplification mechanisms via fire-sales and solvency contagion at a firm-level. This sequential procedure is estimated for 20.000 simulations over 14 quarters allowing us to consistently assess on a firm-basis and over time the P&L distribution of firms, the severity and probability of extreme outcomes, and finally to analyse the system propensity to instability.

2.1 Stochastic Profit and Loss Distribution

2.1.1 Loss Distribution

Leveraging upon Vasicek (1987), we compute the loss distribution on a firm-level (L_i) as a function of each firm's portfolio of loan and security exposures ($EXP_{i,j,e}$), the exposure-specific loss given default parameters ($LGD_{i,j,e}$), and the distribution of shocks to portfolio's obligors ($Y_{j,n}$). Specifically, to model obligor default events we rely on a Monte Carlo sampling method modelling the dependence structure of counterparty defaults across sectors and countries via a Gaussian copula model (Glasserman, 2004; Glasserman and Li, 2005).

$$L_{i,n} = \sum_{j}^{J}((\ EXP_{i,j,e} *\ LGD_{i,j,e}) * Y_{j,n})$$

Where $Y_{j,n}$ is the obligor default indicator matrix, taking value 1 if the obligor defaults or 0 otherwise. The j indicator refers to the set of obligors in a firm's portfolio and the n subscript indicates in which simulation obligor j defaults or not[5]. As we take the loss-given-default parameters as given as well as the network of exposures as described in Section 3 below the problem boils down to the estimation of the matrix $Y_{j,n}$[6].

[5] We perform 20.000 simulations to derive the loss distribution.
[6] We omit from this vector of corporate defaults, and so from the stochastic simulations, UK banks and insurers that we aim to model their default endogenously.

In this respect, we use a sampling method based on a Gaussian-Copula model in order to estimate the default indicator as a function of the counterparty-specific probability of default (PD_j) as well as of the obligors' dependence structure. This latter feature would allow us to realistically model correlated corporate default events by sector and country so as to generate a cluster of defaults. Correlated default events as discussed in Acemoglu et al. (2012, 2015) as well as in Gabaix (2011) may be generated via intersectoral input-output linkages (supply chain spillovers) that is, via common country and sector-specific financial and macro shocks. This interdependence among obligors' default is introduced through a multivariate normal vector $(\xi 1, \ldots, \xi j)$ of latent variables. Each default indicator is represented as:

$$Y_j = 1\{\xi j > x_j\},\ j = 1, \ldots, J.$$

The threshold x_j represents the default boundary (Merton, 1974), which is matched to the marginal default probability of obligor j (PD_j). ξj follow a standard normal distribution and we set $x_j = \varphi^{-1}(1 - PD_j)$, where φ is the cumulative normal distribution, and the correlations among the ξj determine the dependence among the Y_j as follows:

$$P(Y_j = 1) = P(\xi j > x_j) = P(\xi j > \varphi^{-1}(1 - PD_j)) = PD_j$$

To derive the set of obligors' default indicator Y_j, we estimate the correlation structure of ξj, whose calibration is provided in Section 3.2. The key output is a loss distribution of 20.000 simulations, which is firm-specific and time variant on a quarterly frequency[7].

2.1.2 Net Profit and Loss Distribution

Since feedback and amplification mechanisms are a function of firms' realized loss outcomes given that firms are assumed to respond to a change in their regulatory capital or a change in solvency requirements (leverage and solvency ratios), we aim to take firms' gross profits into account to derive a net profit and loss distribution ($PL_{i,n,t}^{EC}$) so as to smooth the overall severity of the loss estimates across simulations and thus avoid an overestimation of financial contagion.

$$PL_{i,n,t}^{EC} = P_{i,n,t} - L_{i,n,t} \sim \text{Operating Profit (loss) when } PL_{i,n,t}^{EC} > 0 \ (<0)$$

Hence, we scale the loss distribution for each firm and time period by the firm-specific realized gross profits reported in that quarter ($P_{i,t}$). We use as proxy for gross profits *operating profits* excluding impairments which instead are endogenously derived from firms' portfolio of

[7] The set of counterparties defaulting in each simulation is the same set for all firms we model so as to have consistency of results across firms in each simulation.

exposures ($L_{i,n,t}$). However, to create consistency between the loss estimates and the realized profit variable across simulation severity - given that higher estimated losses imply a higher number of corporate defaults, and so in turn lower potential gross profits - we want to introduce some heterogeneity and derive a profit distribution ($P_{i,n,t}$). To achieve that, we use as median value firm's realized gross profits and we model the left tail of the profit distribution as an inverse function of the loss estimate calculated for that simulation (n) and adjusted by the historical volatility of firm i's gross profits (σ_i^P)[8]. We then scale the volatility parameter by the distance from the median percentile of the loss distribution, thereby mapping the highest loss percentile into one standard deviation decrease in profits, and the lowest loss percentile into one standard deviation increase in profits relative to the median value ($P_{i,t}$).

$$P_{i,n,t}|0.5 < n < 1 = P_{i,t} + \frac{\sigma_i^P P_{i,t}}{p(L_{i,n,t})} \; if \; L_{i,n,t} < L^{50th}$$

Where $pct(L_{i,n,t}) = 0 \; if \; pct(n) = 0.5 \; and \; pct(L_{i,n,t}) = 1 \; if \; pct(n) = 1 \; or \; 0$

2.2 Feedback and Amplification Mechanisms

Once derived the net profit and loss distribution (operating profits) for each firm, we compute deterministically feedback and amplifications mechanisms as a function of the initial P&L shock in each simulation which affects firms' capital positions. In this respect, banks may be forced to deleverage (Khandani and Lo, 2011; Cont and Wagalath, 2016; Coen et al. 2019; Duarte and Eisenbach, 2021) to restore their targeted leverage ratio, non-life insurers may liquidate assets to restore their targeted solvency ratio (Ellul et al., 2011; Caccioli et al., 2024), whereas life insurers may deleverage to meet potential investor redemptions (Coval and Stafford, 2007; Baranova et al. 2019). In the end, when a firm breaches its minimum regulatory capital requirements, and thus becoming insolvent, it transmits losses via direct financial exposures in the bank-insurance network (Eisenberg and Noe, 2001; Bardoscia et al. 2019).

2.2.1 Fire-Sales

Selling Pressure

Consistently with the relevant literature on fire-sales, conditional to a given stress, banks, non-life insurers, as well as life insurers are assumed to deleverage and thus restore respectively

[8] We have modelled profits as inverse function of the realized loss severity consistently with the negative relationship we observe between firms' historical operating profit and impairments as also argued by Sydow et al. (2024). The variability of gross profits is calibrated according to one-standard deviation of firm-specific gross profits estimated on a quarterly frequency over the period 2014 - 2023.

their initial targeted leverage ratio (LR_B^0), solvency ratio (SII_L^0) or meet the redemption shock (R_{NL}) as in the following set of equations.

Banks: $LR_B^0 = \frac{TA^0 - Tier1^0}{Tier1^0}$; where: $\left(\frac{LR_{i,s,q}^1}{LR_{i,s,q}^0} - 1\right) > CV_i^{LR}$ and $CV_i^{LR} = \frac{\sigma_i^{LR}}{E[LR_{i,q}]}$

Life Insurers: $SII_L^0 = \frac{OWF^0}{SCR^0}$; where: $\left(\frac{SII_{i,s,q}^0}{SII_{i,s,q}^1} - 1\right) > CV_i^{SII}$ and $CV_i^{SII} = \frac{\sigma_i^{SII}}{E[SII_{i,q}]}$

Non-Life Insurers: $R_{NL} = \alpha(PL_{i,n,t})$

Note: TA refers to total assets, Tier 1 to Tier1 Capital, LR to leverage ratio, CV to coefficient of variation; σ to volatility parameter, OWF to own funds, SCR to solvency capital requirements; R to redemption shock. The index = 0 refers to initial targeted values; index =1 refer to computed values.

Moreover, firms are assumed to respond only to sizable negative P&L shocks, that is, when their regulatory thresholds deteriorate such that the change in the bank-specific leverage ratio or insurer-specific solvency ratio is larger than the threshold CV_i^{LR} or CV_i^{SII}, respectively the coefficient of variation of the leverage ratio and solvency ratio. We implement this threshold approach to avoid an overestimation of fire-sales spillovers in those realizations with medium-low severity as highlighted by Pichler et al. (2021). In the end, non-life insurers or unit-linked, are modelled similarly to an investment fund which is forced to deleverage according to a redemption shock which is calibrated with $\alpha = \frac{1}{3}$ as in Baranova et al. (2019), implying 30% selloff rate of the MtM losses experienced. The quantity of assets sold is computed as follow:

$$Q_B^* = TA^1 - TIER1^1(1 + LR^0); \qquad Q_L^* = \frac{TL^1 + TA^1\left(SII^0 * \frac{SCR^1}{TA^1} - 1\right)}{SII^0 * \frac{SCR^1}{TA^1}}; \qquad Q_{NL}^* = \frac{1}{3}(PL)$$

In the end, we assume that firms rely on a pro-rata approach to deleveraging, that is, distributing Q^* - the firm-specific selling pressure – across all securities in a firm's portfolio[9]. This approach is also corroborated by Jiang et al. (2017) and Schaanning (2016) that suggested that a pro-rata approach is more suitable for periods of stress. In the end, we model only one-round of fire-sales losses as in Caccioli et al. (2024) and not multiple rounds since we model institutions as aggressive leverage targeters[10]. In the sensitivity analysis we will be testing this assumption by adopting a pecking-order approach and compare both results.

Price Impact Function (PIF)

[9] We constraint the selling pressure to be smaller or equal to the total amount of securities available for sales, since in some cases a firm may be required to deleverage more than the quantity of security available.

[10] Given this assumption, as shown in Ramadiah et al. (2022) as well as in Duarte and Eisenbach (2021), the inclusion of multiple rounds of asset liquidations may reduce the accuracy of the Fire-sales estimates.

Once we have determined the quantity of assets sold by each firm (i) in each simulation (n) to restore the initial solvency position and we have determined the security-specific quantity sold by implementing a pro-rata approach, we compute the total selling pressure in the market ($Q^{*}_{s,n,t}$) on a security-level (s) as well as the total selling pressure in the system for each simulation so as to track the overall severity of the fire-sales event ($Q^{*}_{n,t}$).

$$Q^{*}_{s,n,t} = \sum_{i}^{I} Q^{*}_{i,s,n,t}\,; \quad and \quad Q^{*}_{n,t} = \sum_{s}^{S} Q^{*}_{s,n,t}$$

Once we have determined the quantity sold for each security $Q^{*}_{s,n,t}$, we rely on heterogeneous price impact functions to derive the security-specific price change $p^{*}_{s,n,t}$. In this respect, the literature has used multiple approaches, homogeneous versus heterogeneous price functions calibrated on a security or asset-class level. One of the most common approach is Cont and Wagalath (2016) which derives a price change conditional to the volumes sold and the depth of the market for the asset (s). However calibrating the market depth on a security-level across time is data intensive and not feasible to extend to a large number of securities. Moreover, this approach does not consider how price changes are affected non-linearly conditional to the severity of the fire-sales. For this set of reasons, we rely on Fukker et al. (2022) which estimates non-linear price impact functions via quantile regression for a wide range of securities (bond and equity) with heterogeneous characteristics, respectively by issuing sectors (NFC, GG, FC, CI) and country as well as by rating (low, medium, high) and size of the firm (small, medium, large). Moreover, conditional to the characteristic of the security, the price impact vary as a non-linear function of the security-specific volume sold (£10, 50, 100 million) and according to the severity of the fire-sale events (rank in percentiles)[11]. Hence, we borrow from Fukker et al. (2022)'s the set of security-specific price impact functions (F_s) and we match them to our set of securities (s) according the above described characteristics. Next, for each F_s we determine the realized price impact according to i) the estimated Security-Specific (s) Selling Pressure ($Q^{*}_{n,s,t}$) in simulation (n) and at time (t) and ii) the estimated Market Selling Pressure ($Q^{*}_{n,t}$) whose severity (n) is determined by its percentile in relative terms across 20.000 simulations: $PIF^{*}_{s,n,t} = F_s\left(Q^{*}_{s,n,t}, Q^{*}_{n,t}\right)$.

This approach allows us to avoid biased estimates due to the application of linear and homogeneous price impact functions (Fukker et al., 2022), which may lead to overestimated

[11] This refers to the fact that for the same exact category a security belongs to, you may have different price effects depending on the percentile of the historical price change distribution.

fire-sales spillovers. Overall, we model the price changes for more than 6000 different securities, classified into 1100 asset classes, across n=20.000 simulations and over 14 different quarters. In Section 3 we will describe the distribution of potential price impact parameters for bond and equities, whereas in Section 4 we will be presenting the estimated price changes.

Loss Function

In the end, we compute Mark-to-Market losses ($L_{i,n,t}^{FS}$) for each firm i's portfolio of security conditional to each simulation (n) and time period (t). In this respect, we both compute direct losses ($L_{i,s,n,t}^{FS|dir}$) on the securities sold ($Q_{i,s,n,t}^{*}$) as well as the indirect losses ($L_{i,s,n,t}^{FS|ind}$) on the remaining security portfolio holdings ($Q_{i,s,n,t}^{P}$). Thanks to this rich set of results, we present in Section 4 a various set of risk metrics capturing the contribution of fire-sales spillovers to feedback and amplification mechanisms. In this respect, we derive distributional estimates of fire-sales spillovers on a system and sectorial level (banks and insurers) as well as we provide estimates for selling pressure and price changes across percentiles of fire-sales severity.

$$L_{i,n,t}^{FS} = \sum_{s}^{S} L_{i,s,n,t}^{FS|dir} + L_{i,s,n,t}^{FS|ind}\,; \qquad L_{i,s,n,t}^{FS|dir} = Q_{i,s,n,t}^{*} * \Delta p_{s,n,t}^{*} \;\; and \;\; L_{i,s,n,t}^{FS|ind} = Q_{i,s,n,t}^{P} * \Delta p_{s,n,t}^{*}$$

3.1.2 Solvency Contagion

Before deriving the augmented profit and loss distribution with feedback and amplification mechanisms, we want also to consider the potential effects of solvency contagion via bilateral direct financial exposures between and among banks and insurers conditional to the insolvency of an institution (i). The solvency contagion channel has been always considered as one of the major channel of risk propagation in the interbank market, and accounted for a large share of interbank losses in the 2008 GFC (Glasserman and Young, 2016). Nonetheless, Bardoscia et al. (2017) has more recently identified a long-term decline in the contagion role played by this channel. Hence, we rely on the standard Eisenberg and Noe (2001)'s approach to estimate potential losses on bilateral exposures conditional to a firm j's (bank or insurer) default event ($Y_{j,n,t}$)[12]. Hence, after computing the |P&L from economic exposures and losses from fire-sales spillovers, we update firms' balance sheet and check whether a firm has defaulted, that is, it has breached is minimum capital requirement. For a bank this is modelled as a breach of minimum CET1 capital requirement ($MC_{i,t}$) and for an insurer as a breach of its solvency ratio ($SII_{i,t}$). We perform two iterative loops of the solvency contagion channel to let the algorithm converging to a stable solution[13].

[12] We test results by implementing the NEVA methodology of Bardoscia et al. (2019) and results do not differ.
[13] Most of the losses take places in the first round.

$$L_{i,n,t}^{SC} = \sum_{j}^{J} EXP_{i,j,n,t} * LGD_{i,j,n,t} * Y_{j,n,t} \quad where\ i\ refers\ to\ a\ bank\ or\ insurer$$

$$where\ \ Y_{j,n,t} = 1\ if\ \frac{CET1_{i,n,t}}{RWA_{i,n,t}} < MC_{i,t}\ or\ \ SII_{i,t} < 1\ and\ 0\ otherwise;$$

2.3 Augmented Profit and Loss Distribution

We aggregate results from the profit and loss distribution ($PL_{i,n,t}^{EC}$) estimated on direct economic exposures with the loss distribution on feedback and amplification mechanisms ($L_{i,n,t}^{FA}$) to derive the final profit and loss distribution augmented with financial contagion ($PL_{i,n,t}^{TOT}$).

$$PL_{i,n,t}^{TOT} = PL_{i,n,t}^{EC} + L_{i,n,t}^{FA}\ \ where\ L_{i,n,t}^{FA} = L_{i,n,t}^{FS} + L_{i,n,t}^{SC}$$

2.4 Balance Sheet Accounting

Balance sheets have been updated at each step of the methodology in order to derive a stock-flow consistent set of outputs and thus model feedback and amplifications as a function of the changes in firms' solvency position.

The stochastic approach used to model firms' P&L leads us to derive (n) number of potential balance sheets for each firm (i) in each time period (t); where n equals to the number of simulations performed (20.000). In this respect, we aim at updating the following set of balance sheet variables according to a three-step sequential approach following the propagation channels described in Section 2.1 and Section 2.2. The stock-flow consistent balance sheet accountings are summarized in Appendix A.

The starting step (S=0) is the original starting conditions of a firm (i) at time (t), that is, actual balance sheet data to be updated, respectively for:

<u>Banks:</u> total assets (TA), risk weighted assets (RWA), CET1 and TIER1 capital and capital ratios as well as leverage ratio (LR).

<u>Insurers:</u> total assets (TA), total liability (TL), capital also defined as own funds (OWF), solvency capital requirements (SCR) and solvency ratio (SII).

Starting balance sheets (S=0) are collected from stress testing and supervisory COREP and FINREP templates. Step1 (S=1) consists in deriving the distribution of a firm's balance sheet (across n simulations) conditional to the estimated stochastic profit and loss shocks ($PL_{i,n,t}^{EC}$). In this respect, we adjust banks' risk-weighted assets ($RWA_{i,n,t}^{1}$) by the P&L shock ($PL_{i,n,t}^{EC}$)

which is proxied by an average bank/time-specific risk weight calculated as $(\frac{RWA^0_{i,t}}{TA^0_{i,t}})$[14]. Subsequently, we update the network of exposures ($EXP^{S+1}_{i,j,n,t}$) to keep track of the defaulted exposures and thus avoid overestimating fire-sales spillovers. Next, feedback and amplification mechanisms are introduced as a function of Step1's outputs. First, we model fire-sales spillovers since the impact propagates in financial markets in the short-term (days and weeks), whereas solvency contagion is the result of insolvency procedures, which take place in the medium-term (quarters)[15]. Hence, Step 2's outputs (S=2) are derived using the fire-sale loss distribution ($PL^{FS}_{i,n,t}$), i.e. substituting $PL^{EC}_{i,n,t}$ in the set of equations as well as by deducting the amount of assets sold ($Q^*_{i,n,t}$). Similarly, Step3's outputs (S=3) are fed with the solvency contagion loss distribution ($PL^{SC}_{i,n,t}$), and all the variables are updated as in Step 1. At the end of this final step, we compute the balance-sheet equilibrium for each firm (i) in each simulation (n) and time period (t). Hence, we derive a distribution for each balance sheet variable.

This procedure is consistently applied to banks and insurers' balance sheets, although for insurers we also model the liability side ($TL^{S+1}_{i,n,t}$) since own funds ($OWF^{S+1}_{i,n,t}$) are derived as the difference between ($TA^{S+1}_{i,n,t}$) and ($TL^{S+1}_{i,n,t}$). This is due to the fact that insurers via asset-liability management or derivative contracts are able to smooth the shock to capital by adjusting/reducing simultaneously the liability side. This liability adjustments are modelled through the Gamma parameter ($\boldsymbol{\gamma_{i,t}}$) which captures insurer-specific time-variant market-risk-sensitivities. Hence, we assume a full passthrough ($\boldsymbol{\gamma_{i,t} = 0}$) of the shock to capital in Step1 and Step3, since the shock is transmitted via corporate defaults, whereas a partial passthrough ($\boldsymbol{\gamma_{i,t} > 0}$) in Step 2, when shocks are modelled via mark-to-market losses and market risk sensitivities do matter. Section 3.4 will discuss the calibration of the Gamma parameter.

[14] This assumption leads us to conservative regulatory ratio estimates (CET1r) since the methodology by construction overestimate post shock RWAs especially in the tail of P&L distribution. More risky obligors (with high probability of default) default more often compared to less risky obligors (with low probability of defaults), thereby determining this overestimation RWA bias. Nonetheless, in this way we address the critique posed by Acharya et al. (2014) which highlight that banks may underestimate their risk-weights given the average risk weight appears unconnected with their actual risk.

[15] We need to acknowledge that with the post GFC regulatory reforms, resolution authorities may react very quickly and bail-in an institution over the weekend. Even in that case, it will take place at closed markets once information has already spread, that is, when likely fire-sales have already taken place.

3. Data and Model Calibration

This section presents the key inputs we use to calibrate the model, respectively real exposure data, the set of risk parameters to model counterparty default risk, and the price impact functions we adopt to quantify fire-sales spillovers. The data collection spans from Q4-2019 till Q1-2023.

3.1 Network of Exposures

We rely on several supervisory data sources to calibrate the methodology and so model UK banks and UK insurers' solvency risk as well as feedbacks and amplification mechanisms. The aim is to reconstruct the UK banking and insurance systems' exposure network across countries and sectors of the economy as well as the financial network of relationships among UK banks and UK insurers so as to model how economic shocks get amplified and transmitted via fire-sales and financial contagion[16].

The UK financial system here described is composed of 9 major UK banking groups as well as 24 UK life and non-life insurance groups. Table 1 reports key summary statistics for the asset side coverage of the UK exposure network and its decomposition across sectors, jurisdictions and asset type. The UK financial system's network of exposures amount up to £4593 billion in Q1-2023, respectively £3714 of assets owned by UK banks and £879 by UK insurers. The sectoral decomposition highlights how UK banks are more exposed to households (HH) and non-financial corporates (NFC) than UK insurers, which are mostly invested in assets issued by financial corporations (FC) and credit institutions (CI). Moreover, we can see that UK banks diversify more their investments outside the UK than UK insurers, which tend to invest mostly into asset issued by UK firms. In the end, UK banks' exposures are mostly in form of loans to corporates and households (£2875 billion), and £839 billion in the form of security exposures, preferably bonds (£731 billion) over equity instruments (£108 billion). Contrary, the UK insurers' network of exposure is composed of only security exposures, mostly equity (£618 billion) over bonds (£261 billion).

Overall, the exposure network capture roughly 50% of UK Banks' total assets as well as 70% of UK insurers' total assets for the selected sample of firms, making our analysis well-representative of the whole UK banking and insurance systems. In the end, the financial network of bilateral exposures among and between UK banks and UK insurers is relevant for

[16] Obligors have been mapped by country according to the location of incorporation.

the direct transmission of shocks between the two systems since it amounts up to £115 billion in Q1-2023.

Table 1 – Exposure Coverage and Decomposition by Sector, Area, and Asset Class
Amounts in £ Billion

ASSET	2019	2019	2019	2020	2020	2020	2023	2023	2023
NETORK	**SYSTEM**	**BANK**	**INS**	**SYSTEM**	**BANK**	**INS**	**SYSTEM**	**BANK**	**INS**
EXPOSURE	4023	3150	873	4125	3264	861	4593	3714	879
NFC	865	687	178	814	643	171	814	689	124
FC	694	425	269	698	425	273	952	631	321
CI	580	279	301	597	308	290	743	404	338
GG	592	468	125	625	498	127	596	500	95
HH	1273	1273	/	1374	1374	/	1454	1454	/
DOMESTIC	2476	1775	701	2429	1746	683	2534	1831	703
FOREIGN	1544	1371	172	1693	1515	178	2054	1877	177
LOAN	2404	2404	/	2535	2535	/	2875	2875	/
BOND	923	600	324	980	649	331	992	731	261
EQUITY	696	147	550	610	80	530	726	108	618

Source: stress testing data, supervisory COREP templates C.27 and C.28, and FINREP F.20.04.

Next, we present a set of exposure-based statistics highlighting the distributional features of the network. In total we capture in Q1-2023 exposures to 88.784 different counterparties located across countries and belonging to various sectors of the economy. Most of them (87.063) belong to UK banks' portfolios, whereas 7491 are the set of UK insurers' counterparties. This is due to the fact that UK insurers' portfolio are made of securities which are issued by a relative small and homogeneous set of large and quoted firms. Contrary, UK banks' portfolios are also materially exposed via the loan book, in which we capture exposures to large, but also mid and small corporates, which are not quoted. In this respect, we can see that the mean exposure amount is much smaller (£18 million) for banks than for insurers (£117), further corroborating the intuition above provided. This difference holds across different percentile of the exposure distribution. Another important distributional feature we want to highlight is the degree of concentration risk and overlapping portfolios in the system since they directly affect the severity and probability (skewness) of the system's capacity to experience extreme negative stress events. Hence, the 10% largest counterparties – SHARE 90th percentile – accounts for 89% of total UK banks' exposures and 83% of UK insurers' exposures, highlighting a high degree of concentration risk. Similarly, the share of exposures that are overlapping across each pair of banks' and insurers portfolios amount to 37% of total exposures, with a relative higher share for UK insurers (49%). This is due to the fact that insurers are exposed to a narrower set of counterparties than banks, that is, those counterparties which issue a security. In the end, we compute the share of overlapping portfolio of exposures between the two sectors whose average is close to 34%.

Table 2 – Granular Exposure Distribution, Concentration Risk and Overlapping Portfolios
Amounts in £ Million

ASSET DISTRIBUTION	2019	2019	2019	2020	2020	2020	2023	2023	2023
NETWORK	**SYS**	**BANK**	**INS**	**SYS**	**BANK**	**INS**	**SYS**	**BANK**	**INS**
N_CP	79910	76814	7245	99933	97790	7320	88784	87063	7491
MEAN	29	19	121	23	15	118	28	18	117
MEDIAN	0.8	0.7	1.8	0.5	0.5	1.7	0.6	0.6	1.0
90^{th} percentile	14	11	114	9	7	107	14	12	87
97^{th} percentile	94	68	536	67	48	512	90	69	481
99^{th} percentile	373	260	1666	283	191	1617	338	239	1499
SHARE 90^{th} percentile	87%	88%	82%	88%	90%	82%	88%	89%	83%
SHARE 97^{th} percentile	73%	74%	67%	75%	76%	67%	73%	74%	70%
SHARE 99^{th} percentile	58%	59%	55%	59%	60%	55%	57%	57%	57%
OVERL. PORT.	42%	39%	55%	41%	39%	54%	37%	37%	49%

Source: stress testing data collection, supervisory COREP templates C.27 and C.28, and FINREP F.20.04.

3.2 Risk Factors

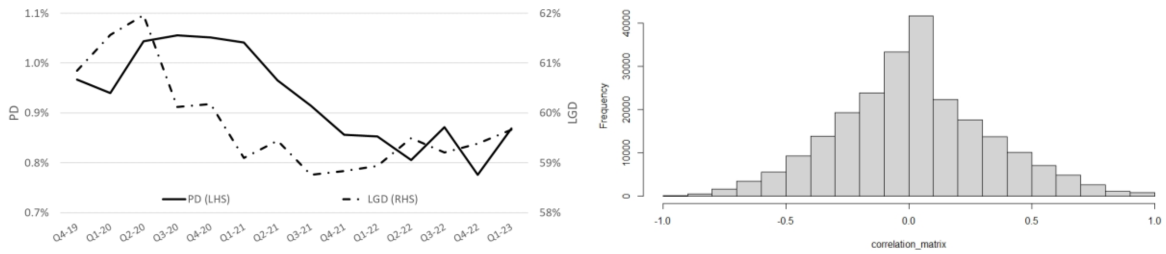
In order to model stochastically the set of obligors' defaults and quantify losses at default for each exposure and counterparty, we collect from supervisory COREP template C.09 time-variant (quarterly), country and sector-specific risk factors such as 1-year ahead probability of defaults (PD) as well as loss-given-default (LGD) parameters. These parameters are matched to each counterparty in the system and represent the key inputs to quantify economic credit and market risk losses over time, which reflect current economic and financial conditions in that specific quarter.

Figure 1a depicts the weighted average probability of default and loss given default parameters (weighted by exposure amounts), which highlights the evolution of counterparty risk in the system since Q4-2019 till Q1-2023. Moreover, we have to acknowledge the presence of strong heterogeneity across sectors and countries, which may determine non-linear effects across reporting firms and time periods (heterogeneous outcomes).

Figure 1: Risk Factors

Panel (a)
Average PD and LGD Parameters

Panel (b)
Dependence Structure by Sector-Country Pairs



Source: COREP C.09

The other key ingredient to model counterparty default risk is the calibration of obligors' dependence structure, that is, to which extent a country-specific corporate default event is correlated to another country-specific corporate default event (Glasserman 2004; Covi et al, 2022). In this respect, we estimate a correlation structure or dependence structure of corporate defaults across all sector (4) and country (134) pairs. We estimate this dependence structure as time-invariant correlation structure of probability of defaults over the period Q1-2018 to Q1-2023 relying on COREP supervisory data template C.09. Figure 1b summarizes the distribution of correlation coefficients for all sector-country pairs, which resembles a normal distribution, with a positive mean/median coefficient close 0.014. This feature implies that shocks to corporates (default events) can be to the same extent positive or negative correlated, reflecting the heterogeneous effects of macro and financial shocks across sectors and countries (Dullman et al. 2008; Lopez, 2004). This dependence structure determines how cluster of corporate defaults materialize across simulations for banks' and insurers portfolios and the shape of the (left) tail of their profit and loss distribution (severity and probability of tail events).

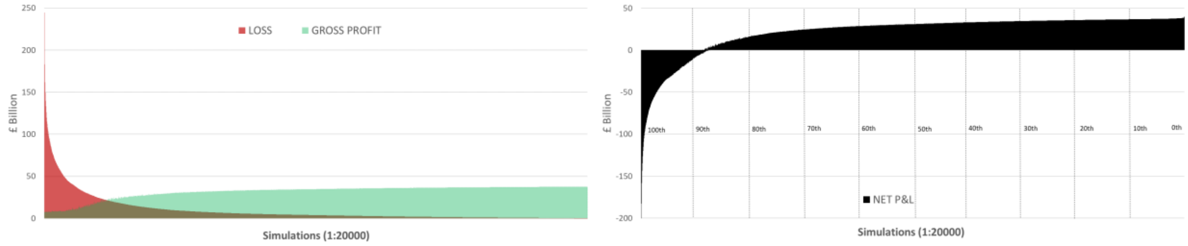
3.3 Profit and Loss Distribution

Overall, we derive a net profit and loss distribution which takes into account two components, the estimated economic losses from direct exposures and gross realized profits derived from actual reported data. Panel (a) of Figure 2 presents the estimated profit and loss distributions for the UK banking system, thereby showcasing the negative correlation between realized profits and losses across scenarios, which are ranked from left to right by the loss severity. Banks' realized gross profits range between £20 and £40 billion, and most of the variation takes place in the 75-100th percentile of the loss distribution. In the end, panel (b) reports the net profit and loss distribution, in which realized losses are adjusted by gross realized profits.

Figure 2: UK Banking System's Net Profit and Loss Distribution

Panel (a)
Estimated Loss and Profit Distributions

Panel (b)
Net Profit and Loss Distribution



Note: The net profit and loss distribution is ranked by the loss severity of the simulation from left to right and approximates operating profits.

3.4 Fire-Sales Price Impact Function

The modelling of feedbacks and amplification mechanisms involve the estimation of fire-sales spillovers so as to quantify direct and indirect losses on the sales of assets at a discounted price as well the re-evaluation effects on those security instruments held. One of the key challenges to accurately estimate the haircut applied to each security sold is the calibration of the price impact function. As shown in Fukker et al. (2022), using a homogeneous price impact function leads to an overestimation of fire-sales spillovers. To avoid that, we implement a heterogeneous price-impact function which differs across the characteristics of the security (bond vs equity, sector, country, rating, size), the volume sold (q<50 Million, 50M<q< 100 M, q >100M) as well as the severity or percentile of the fire-sales event in the system (percentile 5%, 10%, 15%, etc). We rely on Fukker et al. (2022) to calibrate the price impact functions according to this set of characteristics[17]. An important remark concerns the conditioning of the price impact to the severity of the fire-sales event. To achieve that, we first compute the total amount of asset sales in the system in each simulation and then we rank them and allocate into specific percentile according to their relative severity. Hence, the price impact will be also a function of the quantity of assets sold in the system across all asset classes so as to make this a function of the overall market conditions.

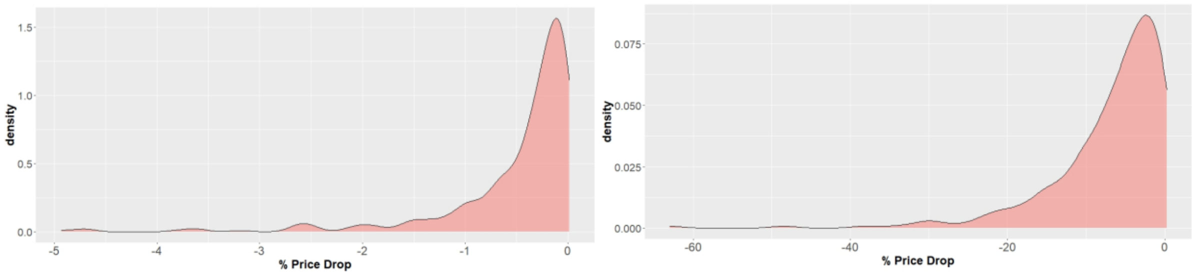
Figure 3 presents the full distribution of theoretical price impact parameters for bond and equity instruments for the full set of characteristics above discussed. We can see that bond instruments may experience a price impact up to 5% in the most extreme cases, whereas equity instruments

[17] We use Fukker et al. (2022)'s estimates for three main reasons. First of all, it is the only paper that provides estimates of price dynamics conditional to the characteristics above mentioned. Moreover, from an empirical perspective, its data coverage is the most comprehensive in terms of panel and time series dimension. Last, the set of asset classes covered by Fukker et al. (2022) perfectly covers the set of asset classes held by UK banks and UK insurers, thereby representing a good fit for our application.

may lose up to 60% of their initial value. Clearly, the large share of parameters are calibrated in the space of 0-1% for bond and 0-20% for equity instruments.

Figure 3: Price Impact Distribution for Bond and Equity Securities

Panel (b) – Bond Panel (b) – Equity



Source: Fukker et al. (2022) and authors' calculations.

Note: Price Impact is estimated by Asset Class (Bond and Equity Instruments), by Issuer Sector (GG, NFC, FC, CI), by Issuer Country (CTY), By Rating (High, Medium, Low), By Firm Size (Large, Mid and Small), by percentile of the historical distribution (0.05, 0.1, 0.15 etc), and by Volume of Sales (<50M, and >50M & <100M, >100M).

3.5 Insurers' Market Risk Sensitivity Parameter

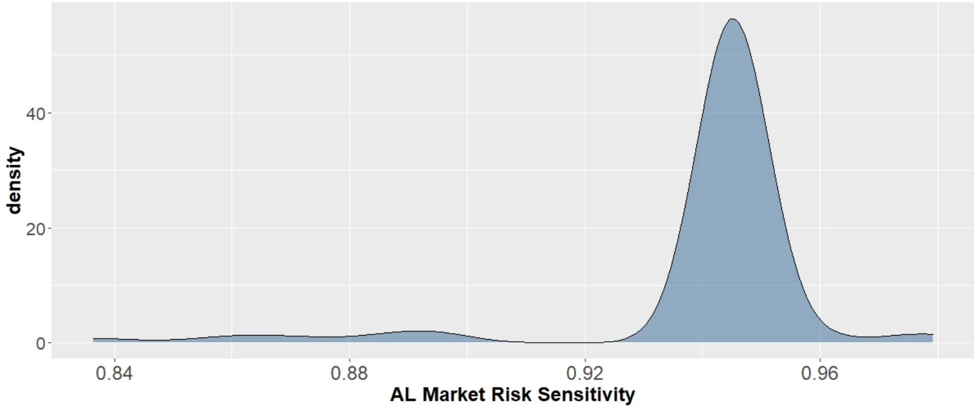
For modelling the transmission of losses to insurers' capital position, we should not only model the revaluation of the asset side, but also consider how the liability side would be affected conditional to that shock. In fact, insurers via asset-liability management or derivative contracts are able to offset a large share of the capital shock by reducing liabilities.

To take this smoothing factors into account, we collect and rely upon the Prudential Regulatory Authority (PRA) data collections on SII market risk sensitivities. In this respect, this template collects insurer-specific time-variant market risk sensitivity parameters conditional to multiple shocks in order to model how a shock to the asset side is offset by a reduction of the liability side. The set of sensitivities cover negative severe shocks to equity and property prices, interest rate risk, rating downgrades, exchange rates, and credit spreads[18].

Since in the methodology we would use these parameters only to model the mark-to-market loss transmission to insurers' balance sheet, that is, focusing exclusively on a subset of the full range of sensitivities, we derive a conservative estimate for an average insurer-specific time-variant market-risk-sensitivity parameter – Gamma ($\gamma_{i,t}$) – which collates all the relevant information for our analysis. Figure 4 depicts the distribution of Gamma, which ranges between 84% and 98%, thereby implying a high degree of liability adjustment. Hence, the passthrough to capital losses of asset sales is materially affected by a reduction in the size of an insurer's liability.

[18] See PRA "Solvency II: Data Collection of Market Risk Sensitivity".

Figure 4: Distribution of Market Risk Sensitivity Parameters – Gamma ($\gamma_{i,t}$)



Source: PRA SII Market Risk Sensitivities, authors' calculations.

4. Results

4.1 Net Profit and Loss Distribution

The methodology has been designed and calibrated to derive a net profit and loss distribution (P&L) for each UK bank and UK insurer in our sample at each point in time (quarterly) over the period Q4-2019 till Q1-2023. The distribution is based on 20.000 Monte Carlo simulations conditional to a central scenario resembling current economic and financial conditions experienced in that quarter. Hence, we aggregate by each single simulation (n), the estimated P&L of each bank/insurer in our sample so as to derive a net P&L distribution for the UK financial system and study financial stability implications using a system-wide perspective[19].

Figure 5a displays the net profit and loss distribution for the UK financial system as of Q1-2023 highlighting the potential impact that feedback and amplification mechanisms may produce. In fact, when taking into account F&A losses, the P&L distribution shifts to the left, both curbing the potential upside (net profits) firms may realize as well as exacerbating the severity of negative realizations (extreme losses) and their likelihood. On the one hand, Figure 5b zooms into those simulations with realized net profits (right tail), on the other hand, Figure 5c zooms into those simulations with realized net losses (left tail) or stress events. In the former, we show that F&A mechanisms shift materially the net profit distribution to the left, thereby reducing the system's overall profitability as well as the severity of extreme positive realizations. Contrary, the latter highlights that F&A mechanisms shift materially the net loss distribution to the left, thereby increasing the likelihood of realizing larger amounts of losses (fatter tail) as well as the severity of extreme stress events (longer tail).

[19] The P&L distribution we derive is net, and not gross, as discussed in Section 2, since in each simulation firms realize both gross profits and losses. Thus, we compute the net realized outcome.

Overall, these charts summarize the main output of the methodology, that is, the distribution of shocks – in terms of severity and probability – the UK financial system may experience in a given period of time using actual data on banks' and insurers' portfolio of loan and security exposures, their balance sheet information and a set of risk parameters reflecting the prevailing macro and financial conditions at time (t). In the following sections we will dig deeper into the left tail of the net profit and loss distribution in order to assess the severity and likelihood of potential tails events affecting the UK financial system and thus explain the drivers and contribution of feedback and amplification mechanisms to the realization of stress tail events, their evolution over time and correlation across firms.

Figure 5a: Net Profit and Loss Distribution as of Q1-2023

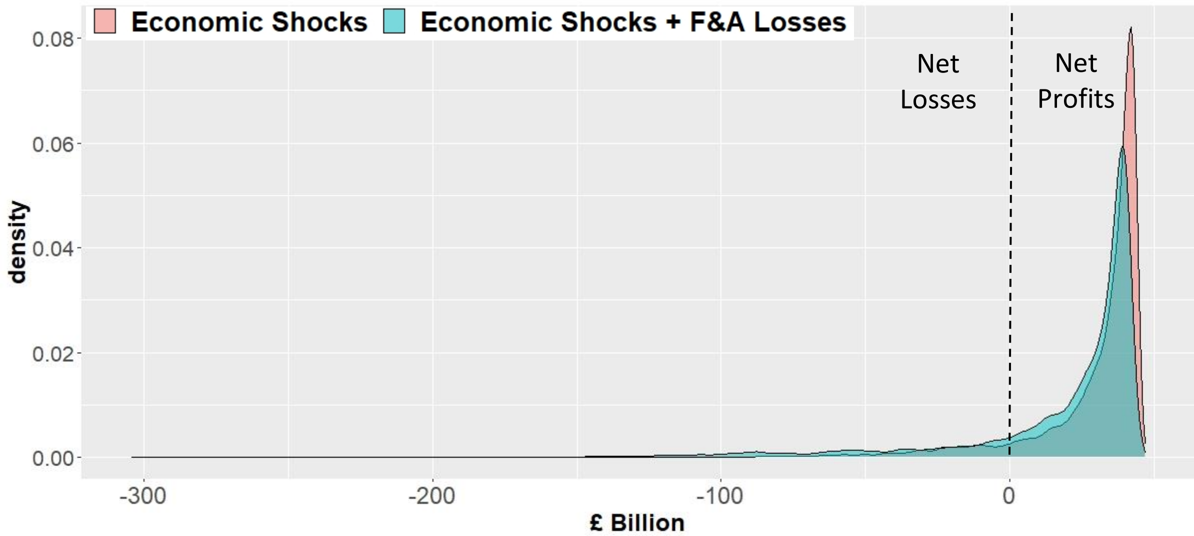


Figure 5b: Net Profit Distribution as of Q1-2023 – Right Tail

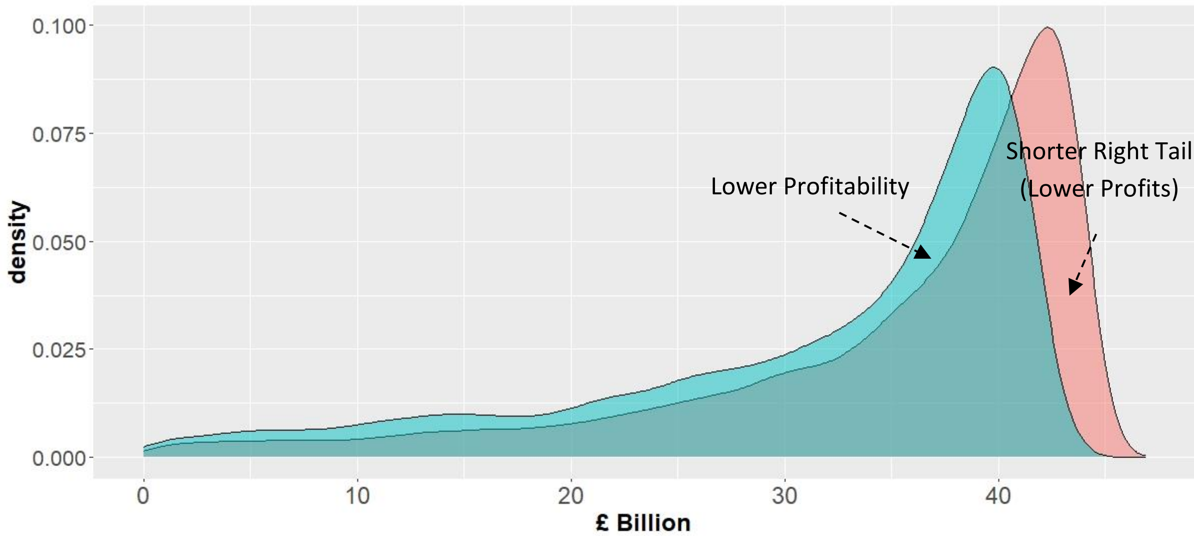
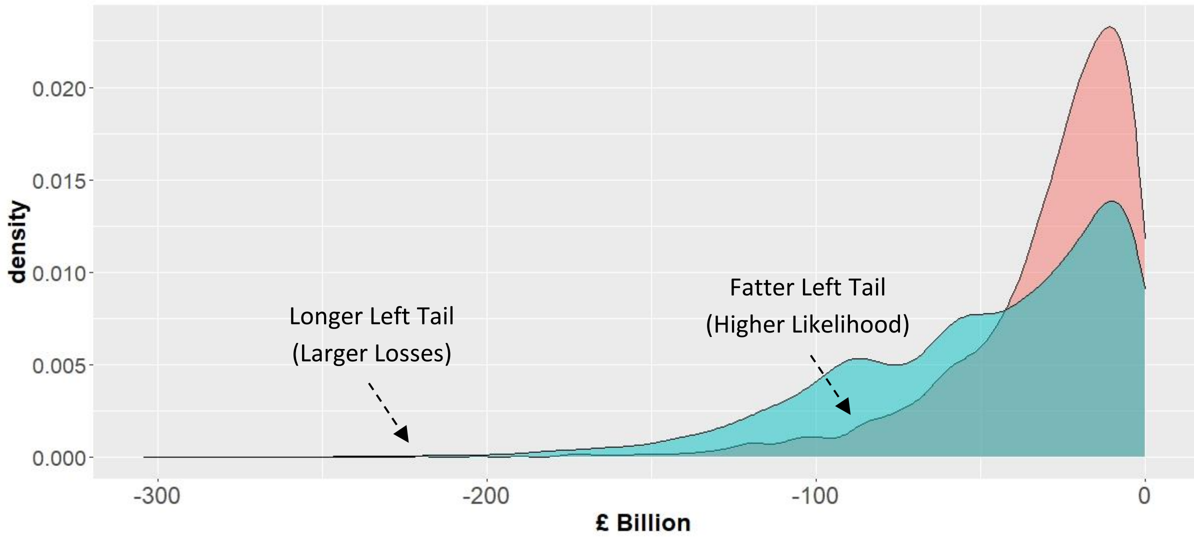


Figure 5c: Net Loss Distribution as of Q1-2023 – Left Tail



Note: the chart depicts the net profit and loss distribution for the UK financial system of banks and insurers for Q1-2023 based on 20.000 simulations.

4.2 Risk Metrics

We provide a set of risk metrics which target different percentiles of the P&L distribution of the UK Financial System in order to disentangle how financial stability risks have been affected over time by changes in the network structure – portfolio size and distribution of exposures – as well as in counterparty risk – obligors' probability of defaults (PD) and exposure-specific loss given default parameters (LGD), and realized gross profits (RGP).

Table 3 reports respectively the median of the profit and loss distribution, the mean or Capital at Risk estimates (CaR) as well as average tail losses conditional to the 90^{th}, 95^{th} and 99^{th} percentile, also defined as Conditional Capital at Risk (CcaR) or expected shortfalls. In this respect, we can see that the median and CaR outcome of the P&L distribution is positive, thereby being an indicator of how profit expectations change over time. Contrary, CCaR estimates are negative, tracking respectively tail risk developments.

Overall, we can assess that the UK Financial System since the Covid-19 Pandemic (2020-21) has experienced an improvement in both profit expectations and tail losses. We thus quantify the severity of extreme stress events which with 1% probability (99^{th} percentile) may lead on average to £133 billion loss in the system.

In the end, we report the ratio of potential expected losses by percentile over total exposures in order to measure the risk per unit of exposure. Since the Covid period, across all percentiles of the distribution, the risk per unit of exposure has materially decreased passing for extreme stress events (CCaR99) from -3.6% in 2021 to -2.8% in 2023, highlighting a relevant de-risking trend.

Table 3: UK Financial System's Capital at Risk and Conditional Capital at Risk Estimates

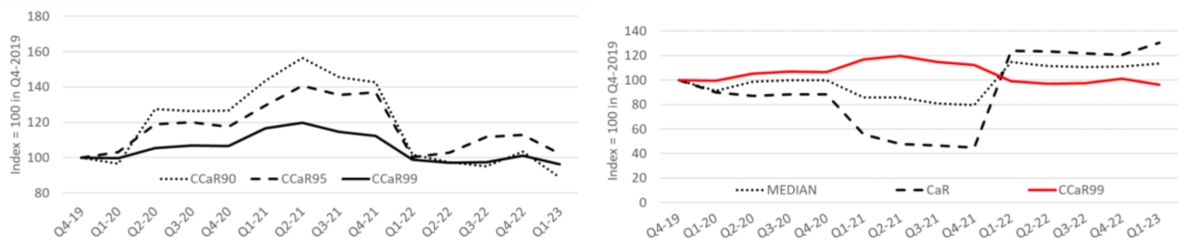
LOSS (£ Bn)	2019	2020	2021	2022	2023	AVG
MEDIAN	28.8	28.0	23.9	32.2	32.7	28
CaR	14	12	7	17	18	13
CCaR90	-31	-37	-45	-31	-27	-36
CCaR95	-63	-72	-85	-67	-64	-73
CCaR99	-127	-133	-147	-125	-122	-133
EXPOSURE	3977	4053	4101	4173	4302	4113
MEDIAN Rate	0.72%	0.69%	0.58%	0.77%	0.76%	0.7%
CaR rate	0.35%	0.30%	0.16%	0.40%	0.42%	0.3%
CCaR90 Rate	-0.8%	-0.9%	-1.1%	-0.7%	-0.6%	-0.9%
CCaR95 Rate	-1.6%	-1.8%	-2.1%	-1.6%	-1.5%	-1.8%
CCaR99 Rate	-3.2%	-3.3%	-3.6%	-3.0%	-2.8%	-3.2%

Figure 5a reports the evolution of CCaR across quarters indexing = 100 at the beginning of the sample of the analysis as of Q4-2019. In this respect, potential expected losses across percentiles tend to co-move, although not perfectly, with the extreme tail (CCaR99) relative more stable compared to severe and medium stress events (95^{th} and 90^{th}).

We also compares the evolution of the Median and Mean (CaR) of the distribution with CCaR99 index. CCaR99 index is also much more stable than the Median and CaR indexes, respectively. The economic intuition is that Median and CaR estimates as well as CCaR90 and CCaR95 are relatively more affected by changes in gross profits (positive realizations) compared to the extreme tail of the loss distribution (99^{th}). This finding highlights that Tail Risk developments (CCaR) do not depend materially on banks' profitability, whereas on other more structural risk factors such as changes in counterparty PD and LGD parameters as well as the network structure.

Figure 5: Risk Developments

Panel (a) - Tail Risk *Panel (b) - Median and CaR*



4.3 Risk Channel Decomposition

Propagation channels may play a different role across simulations depending on the percentile of the P&L distribution we look at. In this section we dig deeper and provide estimates on the contribution of each propagation channel modelled in Section 2. Table 4 decomposes the set of risk metrics (Median, CaR, CCaR99) by propagation channel, respectively by losses and profits from economic exposures (ECL, ECP), and their net P&L outcome (EC) as well as by feedback and amplification channels, respectively fire sales (FS) and solvency contagion (SC). Losses from direct economic exposures (ECL) seems to explain roughly 8.6% of total contribution to the median outcome, and 19% for CaR, whereas in the tail (CCaR99) the contribution increases materially to 61.5%. Contrary, realized gross profits (ECP) explains a larger share of total contribution to the median and CaR metrics than CCaR99, respectively 87.6% and 63% versus 4.9%. This finding highlights that correlated corporate defaults in the real economy are the key driver of tail risk developments, whereas firms' profitability is not a major contributor to systemic risk. Firms' profitability is the key determinant for median and average realized outcome severity, but in the tail it becomes less relevant.

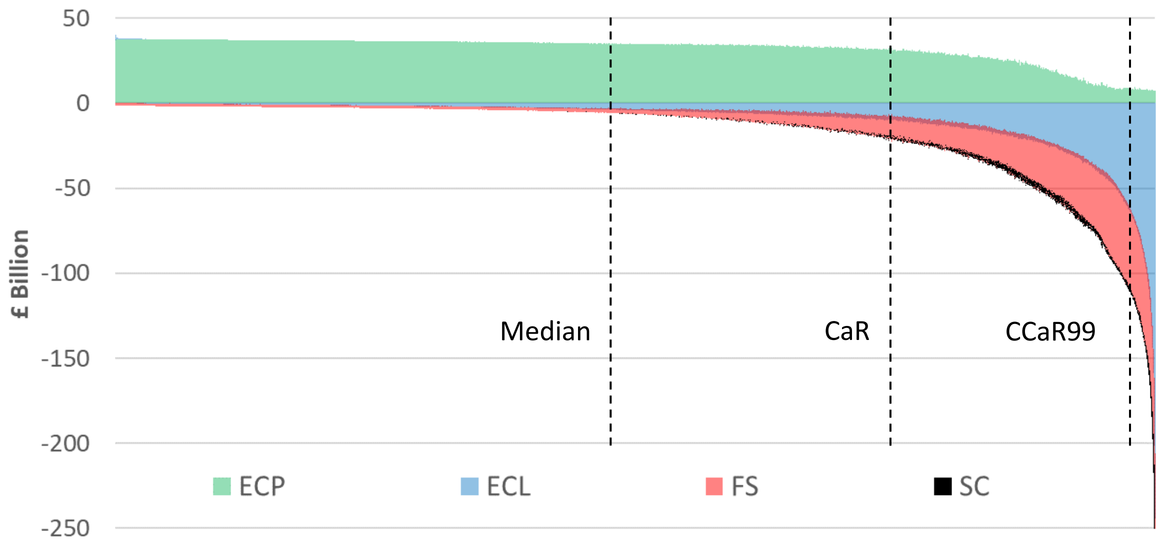
Table 4: Drivers of Median, CaR and CCaR99 for UK Financial System

LOSS (£ Bn)	CHANNEL	2019	2020	2021	2022	2023	AVG	%
MEDIAN	ECL	-3.0	-3.7	-3.4	-3.2	-3.6	-3.4	8.6%
MEDIAN	ECP	35	34	30	40	41	35	87.6%
MEDIAN	EC	32	30	26	36	38	31	/
MEDIAN	FS	-1.9	-0.9	-1.0	-2.4	-2.5	-1.5	3.8%
MEDIAN	SC	0.0	0.0	0.0	0.0	0.0	0.0	0%
MEDIAN	TOT	28.8	28.0	23.9	32.2	32.7	28.4	100%
CaR	ECL	-9.1	-10.4	-10.1	-8.7	-8.9	-9.6	19%
CaR	ECP	32	30	26	36	38	31	63%
CaR	EC	22.4	19.6	15.7	27.2	28.9	21.5	/
CaR	FS	-8.5	-7.4	-9.0	-10.3	-10.8	-9.0	18%
CaR	SC	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	0.2%
CaR	TOT	13.8	12.2	6.7	16.9	18.0	12.5	100%
CCaR99	ECL	-94	-97	-98	-81	-79	-91	61.5%
CCaR99	ECP	10.9	5.1	2.1	11.9	14.8	7.3	4.9%
CCaR99	EC	-83	-92	-96	-69	-64	-84	/
CCaR99	FS	-42	-40	-50	-55	-57	-49	33%
CCaR99	SC	-1.6	-1.5	-0.3	-0.3	0.0	-0.7	0.5%
CCaR99	TOT	-127	-133	-147	-125	-122	-133	100%

Note: CaR refers to expected model outcome, whereas CCaR99 refers to expected shortfalls conditional to the 99th percentile.

Nonetheless, the severity of tail events is not exclusively determined by the realized severity of corporate defaults. Clearly, feedback and amplification mechanisms contribute to roughly 33% of total CCaR99 estimates, and mostly through the fire-sales channel (32%), that is, via indirect contagion. This finding corroborates Poledna et al. (2021)'s conclusion that the exclusion of the overlapping portfolios channel may lead to materially underestimate systemic risk estimates. Furthermore, we find the median outcome is unaffected by F&A effects, whereas for CaR developments it accounts for roughly 18% of total variation. This finding highlights that the materiality of financial stability risks do depend on firms' simultaneous management actions (deleveraging process), which jointly determine the overall severity of the financial market turmoil (systemic stress). This result stems from the high degree of overlapping portfolio of exposures UK firms exhibit, determining a high likelihood of experiencing common shocks from direct economic exposures, but also a high likelihood that the security sold at discount would be held also from another UK bank or insurer. If this result provides evidence at a system-level, it may not always hold on a firm by firm basis. This is important to highlight since on a firm basis the severity realized in the n scenario may not coincide with the same percentile-specific severity at the system level given largest firms do have a stronger role in the determination of the system's propensity to instability. With this intuition in mind, and knowing by construction that fire-sales are a function of the initial P&L shocks, it means that in expectations there could be idiosyncratic shocks to firms which require them to deleverage materially and thus contribute to fire-sale spillovers. However, those idiosyncratic shocks are not material enough to trigger a systemic event via this indirect contagion channel ($L_{i,s,n,t}^{FS|ind}$). Overall, Figure 6 summarizes the contribution of each risk channel across all simulations ranked from left to right according to their total severity. In this respect, the curvature of the function clearly shows that F&A mechanisms are a positive and increasing function of the P&L shock distribution (ECP-ECL).

Figure 6: Drivers of the Profit and Loss Distribution for the UK Financial System



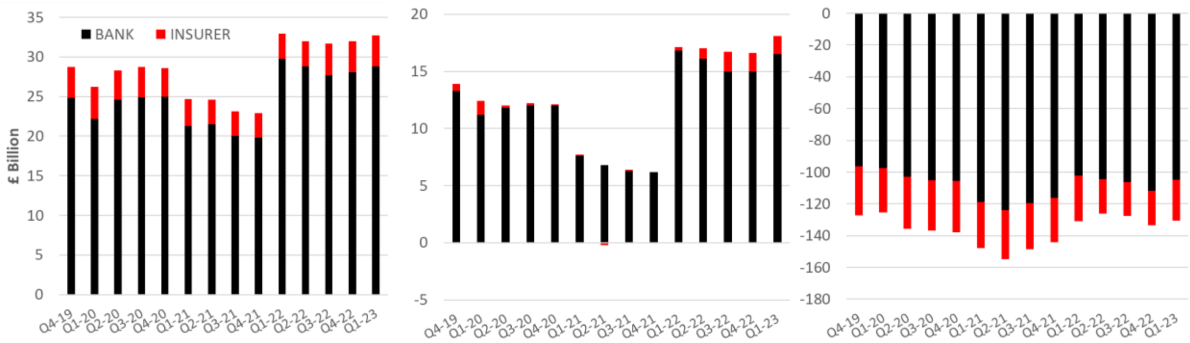
Note: ECP refers to economic profits, whereas ECL to economic credit and traded risk losses. Moreover, FS refers to fire-sale losses and SC to solvency contagion losses.

4.4 Sector Decomposition

In previous sections we have looked at the dispersion of the profit and loss distribution and at the drivers determining that dispersion at an aggregated system level. Contrary, in this section we break down the results by contribution of each sector, respectively the role of banks and insurers in determining systemic events. Figure 7 summarizes the overall contribution of the banking sector and the insurance sector to the median, CaR and CCaR99 estimates. On average, the UK banking system contributes to roughly 87% of the median P&L outcome, 95% of total CaR estimates, and 80% of CCaR99 estimates, against 81% of total exposure coverage in the system. Hence, UK banks per £ pound exposure tend to contribute to systemic risk (negative realizations) consistently with their exposure share.

Figure 7: Decomposition of Risk metrics by Sector

Panel (a) – Median Panel (b) – CaR Panel (c) – CcaR99



We dig deeper into each sector's propagation channel contribution by risk percentile in order to highlight potential differences across sectors. Table 5 which resembles the structure of Table 4, reports the breakdown by sector, respectively Panel (a) for banks and Panel (b) for insurers. UK banks' results tend to align with the decomposition at the system level since they account for 80% of total exposures, and so drive the overall results. Moreover, banks and insurers' realized profits contribution (ECP) to the median are quite close, respectively 88% and 86%, whereas their contribution to CaR estimates slightly differ, respectively 63.8% and 54.5%, with ECL relatively more material for insurers than banks. Nonetheless, the more we move into the tail, here captured by CCaR99 estimates, ECL becomes the highest contributor for both banks and insurers, respectively 60% and 68%, and fire-sales (FS) become the second largest factor, respectively explaining 33% and 25% of tail losses. Realized profits (ECP) show a relative low contribution to CCaR99, and for the insurer sector they have a negative sign, thereby highlighting a higher dispersion than banks in the tail. Finally, the solvency contagion channel (SC) tends to matter more for insurers than banks in % terms. The finding is partially explained by the modelling assumption we made in Section 2 on the calibration of Market Risk Sensitivity parameter - Gamma. In fact, for the insurers, we have used a full pass through assumption of shocks to capital ($\gamma_{i,t} = 0$) when modelling shocks conditional to corporate defaults, that is for quantifying losses from ECL and SC, and a partial pass through assumption ($\gamma_{i,t} > 0$) when modelling fire-sales (FS). This result further corroborates the key role played by the fire-sales channel in potentially triggering tail events in the insurance sector.

Table 5: Drivers of Median, CaR and CCaR99

Panel (a) - UK Banking System

LOSS (£ Bn)	**CHANNEL**	**2019**	**2020**	**2021**	**2022**	**2023**	**AVG**	**%**
MEDIAN	ECL	-2.5	-3.1	-2.8	-2.8	-3.1	-2.9	8.2%
MEDIAN	ECP	30.0	29.4	25.8	35.3	36.6	30.6	88.1%
MEDIAN	FS	-1.6	-0.6	-0.8	-2.1	-2.2	-1.3	3.7%
MEDIAN	SC	0.0	0.0	0.0	0.0	0.0	0.0	0.0%
MEDIAN	TOT	24.8	24.2	20.7	28.6	28.8	26.5	100%
CaR	ECL	-7.2	-8.3	-8.3	-7.3	-7.5	-7.9	18.2%
CaR	ECP	27.5	26.3	22.8	32.3	33.7	27.6	63.8%
CaR	FS	-7.0	-6.3	-7.8	-9.2	-9.7	-7.8	18.1%
CaR	SC	0.0	0.0	0.0	0.0	0.0	0.0	0.0%
CaR	TOT	13.3	11.8	6.7	15.7	16.5	11.9	100%
CCaR99	ECL	-73.6	-76.9	-81.0	-69.7	-68.2	-75.1	60%%
CCaR99	ECP	12.0	7.0	4.4	12.5	14.4	8.7	6.9%
CCaR99	FS	-34.2	-32.6	-42.9	-48.9	-51.1	-41.6	33.1%
CCaR99	SC	-0.7	-0.4	-0.1	-0.2	0.0	-0.3	0.2%
CCaR99	TOT	-96	-103	-120	-106	-105	-108	100%

Panel (b) - UK Insurer System

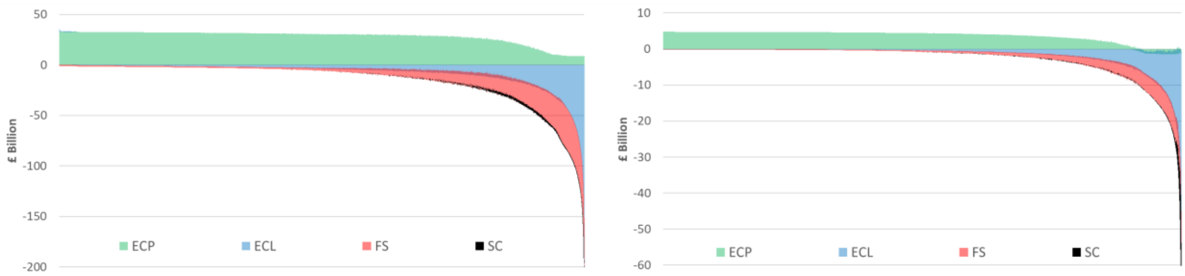
LOSS (£ Bn)	**CHANNEL**	**2019**	**2020**	**2021**	**2022**	**2023**	**AVG**	**%**
MEDIAN	ECL	-0.4	-0.6	-0.5	-0.3	-0.3	-0.4	8.5%
MEDIAN	ECP	4.8	4.6	3.9	4.3	4.7	4.3	86.5%
MEDIAN	FS	-0.4	-0.2	-0.2	-0.3	-0.3	-0.3	5.0%
MEDIAN	SC	0.0	0.0	0.0	0.0	0.0	0.0	0.0%
MEDIAN	TOT	3.9	3.8	3.2	3.6	3.9	3.7	100%
CaR	ECL	-1.9	-2.1	-1.8	-1.4	-1.4	-1.7	26.8%
CaR	ECP	4.0	3.7	3.0	3.7	4.1	3.5	54.5%
CaR	FS	-1.4	-1.1	-1.2	-1.1	-1.1	-1.1	17.6%
CaR	SC	-0.1	-0.1	-0.1	-0.1	0.0	-0.1	1.1%
CaR	TOT	0.6	0.4	0.0	1.1	1.6	0.6	100%
CCaR99	ECL	-20.4	-21.0	-19.6	-16.5	-19.3	-19.1	68.1%
CCaR99	ECP	-1.1	-1.9	-2.3	-0.7	0.4	-1.4	5.1%
CCaR99	FS	-8.4	-7.2	-7.4	-6.5	-6.6	-7.1	25.3%
CCaR99	SC	-0.9	-0.9	-0.2	-0.2	0.0	-0.4	1.5%
CCaR99	TOT	-31	-31	-29	-23	-25	-28.1	100%

Note: ECP refers to economic profits, whereas ECL to economic credit and traded risk losses. Moreover, FS refers to fire-sale losses and SC to solvency contagion losses.

In the end, Figure 8 depicts the final estimated profit and loss distribution decomposed by the contribution of propagation channel across simulations and by sector, respectively Panel (a) for banks and Panel (b) for insurers. The comparison of the distributions highlights that the tail of the loss distribution becomes steeper for the insurer sector than for the banking sector especially in the most extreme stress events. The growth rate in expected tail losses between the 95th and the 99th percentile is 80% for banks and 95% for insurers, whereas between the 90th and 95th percentile is higher for banks (114%) than for insurers (84%).

Figure 8: Drivers of the Profit and Loss Distribution

Panel (a) – Banks Panel (b) - Insurers



Note: ECP refers to economic profits, whereas ECL to economic credit and traded risk losses. Moreover, FS refers to fire-sale losses and SC to solvency contagion losses.

4.5 Profit and Loss Correlation

In this section we aim at exploring how results are correlated across propagation channels at a sectoral level and how correlations vary across percentiles of the loss distribution. Moreover, we highlight how the model generate correlated shocks and whether the banking and insurer sectors tend to be jointly affected by severe shocks. In this respect, Table 6 shows results on how profit and loss outcomes are correlated within each sector (Panel a) and between the two sectors (Panel b) across propagation channels. In Panel (a) we find that for both the banking sector and the insurer sector P&L generated from economic exposures (EC) are strongly and positive correlated with total losses (TOT), followed by the fire sales losses and total losses (FSL-TOT), as well as economic losses and fire sales losses (EC-FSL). Also solvency contagion losses are correlated with losses experienced in all the other propagation channels, although to a lesser extent than FSL and EC channels. Moreover, panel (b) highlights that losses experienced by the banking sector are positive and strongly correlated with losses experienced by the insurance sector across all simulations, although the degree varies according to the propagation channel pair we observe. For instance, we observe that the strongest correlation (0.97) for the fire-sale channel (FSL – FSL), for which the higher the FS losses experienced by banks, the higher FS losses experienced by insurers. Next, economic losses experienced by banks tend to strongly co-move (0.88) with fire-sales losses experienced by insurers (EC - FSL) as well as total losses experienced by banks tend to strongly co-move with total losses experienced by insurers (TOT - TOT). Nonetheless, the degree of correlated outcomes may depend and thus vary according to the realized severity we look at, that is, on the part of the distribution we analyse. In Table 6 the sample of the analysis was the entire distribution, therefore the results were strongly driven by the positive realizations or median outcomes.

Table 6: Loss Correlation between Propagation Channels and by Sector

Panel (a) - Within Sector

SECTOR	CHANNEL	SIM	2019	2020	2021	2022	2023	AVG
BANK	EC - TOT	ALL	0.97	0.98	0.98	0.97	0.96	0.97
BANK	FS - TOT	ALL	0.94	0.94	0.96	0.96	0.95	0.95
BANK	ECL - FS	ALL	0.83	0.86	0.88	0.85	0.84	0.85
BANK	ECL - SC	ALL	0.72	0.61	0.47	0.52	0.57	0.58
BANK	SC - TOT	ALL	0.64	0.54	0.38	0.43	0.47	0.49
BANK	FSL - SCL	ALL	0.44	0.35	0.23	0.28	0.32	0.32
INS	ECL - TOT	ALL	0.99	1.00	0.99	0.99	0.99	0.99
INS	FS - TOT	ALL	0.94	0.95	0.94	0.91	0.89	0.93
INS	ECL - FSL	ALL	0.93	0.94	0.93	0.89	0.85	0.91
INS	SC - TOT	ALL	0.47	0.41	0.47	0.43	0.45	0.45
INS	ECL - SC	ALL	0.42	0.35	0.40	0.36	0.37	0.38
INS	FS - SC	ALL	0.26	0.21	0.22	0.16	0.17	0.20

Panel (b) – Between Banking Sector and Insurance Sector

SECTOR	CHANNEL	SIM	2019	2020	2021	2022	2023	AVG
BANK vs INS	FS - FS	ALL	0.98	0.98	0.98	0.97	0.96	0.97
BANK vs INS	ECL - FS	ALL	0.88	0.90	0.91	0.87	0.84	0.88
BANK vs INS	TOT - TOT	ALL	0.92	0.91	0.89	0.83	0.75	0.86
BANK vs INS	FS - TOT	ALL	0.87	0.88	0.86	0.82	0.75	0.83
BANK vs INS	ECL - TOT	ALL	0.88	0.88	0.86	0.78	0.69	0.82
BANK vs INS	ECL - ECL	ALL	0.88	0.89	0.86	0.77	0.66	0.81
BANK vs INS	FS - ECL	ALL	0.85	0.86	0.85	0.78	0.69	0.80
BANK vs INS	SC - TOT	ALL	0.66	0.56	0.46	0.41	0.40	0.50
BANK vs INS	SC - ECL	ALL	0.65	0.56	0.43	0.40	0.37	0.48
BANK vs INS	SC - FS	ALL	0.55	0.47	0.32	0.36	0.40	0.42
BANK vs INS	SC - SC	ALL	0.51	0.39	0.51	0.22	0.20	0.37
BANK vs INS	ECL - SC	ALL	0.29	0.18	0.20	0.10	0.10	0.17
BANK vs INS	FS - SC	ALL	0.18	0.15	0.14	0.12	0.11	0.14

Note: The table reports correlation coefficients for Losses measured across all propagation channels (CHANNEL): Economic Channel (EC), Fire-Sales (FSL), Solvency Contagion (SCL) and Total Losses (TOT). The correlation is quantified within the Banking Sector (BANK), within the Insurance Sector (INSURANCE), and between the two sectors (BANK vs INSURANCE). SIM refers to the number of simulations considered, that is, correlation estimated across all realized simulations (n=20000) and ranked by the overall severity at the system level.

Contrary, in Table 7 we shed light upon the correlation degree in the tail of the distribution, that is, considering how losses correlate in the 90^{th}, 95^{th} and 99^{th} percentiles. Panel (a) reports results for correlated losses between banks and insurers ranking the severity of simulations by the severity of total losses experienced at the system level (banks + insurers), whereas Panel (b) by ranking the severity of simulations by the severity of total losses experienced by each sector, respectively banks and insurers.

We find that the degree of loss correlation decreases by comparing the whole distribution with selected tail percentiles. This highlights that positive outcomes tend to be more correlated than the negative ones. In fact correlation of total losses for banks and insurers in the 90^{th} percentile is close to 0.48, almost half the size compared to the whole distribution (0.86). Moreover, the more we move into the extreme tail, the correlation tends to further decrease to 0.41 in the 95^{th} percentile and to 0.21 in the 99^{th} percentile. This pattern is similar across propagation channels. Remarkably, losses from the fire-sales channel become negatively correlated between banks and insurers in the 99^{th} percentile, highlighting that the severity of fire sales outcomes differ between the two sectors across realizations in the tail. Overall, this result highlights that may exist specific idiosyncratic shocks in the extreme tail (whether corporate defaults or sales of assets) that may affect banks and insurers heterogeneously.

In the end, Panel (b) further slices the correlation results by ranking the severity of extreme outcomes by the severity experienced from each sector. This exercise highlights that higher total losses of banks in the 99^{th} percentile are associated with higher total losses for insurers (0.8), but not vice versa (0.00). This result is consistent with the correlation coefficient displayed for economic losses (EC), which has a similar behaviours are for total losses. This means that the shock distribution of corporate defaults has a limited overlapping between the two sectors in the tail. Nonetheless, the more we move out from the extreme tail, the severity of losses become more correlated consistently with what observed in panel (a). In the end, FS losses are positively correlated across all percentiles of the distribution, highlighting the indirect contagion spillover effects between the two sectors due to price-mediated contagion. In the end we want to highlight that the degree of loss correlation tends to vary over time, and that it has progressively decreased, reaching the smallest value in Q1-2023. This results is consistent with the decreasing share of overlapping portfolio of exposures reported in Table 2.

Table 7: Loss Correlation between Propagation Channels by Percentiles (99^{th}, 95^{th}, and 90^{th})

Panel (a) – Ranked by Overall System Severity

SECTOR	CHANNEL	SIM	2019	2020	2021	2022	2023	AVG
BANK vs INS	TOT - TOT	90th	0.69	0.66	0.56	0.33	0.15	**0.48**
BANK vs INS	ECL – ECL	90^{th}	0.67	0.67	0.58	0.34	0.08	**0.47**
BANK vs INS	FS – FS	90^{th}	0.84	0.80	0.76	0.73	0.70	**0.77**
BANK vs INS	SC – SC	90^{th}	0.70	0.48	0.53	0.22	0.20	**0.43**
BANK vs INS	TOT – TOT	95^{th}	0.66	0.61	0.47	0.26	0.03	**0.41**
BANK vs INS	ECL – ECL	95^{th}	0.62	0.65	0.51	0.30	0.04	**0.42**
BANK vs INS	FSL – FSL	95^{th}	0.36	0.18	0.06	0.14	0.03	**0.15**
BANK vs INS	SCL – SCL	95^{th}	0.77	0.53	0.56	0.31	0.30	**0.49**
BANK vs INS	TOT – TOT	99^{th}	0.40	0.25	0.36	0.18	-0.15	**0.21**
BANK vs INS	ECL – ECL	99^{th}	0.20	0.30	0.23	0.17	-0.18	**0.14**
BANK vs INS	FSL – FSL	99^{th}	-0.59	-0.23	-0.29	-0.43	-0.45	**-0.40**
BANK vs INS	SCL – SCL	99^{th}	0.90	0.40	0.61	0.42	0.33	**0.53**

Panel (b) – Ranked by Each Sector

SECTOR	RANK	CHANNEL	SIM	2019	2020	2021	2022	2023	AVG
BANK vs INS	BANK	TOT - TOT	99th	0.88	0.85	0.79	0.89	0.62	**0.80**
BANK vs INS	INS	TOT - TOT	99th	0.25	0.06	-0.02	-0.24	-0.06	**0.00**
BANK vs INS	BANK	TOT - TOT	95th	0.82	0.76	0.76	0.75	0.53	**0.72**
BANK vs INS	INS	TOT - TOT	95th	0.47	0.36	0.24	-0.03	-0.18	**0.17**
BANK vs INS	BANK	TOT - TOT	90th	0.82	0.81	0.71	0.60	0.42	**0.67**
BANK vs INS	INS	TOT - TOT	90th	0.64	0.56	0.47	0.28	0.13	**0.42**
BANK vs INS	BANK	EC - EC	99th	0.82	0.88	0.72	0.85	0.60	**0.77**
BANK vs INS	INS	EC - EC	99th	0.21	0.22	0.01	-0.19	-0.09	**0.03**
BANK vs INS	BANK	EC - EC	95th	0.80	0.79	0.75	0.73	0.52	**0.72**
BANK vs INS	INS	EC - EC	95th	0.45	0.43	0.28	0.01	-0.20	**0.19**
BANK vs INS	BANK	EC - EC	90th	0.80	0.82	0.73	0.58	0.34	**0.65**
BANK vs INS	INS	EC - EC	90th	0.63	0.59	0.48	0.25	0.06	**0.40**
BANK vs INS	BANK	FS - FS	99th	0.28	0.43	0.17	0.48	0.53	**0.38**
BANK vs INS	INS	FS - FS	99th	0.58	0.62	0.47	0.35	0.41	**0.49**
BANK vs INS	BANK	FS - FS	95th	0.59	0.39	0.40	0.51	0.44	**0.46**
BANK vs INS	INS	FS - FS	95th	0.51	0.48	0.39	0.34	0.24	**0.39**
BANK vs INS	BANK	FS - FS	90th	0.87	0.84	0.80	0.80	0.79	**0.82**
BANK vs INS	INS	FS - FS	90th	0.80	0.76	0.74	0.73	0.67	**0.74**
BANK vs INS	BANK	SC - SC	99th	0.97	0.65	0.71	0.76	0.61	**0.74**
BANK vs INS	INS	SC - SC	99th	0.60	0.11	0.29	-0.06	0.04	**0.20**
BANK vs INS	BANK	SC - SC	95th	0.80	0.59	0.69	0.77	0.54	**0.68**
BANK vs INS	INS	SC - SC	95th	0.67	0.40	0.50	0.19	0.16	**0.38**
BANK vs INS	BANK	SC - SC	90th	0.78	0.59	0.59	0.38	0.37	**0.54**
BANK vs INS	INS	SC - SC	90th	0.69	0.45	0.52	0.22	0.20	**0.42**

Note: The table reports correlation coefficients for Losses measured for the same propagation channel (CHANNEL): Economic Channel (EC), Fire-Sales (FSL), Solvency Contagion (SCL) and Total Losses (TOT). The correlation is quantified between the two sectors (BANK vs INS). SIM refers to the number of simulations considered, that is, correlation estimated according to 99^{th}, 95^{th} and 90^{th} percentiles of the profit and loss distribution ranked by total loss experienced by the Banking System (RANK = Bank) or by Insurance System (RANK = Ins).

4.6 Systemic Event Probability

In this section we aim at exploring how the severity of the realized outcomes is correlated on a firm-by-firm basis in the tail, thereby capturing firms' tail event severity correlation. Thus we compute the conditional tail event probability ($CTEPr$) defined as the probability of firm j's tail event severity in scenario s and at time t $\left(PCT_{j,s,t}\right)$ being equal to firm i's tail event severity in the same scenario s and time t $\left(PCT_{i,s,t}\right)$ conditional to firm i experiencing a tail event of severity $90^{th}, 95^{th}, 99^{th}$.

$$CTEPr_{i,j,t|pct} = \Pr\left(PCT_{j,s,t} = PCT_{i,s,t} \middle| PCT_{i,s,t} = (90^{th}, 95^{th}, 99^{th})\right)$$

This probabilistic risk measure tells us how likely two firms may experience jointly a tail event of the same realized severity $(90^{th}, 95^{th}, 99^{th})$, that is, the likelihood of negative severe correlated outcomes on a firm-basis conditional to the fact that a firm has experienced a tail event. In this respect, Figure 9a depicts the distribution of conditional tail event probabilities ($CSRPr$) estimated across all three severity percentiles $(90^{th}, 95^{th}, 99^{th})$ for all firm-pairs and for all time periods. Overall, we can see that the distribution is centred around 0.74, implying that a random firm j has a probability of 74% to experience a tail event of the same severity of firm i's when firm i faces a tail event. We highlight that 90% of the mass of the distribution belong to the interval 40%-97%, thereby implying a high degree of tail event correlation.

Next, Figure 9b summarizes the Conditional Tail Event Probability according to the realized severity of the tail event. Clearly, extreme tail events (pct99) tend to be less correlated across pair of firms (median ~ 58%) than medium (median ~ 76%) and severe (median ~ 0.76%) tail events, nonetheless the conditional probability is still high and material. This implies that with 3.8% of probability we may have a severe systemic event (0.05 * 0.76) and with 0.58% of probability we may have that an extreme systemic event realize (0.01 * 0.58). All these evidences corroborate that systemic events with various degree of severity may happen with a non-negligible probability[20].

In the end, Figure 9c isolate the impact of feedback and amplification mechanism on the likelihood of joint extreme stress events among UK banks and UK insurers. Without F&A mechanisms (ECL), the conditional tail event probability for extreme stress events (99pct) decreases from 58% to 10%. This finding highlights that that systemic events may take place without the presence of F&A mechanisms, but their role is fundamental in strengthening materially the loss correlation of financial firms.

[20] In the Appendix (chart A1 and A2), we shed light whether there is a higher likelihood of experiencing correlated tail events across firms belonging to the same sector, respectively among banks (BK_BK) and among insurers (INS_INS) or across firms of opposite sector, that is, between banks and insurers (BK_INS). Insurers' joint tail event probability within sector and across sectors are very similar to each other (median = 73%/74%), whereas for banks it is higher within sector than across sectors (median = 82%). We also show that the systemic event probability has decreased in recent quarters, especially for extreme stress events.

Figure 9a: Conditional Tail Event Probability for Medium, Severe and Extreme Stress Events

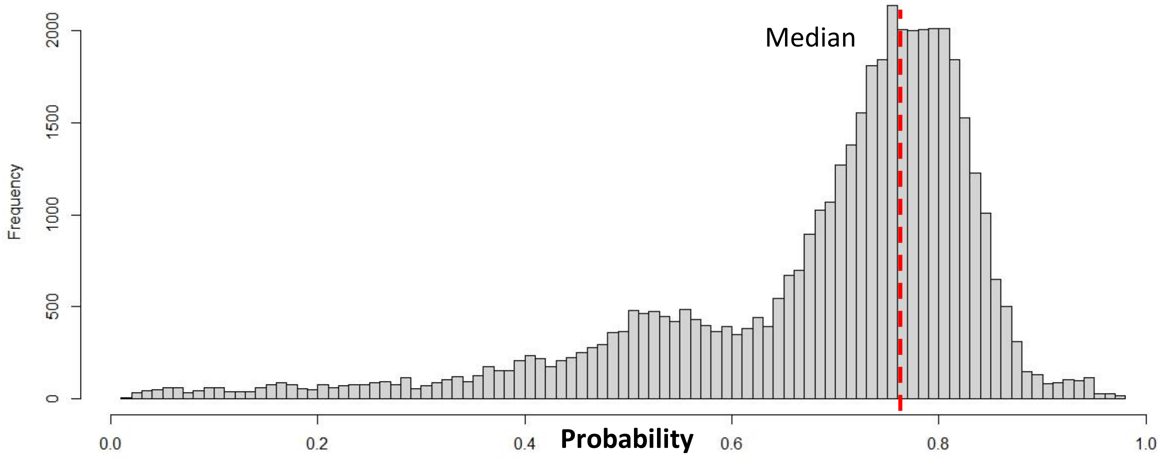


Figure 9b: Conditional Tail Event Probability - By Severity of Stress Event

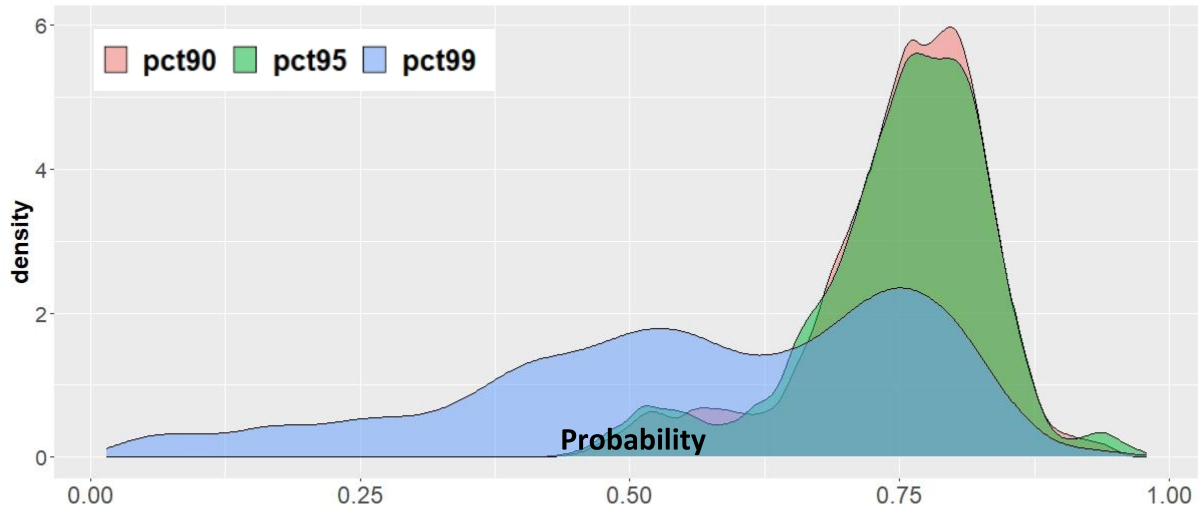
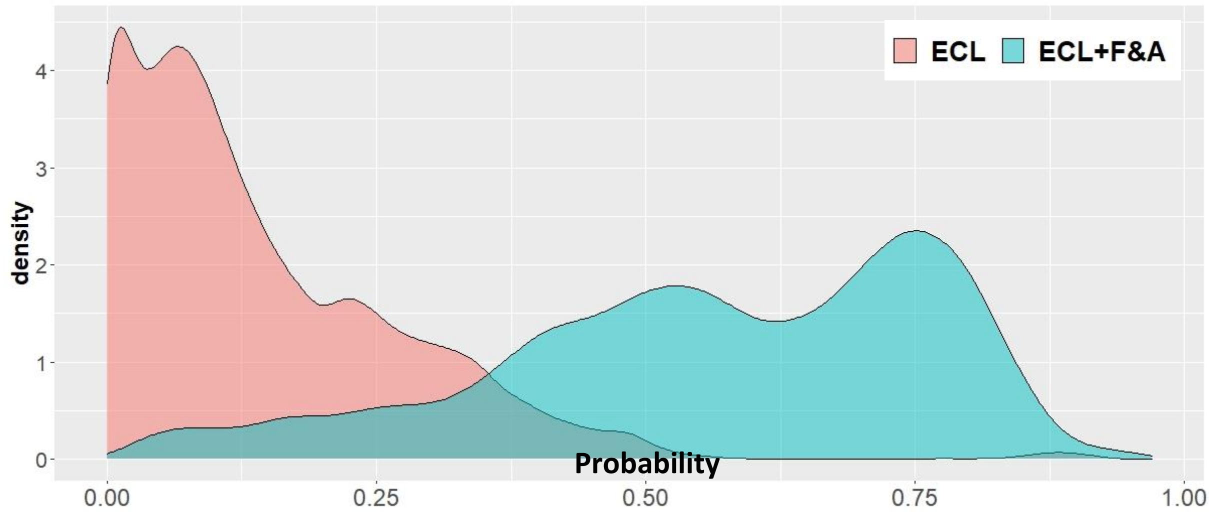


Figure 9c: Conditional Tail Event Probability without F&A for Extreme Stress Events (pct99)



Note: “ECL” refers to Economic Credit Risk Losses, and “ECL+F&A” to total losses.

4.7 Fire-Sales Spillovers

In this last section we provide insights into the drivers of fire sales spillovers by focusing on the severity of selling pressures and price impacts across asset class and percentiles. In Table 2 we have shown that the UK financial system seems to be more exposed on bond instruments (£992 bn) than equity (£726 bn) and that banks' portfolio tend to be more invested into bonds (£731 bn) than equities (£108 bn), while insurers are more invested into equities (£618 bn) than bonds (£261 bn). Moreover we have calibrated the fire sale mechanisms using a pro-rata approach, that is, by assuming an equal sale split across securities. Hence, if we had assumed homogeneous shocks and homogeneous firms' starting conditions, we should have obtained that 57% of security sales (992 / (992+726)) are made of bond and that the remaining 43% are made of equity. However this is not the realized outcome since the overall selling pressure is a function of heterogeneous shocks and heterogeneous starting conditions. Moreover, the overall equilibrium also depends on which firm is forced and more inclined to de-leverage and on the firm-specific portfolio composition.

In this respect, Table 8 summarizes the realized selling pressures by asset class and severity of the fire sale event conditional to a pro-rata approach. Hence we see that the UK financial system, according to a pro-rata approach, tends to sell more bonds over equity, respectively 87% vs 13% of total security sold (Ratio %), and this result holds across different fire sale severities. This is due to the fact that banks tend to deleverage more than insurers. Moreover, we can see that in the most extreme events (99^{th} percentile), the UK financial system would sell 58% of their bond holdings and only 13% of their equity holdings. The selling pressure materially decreases across percentiles, halving in the 95^{th} percentile, and approaching 3.3% (3.1% + 0.2%) of total security sales in the 90^{th} percentile.

On the other hand, Table 9 summarizes the average realized price impact for bond and equity instruments. Conditional to the most extreme fire sale stress event (99^{th}) the price of bond instruments would decrease on average by -1.6%, whereas equity instruments would experience an average price drop of -20.3%. Consistently, the price impact reduces by moving away from the 99^{th} percentile. Overall, although the UK financial system deleverages by selling way more bonds than equities (6.3 times), the average price impact is much more material for equity than bond instruments (12.5 times). This implies that fire sales losses are driven mostly by realized mark to market losses on equity instruments. Overall, the pro-rata approach leads on average to a fire-sale loss rate (over total security portfolio holdings) of 3% conditional to an extreme stress event (CCaR99). FS loss rate estimates range between 2.4% and 3.6% across quarters. Moreover, the FS loss rate tends to be higher for banks than for insurers, respectively 5.5% vs 0.8%. This set of results corroborate Caccioli et al. (2024)'s findings whose fire sale estimates, which are based on a pro-rata approach conditional to the Bank of England stress scenario as initial shock, exhibit a FS loss rate close to 5.35% (£109 billion). We find lower estimates since the set of shocks we endogenously derive via Monte Carlo simulation method is on average 1/3 smaller than the Bank of England stress scenario[21].

Table 8: Estimated Selling Pressure based on a Pro-rata Approach
(*Amount in £ Billion*)

ASSET	SIM	2019	2020	2021	2022	2023	AVG	SHARE %	Ratio %
BOND	99th	494	531	601	559	550	558	58%	86%
BOND	95th	129	281	296	151	90	224	23%	85%
BOND	90th	13.6	52.8	47.9	0.8	0.5	30.0	3.1%	96%
EQUITY	99th	79	70	100	96	93	88	13%	14%
EQUITY	95th	23	39	54	31	22	38	5.6%	15%
EQUITY	90th	1.1	1.4	1.7	1.0	0.8	1.3	0.2%	4.2%

Note: The variable "Share %" refers to the amount of bond (equity) sold over total bond (equity) holdings, whereas the variable "Ratio %" refers to the amount of bond (equity) sold over the total amount of securities sold.

Table 9: Estimated Realized Price Impact

ASSET	SIM	2019	2020	2021	2022	2023	AVG
BOND	99th	-1.6%	-1.6%	-1.6%	-1.5%	-1.4%	-1.6%
BOND	95th	-0.9%	-0.9%	-0.9%	-0.8%	-0.8%	-0.9%
BOND	90th	-0.5%	-0.5%	-0.5%	-0.4%	-0.4%	-0.5%
EQUITY	99th	-21.5%	-21.6%	-19.6%	-19.7%	-19.0%	-20.3%
EQUITY	95th	-17.7%	-17.3%	-15.6%	-15.4%	-14.9%	-16.1%
EQUITY	90th	-13.6%	-13.0%	-11.6%	-11.2%	-11.0%	-12.0%

Note: The realized price impact is computed as the average price drop per asset class weighted by the volume sold of each asset class.

Nonetheless, a pro-rata approach, as shown in Caccioli et al. (2024) among other papers in the literature, tends to overestimate FS losses since it does not minimize the price impact given that institutions are assumed to sell their illiquid assets too, which in turn leads to a more severe price impact. In this respect, using a pro-rata approach may overestimate FS losses by roughly 30% relative to a pecking order approach in which only HQLA securities are sold (Caccioli et

[21] We take the expected 99th realized outcome of our loss distribution based on quarter-specific economic conditions which is on average £84 billion (see Table 4), whereas Caccioli et al. (2024)'s estimates are based on an extreme stress scenario resembling the Great Financial Crisis (initial shock ~ £124 billion).

al., 2024). For instance, Caccioli et al., (2024) relying on HQLA pecking-order approach estimate a FS loss rate of 3.7% (£75 billion) instead of 5.35% (£109 billion). Hence, the results we have shown in this Section 4 - based on pro-rata FS approach - could be considered relatively more conservative in terms of loss estimation.

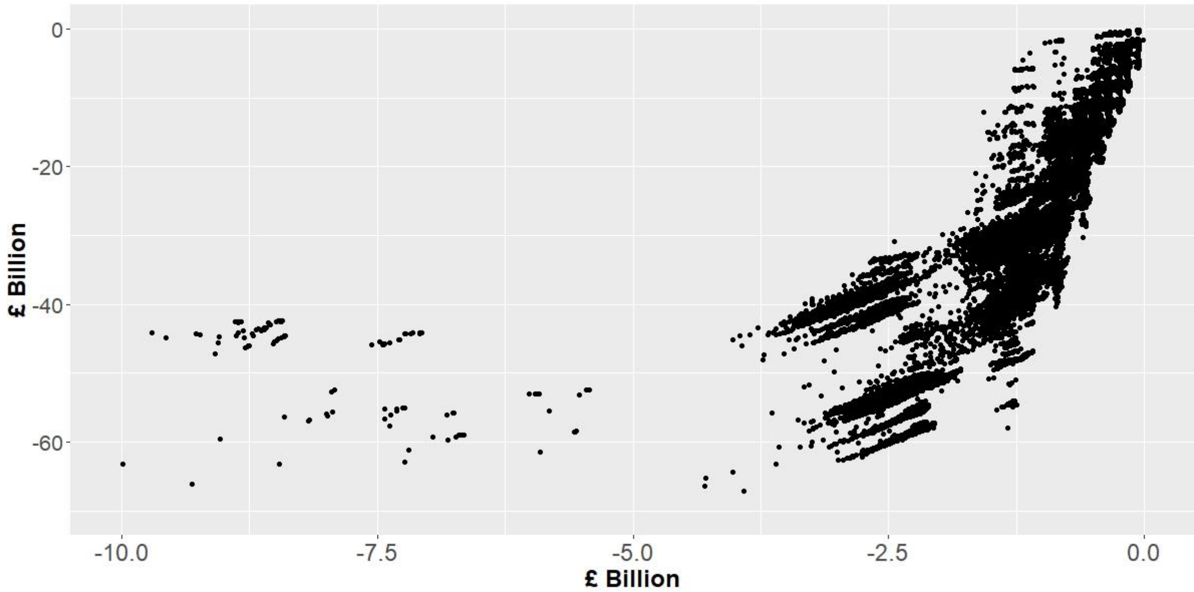
Given this evidence, we also test how our loss estimates would change conditionally to a fire-sale mechanisms based on a HQLA pecking-order approach. In this respect, we design the least conservative pecking-order approach which consists in allowing institutions to sell only High-Rated Government Bonds, that is, those securities with the lowest price impact function (i.e. Gilt or Tbill)[22]. This set of securities has a median and average price impact respectively of -0.8% and -1%, with very few outliers smaller than -2%. Figure 10 reports the fire-sales losses for all simulations across all quarters for this counterfactual exercise and compare them with baseline estimates derived using the pro-rata approach. We see that FS losses in the most extreme realizations (99th percentile) can be smaller by 7.5 times (£49 billion / £6.5 billion). Nonetheless, the largest FS loss delta appears in the central part of the distribution, that is, in those least severe realizations. In fact, the more we move away from the extreme tail, the overestimation of FS losses may reach also multiples of 20x (£40 billion / £2 billion). Hence our fire-sale loss rate (over total security portfolio holdings) decreases from 3% (pro-rata) to 0.4% (pecking-order HQLA). These two exercises and related loss rates may represent well the upper and lower bounds of potential FS losses. Hence, the realized outcome and impact to the system materially depend on the fire-sale strategy and behaviours financial institutions chose to adopt. Said that, we need to acknowledge that, although the pecking order approach is way less harmful from a financial institution's solvency perspective, may not represent the most probable outcome as suggested by Jiang et al. (2017) and Schaanning (2016).

Fire-sales events originate from sudden and herd behaviours of agents which combined together determine the severity of the market-specific reaction. Agents' behaviours in first place aim at off-loading those assets which are most likely (or expected) to experience a severe price decrease and that are prone to larger price swings. Furthermore, traders try to anticipate the market reaction or a severe price drop - before it is too late. In turn, these idiosyncratic behaviours generate in aggregate systemic pressures to the same asset class or type of securities (market, sector, country or risk-specific) since you aim to off-load them before anybody else does. According to the historical evidence, these herding behaviours, as described by Lo (2004), drives the market to unstable equilibria so as to trigger tipping points and thereby

[22] See Chart B in the appendix for this subset of price impact functions.

originating non-linear price dynamics. A clear and recent example was the severe dysfunction experienced by the UK government bond market in September 2022, when distressed forced selling of gilts by liability-driven investment funds (LDI), led to fire-sale dynamics which forced the Bank of England to introduce a temporary and targeted backstop gilt purchase facility to restore confidence and improve market functioning. This event clearly proved that fire-sale events may not only take place in those markets of highly risky and less liquid securities, but also in the HQLA high-rated government bond ones such as the Gilt market. Overall, Figure 10 framed the wide range of fire-sale event outcomes whose realized severity depends on a combination of behavioural and structural factors which are uncertain and unpredictable by nature. Given our financial stability angle, we base our main results on a pro-rata approach since it provides conservative FS estimates and more accurate ones during period of stress (Jiang et al. 2017; Schaanning, 2016)[23].

Figure 10: Counterfactual – FS Losses based on HQLA Peking Order of High-Rated Government Bonds



Note: estimates are based on 20.000 simulations and reported across all quarters. The sample of HQLA used for this exercise is a narrower set of all HQLA security universe hold by UK banks and UK insurers, precisely high-rated government bonds so as to minimize the price impact derived from the deleveraging process.

[23] Using a pecking order approach based on risky assets would lead to even more conservative estimates (higher FS losses), though it is not a viable solution since the quantity of assets to be sold would not be sufficient to restore the targeted leverage constraint in the tail of loss distribution.

5. Sensitivity Analysis

In this last section we test the implications of three main assumptions related to the modelling of fire sale dynamics, respectively i) the role played by heterogenous price impact function parameters, ii) the contribution played by the insurance sector in exacerbating fire-sales spillovers, as well as iii) the relevance of insurers' market risk sensitivity parameter - Gamma. In order to highlight the marginal contribution of this set of assumptions, we perform counterfactual exercises and compare the loss outcome in the counterfactual with baseline results presented in Section 4.

5.1 Heterogeneous Price Impact Functions

We test how results change conditional on the adoption of a more homogeneous price impact function by removing the parameter capturing the Market Selling Pressure ($Q^*_{n,t}$), that is, losing information on the severity of the fire-sale event. Hence, we transform the quantile estimation into a linear estimation of the average effect across fire sales event severity.

$$PIF^*_{s,n,t} = F_s\ (Q^*_{s,n,t}, Q^*_{n,t}) \rightarrow PIF^*_{s,n,t} = F_s\ (Q^*_{s,n,t})$$

Figure 11a highlights how total losses in the system conditional to this counterfactual exercise have changed relative to the baseline case (y axis) across affected simulations (15%) and plot them against total losses in each simulation in the baseline case (x axis). From the chart it is evident that the impact is heterogeneous across simulation severity. We find that, on average, the lower the severity of the simulation (x axis), the larger is the % variation in total losses. But we also find that for those simulations with a realized severity larger than £ -25 billion (medium stress), the impact is always negative, thereby leading to a potential underestimation of total fire sales losses (-13% to -50%) in the tail of the loss distribution.

Next, we test how results change conditional on the adoption of a more homogeneous price impact function. We achieve this by removing the parameter capturing the Security-Specific Selling Pressure ($Q^*_{s,n,t}$), that is, losing information on the security-specific volume of sales.

$$PIF^*_{s,n,t} = F_s\ (Q^*_{s,n,t}, Q^*_{n,t}) \rightarrow PIF^*_{s,n,t} = F_s\ (Q^*_{n,t})$$

Figure 11b highlights how total losses in the system based on this counterfactual exercise have changed relative to the baseline case (y axis) across affected simulations (16%) and plot them against total losses in each simulation in the baseline case (x axis). From the chart it is evident that also here the impact is heterogeneous across simulation severity. Consistently with the previous exercise, on average the lower the severity of the simulation (x axis), the larger is the percentage variation in total losses, with more positive outcomes than negative ones in the low interval of the distribution (0 to -25bn). On the other hand, for those simulations with a realized severity higher than £ -65 billion, the impact is always negative, thereby leading to a potential underestimation of total fire sales losses (-2% to -11%) in the tail of the loss distribution. Overall, not considering the price impact heterogeneity due to market selling pressure as well as to security-specific selling pressure may lead to materially underestimate losses in the tail of the distribution as well as potentially overestimate losses when median-medium stress outcomes realize outcomes realize.

Figure 11a: Counterfactual - Total Losses in the System relative to Baseline Estimates in Q1-2023 conditional to Homogeneous Price Impact Function without Market Selling Pressure

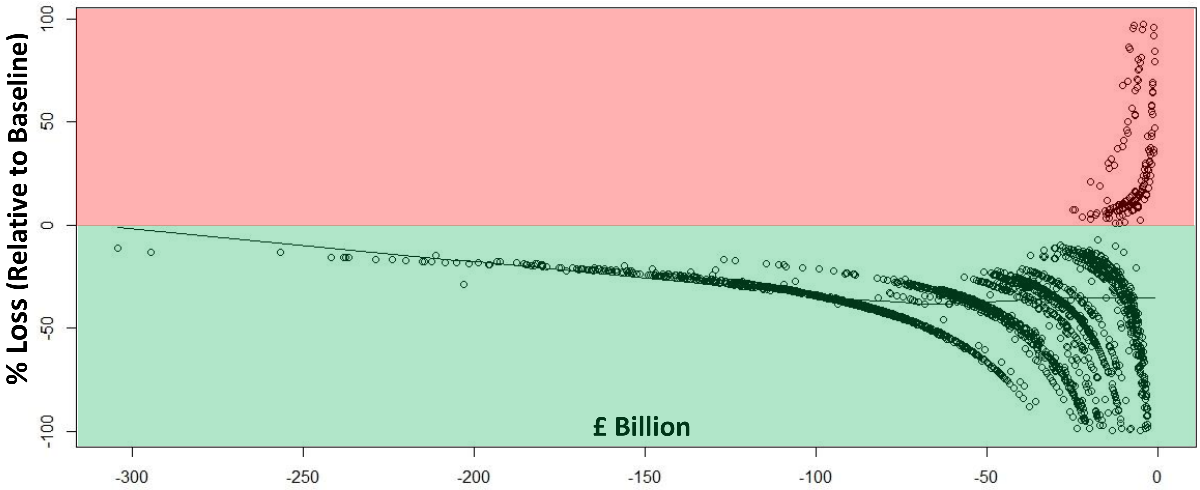
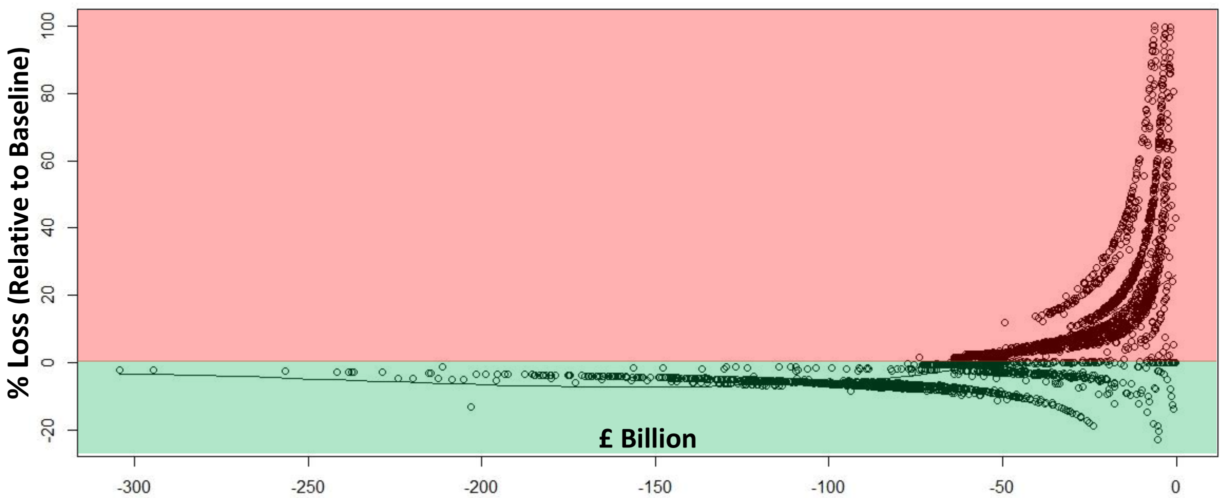


Figure 11b: Counterfactual - Total Losses in the System relative to Baseline Estimates in Q1-2023 conditional to Homogeneous Price Impact Function without Security-Specific Selling Pressure



Note: We remove outliers for visualisation purposes. Roughly 26% of simulations are affected by this assumption.

5.2 Insurance Sector Contribution to Market and Security-Specific Selling Pressure

We test how results change conditional on the size and coverage of the financial system we model, that is, the contribution of the Insurance Sector to the determination of the fire sale loss outcome. To achieve this, we remove the contribution of the insurance system to the overall volume of sales, and we model the security-specific realized price impact functions ($PIF^{*}_{s,n,t}$) exclusively conditional to banks' contribution to Market Selling Pressure ($Q^{B}_{n,t}$) and Security-Specific Selling Pressure ($Q^{B}_{s,n,t}$).

$$Q^{B}_{s,n,t} = \sum_{i}^{I} Q^{B}_{i,s,n,t}\,; \quad and \quad Q^{B}_{n,t} = \sum_{s}^{S} Q^{B}_{s,n,t}$$

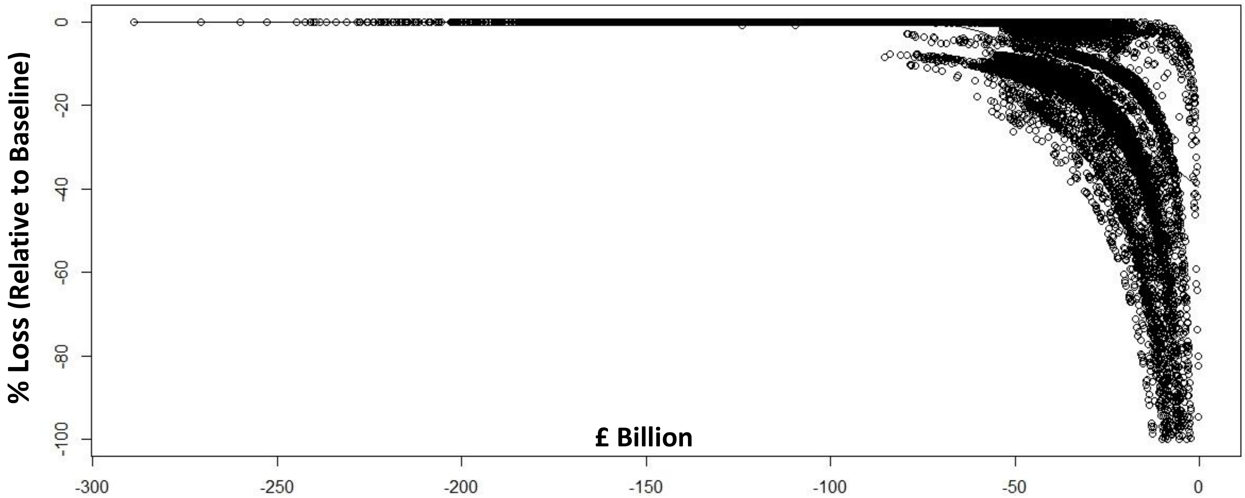
$$for\ I \in banks,\ \ PIF^{*}_{s,n,t} = F_s\left(Q^{*}_{s,n,t}, Q^{*}_{n,t}\right) \ \rightarrow \ PIF^{B}_{s,n,t} = F_s\left(Q^{B}_{s,n,t}, Q^{B}_{n,t}\right)$$

Figure 12 highlights how banks' total losses conditional on this counterfactual exercise have changed relative to the baseline case (y axis) across affected simulations (10%) and plot them against total losses in each simulation in the baseline case (x axis). From the chart it is evident that the impact is always negative and heterogeneous across simulation severity. Consistently with the set-up of the fire-sale methodology, which models the price impact function as a positive function of quantity of securities sold, a reduction of the market selling pressure and security-specific selling pressure materially decreases the realized severity of the simulation.

We notice that the most extreme events (higher than -£75 billion), are negatively affected, but not materially, consistently with what we have highlighted in Panel (a) of Table 7. The rationale behind this finding is that insurers' extreme stress outcomes stemming from high economic credit risk losses (pct99) are not that correlated with banks' extreme stress outcomes. Second, the price impact functions tend to reach the most severe price impact calibration exclusively relying on banks' volumes of sales since banks are mostly invested in bonds rather than in equity, thereby contributing majorly to the determination of the asset-specific selling pressure[24]. Nonetheless, severe and medium stress events (< £-75 billion) are more materially impacted by insurers' sale volumes, making banks' medium fire-sale events (90th) become more severe stress events (95th) via price-mediated equity contagion. Overall, we can conclude that limiting the analysis to UK banks' fire-sale volumes in the determination of the price-impact may lead us to materially underestimate losses across all percentiles of the loss distribution, with the exception of the extreme tail (99th percentile).

[24] Thereby adding the insurers' selling pressure on top of banks' selling pressure does not exacerbate further the price impact dynamics on bonds.

Figure 12: Counterfactual - Banks' Total Losses relative to Baseline Estimates conditional to the removal of Insurers' Contribution to Price Impact Function Determination



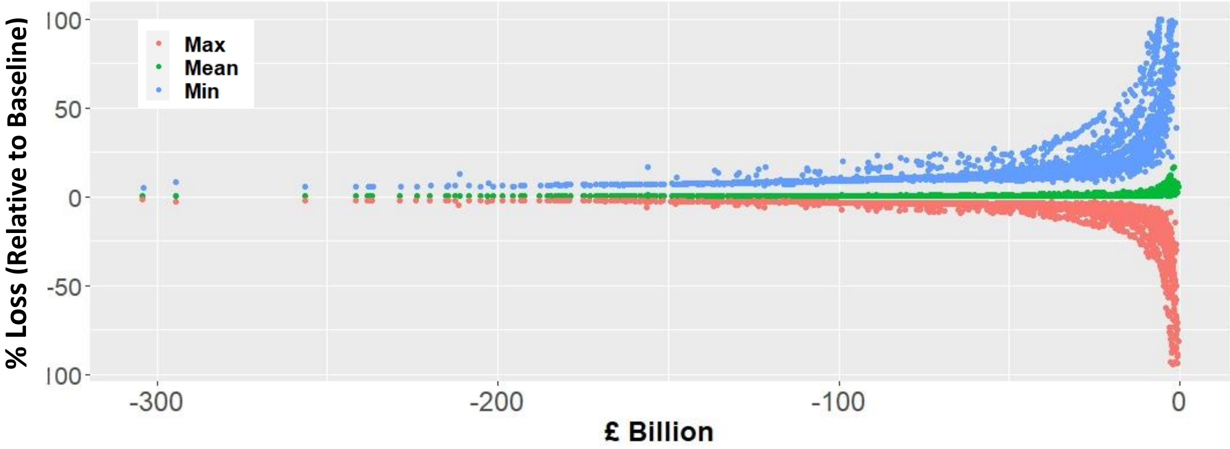
Note: We remove outliers for visualisation purposes. This set of counterfactual results are derived using a different set of price impact functions relative to baseline results. Roughly 15% of simulations are affected by this assumption.

5.3 Market Risk Sensitivity Parameter

We test how results change conditional on the adoption of a homogeneous Gamma parameter ($\boldsymbol{\gamma}$) which models insurers' market-risk-sensitivities affecting the passthrough to capital of an asset price shock. Hence, instead of using insurer-specific time-variant gamma parameters, we perform three counterfactual exercises using the mean (0.94), max (0.97) and min (0.85) of the entire Gamma sample so as to remove firm heterogeneity and create upper and lower bounds. The higher the gamma parameter ($\boldsymbol{\gamma}$), the smaller the loss impact $(1-\boldsymbol{\gamma})$ since it implies a larger decrease in insurer's liability given an asset shock.

In this respect, Figure 13 shows how a homogeneous Gamma parameter affects total losses in the system relative to baseline results. Roughly 45% of simulations are affected by this assumption. Respectively, setting the Gamma parameter equal to the minimum of the sample increases total losses in the system by 9% in the most severe simulations (90^{th}), up to 13% at median outcome (50^{th}) and up by 25% in the least severe events (25^{th}). However, setting the Gamma parameter equal to the maximum of the sample decreases total losses in the system by 3% in the most severe simulations (90^{th}), up to 5% at median outcome (50^{th}) and by 10% in the least extreme outcomes (25^{th}). In the end, setting the gamma parameter equal to the average of the sample does not lead to a material over-estimation bias (less than 2%) since insurers tend to have a similar passthrough to capital (Figure 4). Nonetheless, an overestimation of the gamma parameter may materially lead to an underestimation of potential tail losses on an insurer-basis, therefore highlighting from a supervisory perspective the importance of a proper calibration of insurers' asset-liability passthrough calibration.

Figure 13: Percentage Contribution of Gamma Parameter to Total Losses relative to baseline Estimates



Note: We remove outliers for visualisation purposes. Roughly 25% of simulations are affected by this assumption.

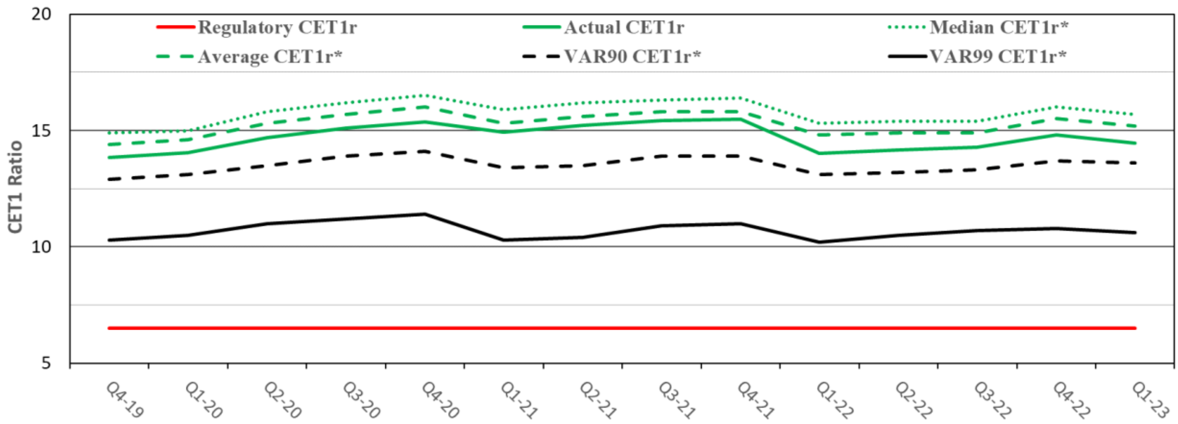
5.4 Benchmarking and Sensitivity to Retained Earnings

Finally, we showcase the model accuracy in estimating the set of main regulatory ratios, CET1 ratio (CET1) and Leverage ratio (LR) for the UK banking sector and Solvency ratio for the UK insurance sector, respectively reported in Figure 14a, and Chart C and Chart D in Appendix B. We find that the microstructural methodology replicates well the actual estimates of regulatory ratios both for banks and insurers, although the expected model-based estimates (average output) tend to overestimate the actual estimates consistently across quarters. On average, the CET1 ratio is higher by 60 basis points of RWAs, with a narrower gap during the COVID period (50 basis points) and larger gap in the post-COVID period (70 basis points). This is due to the assumption we made on retained earnings, which were set equal to 100% of realized net profits. However, in the real world, retained earnings vary over time (40%-80%) and they depend on each institution's performance and dividend strategy adopted as well as on potential regulatory interventions. In fact, during the Covid-19 period, several authorities, among which the Bank of England, introduced temporary dividend distribution restrictions in order to strengthen banks' resilience during this period of systemic stress (Acosta-Smith et al., 2024)[25]. Our results are also consistent with this stylized fact since during COVID the actual retained earnings ratio was higher, thereby showing a smaller gap between the average CET1 ratio and the actual value, whereas in the post-COVID period, in which the dividend distribution restrictions were removed, the estimated gap widens. The result sensitivity to retained earning

[25] See: https://www.bankofengland.co.uk/coronavirus

ratio is showcased in Figure 14b, in which we calculate the counterfactual CET1 ratio when the retained earnings ratio is equal to 50% and 0%. In this respect, we see that setting the retained earnings ratio equal to 50%, which is the median of the sample, make our model-based CET1 ratio estimates get very close to the actual ones. The gap between model-based expected CET1 ratio estimates and actual values reduces to 10 basis points during 2020, to 0 in 2021 and 20 basis points in 2022-23. Contrary the CET1 ratio would have materially deteriorated by roughly 140 basis points of RWAs relative to baseline estimates (Average CET1r 100%RE) if banks were allowed to pay out 100% of their retained earnings as dividends (Average CET1r 0%RE). Hence, this result shows that temporary dividend distribution restrictions were effective policy instruments in strengthening banks' capital base and in turn the banking system's stability. In the end, we want to emphasize that the retained earnings ratio assumption only matters for the median and average outcomes and does not affect tail estimates. Overall, the microstructural methodology seems to replicate well the stylized facts here presented - regulatory ratios - and this allows us to evaluate more accurately the banking system's stability under extreme stress conditions (VAR99 CET1r*). In this respect, the CET1 ratio during extreme stress events remains well above the regulatory minimum requirement as well as above the 10% level which approximates the average regulatory capital buffer requirement[26].

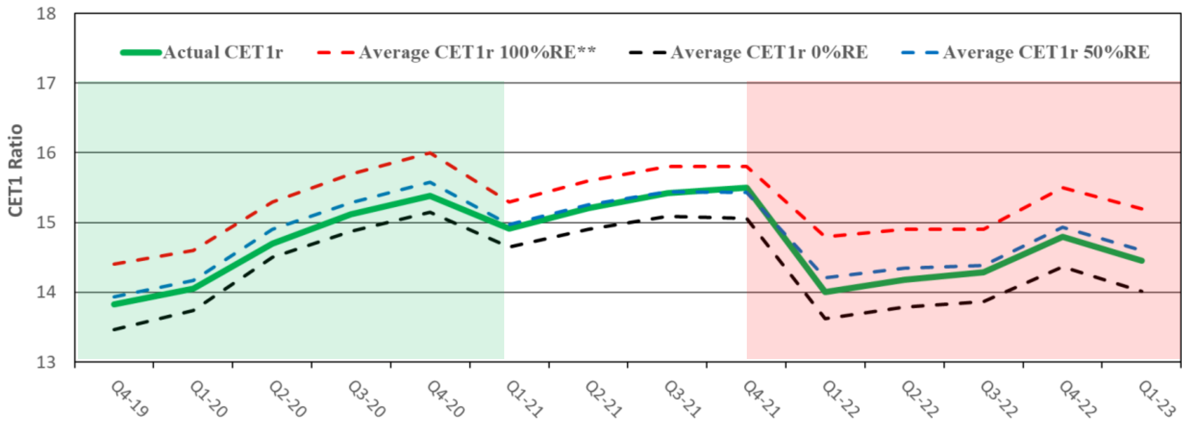
Figure 14a: Banking System's CET1 Ratio Model-Based Estimates



Note: Variables flagged with (*) refer to model stimates based on 20.000 simulations, whereas "actual" refers to the real values realized in that quarter, and "regulatroy" refers to the regulatory minima requirements. Model estimates assumed 100% of retained earnings.

[26] Th stress test results based on the Annual Cyclical Scenario 2022-23 of the Bank of England estimate that after the first year of stress UK banks' CET1 ratio would fall to 10.8%. See: https://www.bankofengland.co.uk/-/media/boe/files/stress-testing/2023/stress-testing-the-uk-banking--system-2022-23-results.pdf

Figure 14b: Banking System’s Expected CET1 Ratio Estimates with Variation in Retained Earnings Assumption



Note: Tag “%RE” refers to the percentgae of retained earnings assumed. Baseline estimates assume 100% of retained earnings and are flagged with (**), whereas “actual” refers to the real values realized in that quarter. Model estimates are based on 20.000 simulations. The counterfactual exercises are computed ex-post without taking into account the capital impact that a lower CET1 capital base have on feedback and amplification effects.

Discussions and Conclusion

This paper illustrates that feedback and amplification mechanisms - primarily fire-sales spillovers - materially increase the likelihood of experiencing extreme stress events - fatter left tail - as well as their severity - longer left tail. On top of this, amplification mechanisms also decrease the system’s profitability. We showcase that the profit channel is materially less important in the extreme tail (99th percentile) than the economic credit loss channel, respectively explaining 5% and 62% of total variation. This result corroborates findings in the existing literature on the significance of correlated exposures in determining systemic financial externalities (Elsinger et al. 2006; Acharya, 2009; Billio et al. 2012; Patro et al., 2013; and Glasserman and Young, 2015). Even in isolation, obligors’ idiosyncratic default shocks in the real economy due to intersectoral linkages (correlated defaults) may lead to material tail risk developments and to a non-negligible systemic event probability, whose severity and likelihood are further exacerbated via amplification mechanisms in the financial sector.

Next, we disentangle the sectorial contribution of banks and insurers to the UK financial system’s profit and loss distribution, and especially tail risk developments, in which banks play a leading role (80% of total CCaR99) consistently with the larger share in the exposure network (81%). Nonetheless, we provide evidence that the importance of propagation channels differs across sectors as well as across percentiles of the profit and loss distribution. Specifically, in the extreme tail, approximated by expected shortfalls in the 99th percentile (CCaR99), we find that insurers are more affected than banks by economic credit losses, respectively 68% and

60%, while gross profits in both sectors play a less relevant contribution, 7% versus 5%. Moreover, fire-sale spillovers affect more banks (33%) than insurers (25%), although banks only hold 23% of their assets as securities, while insurers' portfolio composition is made exclusively of securities. The low relative contribution of fire-sales to insurers' tail risk is due to the limited passthrough of asset shock to capital which is modelled via the gamma parameter which captures insurers' asset-liability adjustments, whose average of the sample is set around 5%. This assumption on the market-risk sensitivity parameter is key to properly model shocks to insurers' solvency position, which, when stressed, may further exacerbate losses in the range of 9% to 25%, depending on the realized stress level. Despite this limited pass-through to capital, the large share of insurers' security portfolios invested into equity rather than bonds (70%-30%), for which the price impact distribution is more negatively affected (0-20% for equity versus 0-1% for bond and) exacerbate materially the fire-sale outcome. In this respect, we find that in the tail, insurers' fire-sales losses seem to exacerbate those of banks, especially for severe (CCaR95) and medium (CCaR90) stress fire-sale events, but to a lesser extent in the extreme tail (CCaR99). This effect takes place via price-mediated equity contagion given that insurers are mostly invested into equity. This finding corroborates the role of the insurance sector in amplifying systemic stress (Weiß and Mühlnickel, 2014).

Moreover, we show that using a homogeneous price impact function without either security-specific selling pressures or market selling pressure may lead to overestimate losses in the right tail of the distribution (low stress events), consistently with the findings provided in Fukker et al. (2022). Nonetheless, we show that for medium (90^{th}), severe (95^{th}) and extreme stress events (99^{th}) an homogeneous price impact function leads us to materially underestimate fire-sale losses in the range of -9% to -50%. Moreover, also related to the modelling of fire-sale dynamics, we provide evidence on the delta impact of a HQLA pecking order strategy versus a pro-rata approach. Consistently with Caccioli et al. (2024), we find that on average a pro-rata approach does overestimate FS losses compared to a HQLA pecking-order strategy. In this respect, we find a non-linear FS impact between the two strategies, which gets wider the lower the severity of the stress event the system experiences, respectively ranging from a factor of 7 times to 20 times. This result corroborates findings by Jiang et al. (2017) and Schaanning (2016) that a pro-rata approach is more suitable for periods of stress (tail outcomes), whereas a HQLA pecking order strategy bring much larger benefits given a medium-low stress environment.

Our interpretative framework, although with some limitations related to the exclusion of liquidity contagion and solvency-liquidity interactions which may further amplify the results here documented, and the lack of the investment fund sector which plays an important role in the determination of the fire-sale price dynamics as shown by Sydow et al. 2024, we showcase that systemic events may take place in isolation via idiosyncratic shocks to firms' counterparties and that financial amplification mechanisms exacerbate materially the outcome both in terms of severity and loss correlation between the two sectors. The contribution of the drivers to the realized severity differs across percentile of the profit and loss distribution as well as across sectors and on a firm-basis, highlighting that a probabilistic approach combined with firm heterogeneity and multiple risk channels is necessary to unfold the role of interconnectedness and financial contagion in triggering market disruptions in modern financial systems.

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Appendix A – Balance Sheet Accounting

Banks – *Profit and Loss Step*

$$TA^1_{i,n,t} = TA^0_{i,t} + PL^{EC}_{i,n,t} \quad and \quad RWA^1_{i,n,t} = RWA^0_{i,t} + \left(PL^{EC}_{i,n,t} * \frac{RWA^0_{i,t}}{TA^0_{i,t}}\right)$$

$$CET1^1_{i,n,t} = CET1^0_{i,t} + PL^{EC}_{i,n,t} \quad and \quad TIER1^1_{i,n,t} = TIER1^0_{i,t} + PL^{EC}_{i,n,t}$$

$$CET1r^1_{i,n,t} = \frac{CET1^1_{i,n,t}}{RWA^1_{i,n,t}} \quad and \quad LR^1_{i,n,t} = \frac{TA^1_{i,n,t} - TIER1^1_{i,n,t}}{TIER1^1_{i,n,t}}$$

Banks: Fire-Sale Step

$$TA^2_{i,n,t} = TA^1_{i,n,t} - Q^*_{i,n,t} + PL^{FS}_{i,n,t}$$

$$RWA^2_{i,n,t} = RWA^1_{i,n,t} - \left(\left(Q^*_{i,n,t} - PL^{FS}_{i,n,t}\right) * \frac{RWA^1_{i,n,t}}{TA^1_{i,n,t}}\right)$$

$$CET1^2_{i,n,t} = CET1^1_{i,t} + PL^{FS}_{i,n,t} \quad and \quad TIER1^2_{i,n,t} = TIER1^0_{i,t} + PL^{EC}_{i,n,t}$$

Insurers: *Profit and Loss Step*

$$TA^1_{i,n,t} = TA^0_{i,t} + PL^{EC}_{i,n,t} \quad and \quad TL^1_{i,n,t} = TL^0_{i,t} + \left(\gamma_{i,t} * PL^{EC}_{i,n,t}\right);$$

with $\gamma_{i,t} = 0$, i.e. full passthrough

$$OWF^1_{i,n,t} = TA^1_{i,n,t} - TL^1_{i,n,t} \quad and \quad SCR^1_{i,n,t} = TA^1_{i,n,t} * \frac{SCR^0_{i,n,t}}{TA^0_{i,n,t}}$$

$$SII^1_{i,n,t} = \frac{OWF^1_{i,n,t}}{SCR^1_{i,n,t}}$$

Insurers: *Fire-Sales Step*

$$TA^2_{i,n,t} = TA^1_{i,t} - Q^*_{i,n,t} + PL^{FS}_{i,n,t} \quad and \quad TL^2_{i,n,t} = TL^1_{i,t} - Q^*_{i,n,t} + \left(\gamma_{i,t} * PL^{FS}_{i,n,t}\right);$$

with $\gamma_{i,t} > 0$, i.e. limited passthrough

Network of Exposures

$$EXP^1_{i,j,n,t} = EXP^0_{i,j,t} - \left(EXP^0_{i,j,t} \middle| \left(Y_{j,n} = 1\right)\right)$$

Appendix B – Sensitivity Analysis

Chart A1: Conditional Tail Event Probability – By Firm Type (All Stress Events)

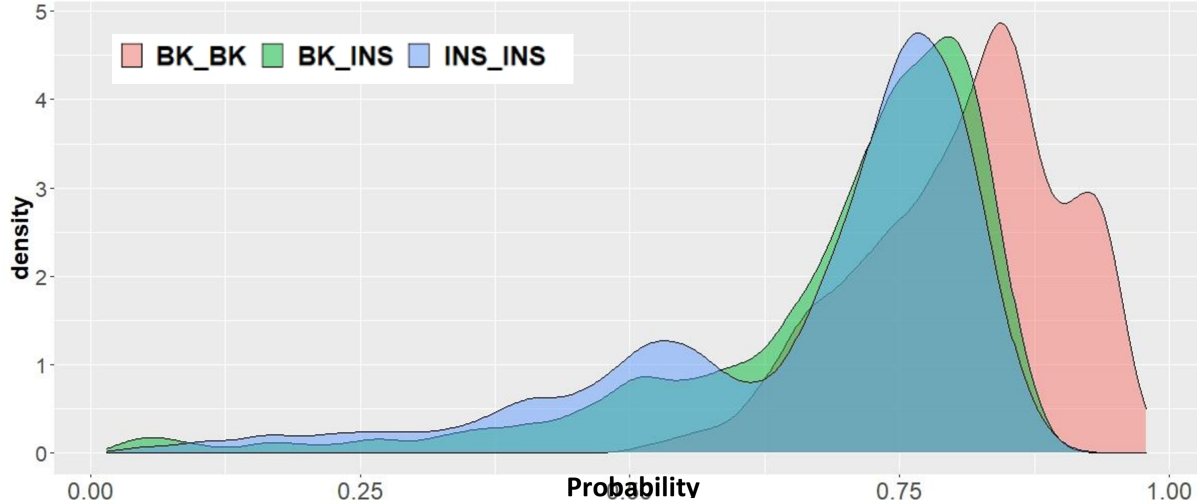


Chart A2: Conditional Tail Event Probability – Time Series Evolution

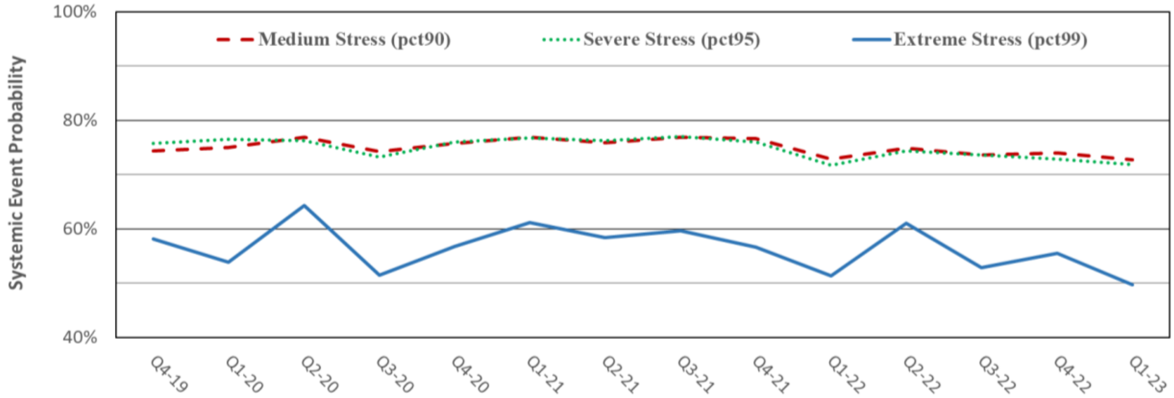


Chart B: HQLA High-rated Government Bond Price Impact Distribution

Panel (a)
All Percentiles and All Volumes

Panel (b)
5th percentile and 100M Volume

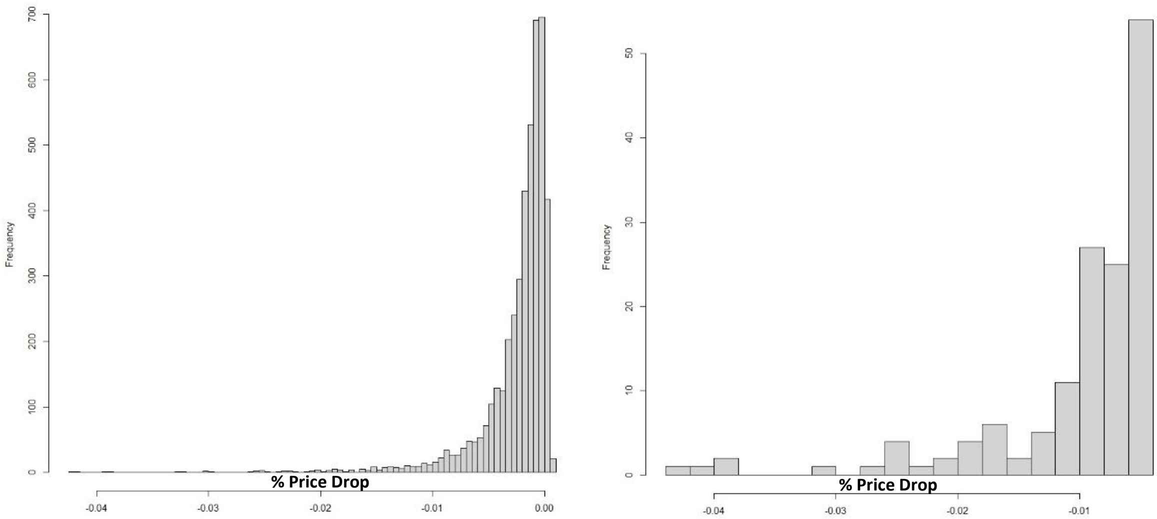


Chart C: Banking System's Leverage Ratio Model-Based Estimates

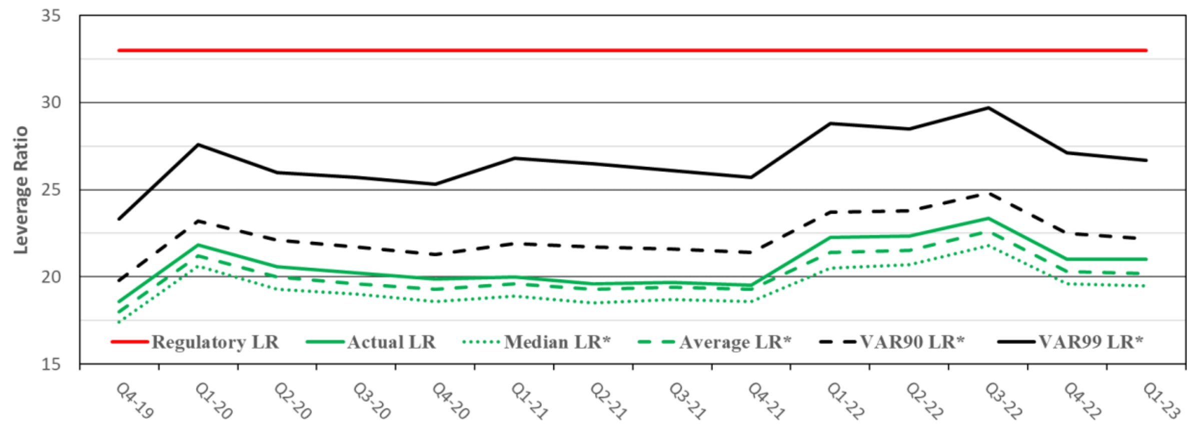


Chart D: Insurance System's Solvency II Ratio Model-Based Estimates

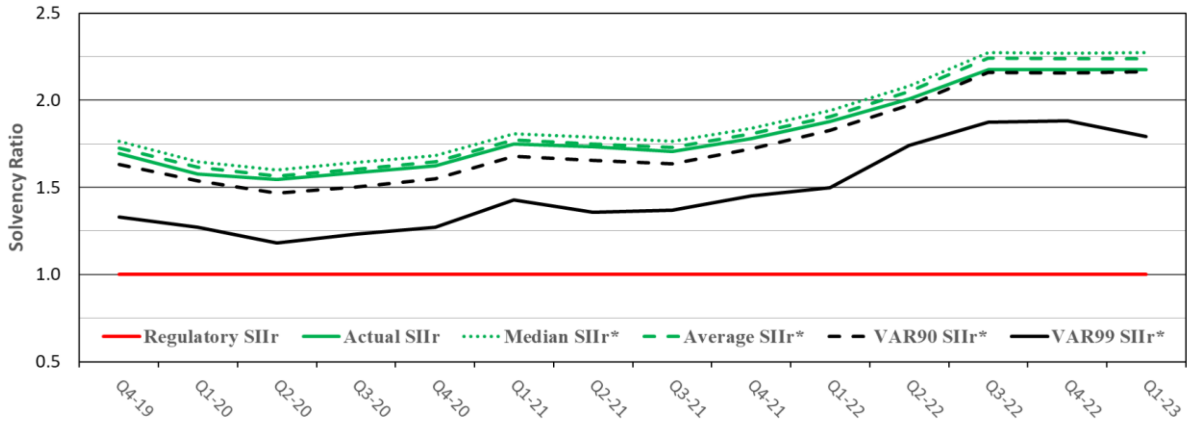
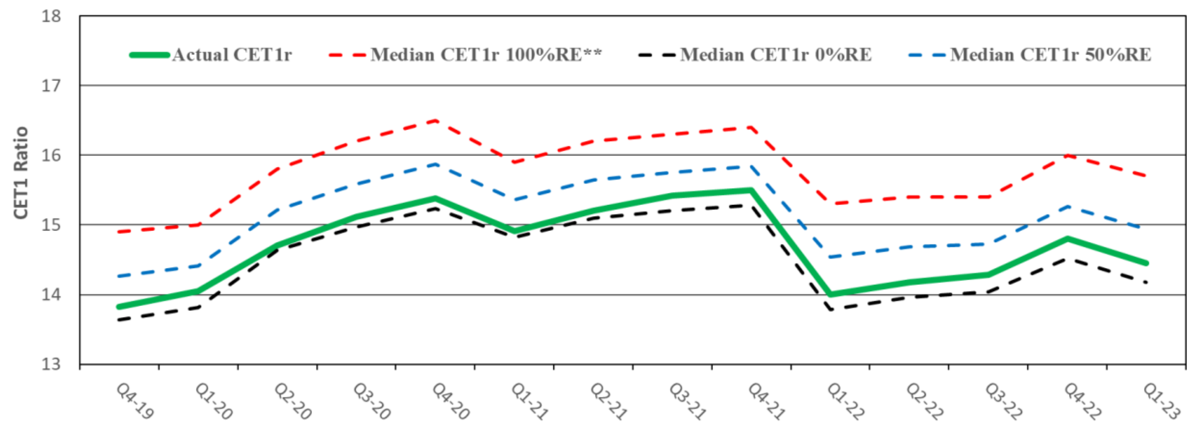


Chart E: Banking System's Median CET1 Ratio Estimates with Variation in Retained Earnings Assumption



Note: Tag "%RE" refers to the percentgae of retained earnings assumed. Baseline estimates assume 100% of retained earnings and are flagged with (**), whereas "actual" refers to the real values realized in that quarter. Model estimates are based on 20.000 simulations