CAHIER D'ÉTUDES
WORKING PAPER

N° 199

SYSTEM-WIDE FINANCIAL STRESS TESTING IN LUXEMBOURG

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SEPTEMBER 2025

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME

A System-Wide Stress Testing for Luxembourg Financial Sector

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September, 2025

Abstract

We develop a structural framework for system-wide financial stress testing with multiple interacting contagion and amplification effects acting through a dual channel of liquidity and solvency risk. The framework allows us to identify vulnerabilities arising from the increasingly intricate and complex financial system of banks and investment funds in Luxembourg. Based on exogenous shocks stemming from hypothetical adverse scenarios, several important findings are documented for banks and three types of investment funds (Bond Funds, Equity Funds and Mixed Funds) during 2020-2023. First, the simulated shocks have significant first-round and higher-order effects on investment funds, in particular on Equity Funds. Moreover, Bond Funds display a stronger amplification factor than other types of investment funds. Second, the impact on Luxembourg banks is substantially muted. The overall bank capital depletion, measured by the total risk exposure amount, is low even in view of the tail risk metrics, which reflects the strong resilience of the Luxembourg banking sector as a whole. Third, for both investment funds and banks, their vulnerabilities still reflect the procyclicality of the financial system. Overall, the joint modelling of banks and non-banks delivers clear benefits to the analytical capabilities of central banks and informs policymakers in developing the non-bank macroprudential toolkit of the future.

JEL Classification: D85, G01, G21, G23, L14

Keywords: financial stability; systemic risk; macro-prudential policy; fire sales; banking business model; stress testing; liquidity; macro-financial linkages.

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We are grateful to colleagues for the comments received, in particular to Sara Ferreira Filipe, Abdelaziz Rouabah and Jean-Pierre Schoder. Correspondent author: Xisong Jin, e-mail: xisong.jin@bcl.lu. José Fique contributed to this study during his previous employment at the Banque centrale du Luxembourg.

Non-Technical Summary

System-wide financial stress testing has gained prominence in the academic and policy literature as a crucial framework for assessing the resilience of the financial system. It involves evaluating the capability of the financial system to absorb shocks while maintaining its critical functions. Given the increasingly intricate and complex financial system in Luxembourg, it is important to step up the oversight of the financial sector in Luxembourg from a system-wide perspective. Such a system-wide perspective would also be appropriate for other complex financial systems abroad.

This paper develops a structural framework for system-wide financial stress testing with multiple interacting contagion and amplification effects acting through a dual channel of liquidity and solvency risk. The framework allows us to identify vulnerabilities arising from banks and investment funds in Luxembourg. It follows the system-wide stress testing framework of the ECB by incorporating the flow-performance relationship and the liquidity management with both leverage and cash targets for investment funds. By capturing the market risk, credit risk and liquidity risk simultaneously, the framework highlights liquidity and solvency interactions, allowing for dynamic balance sheet adjustments, an advanced integration of regulatory constraints and endogenous market price formation.

This study considers almost all banks (excluding branches) and three main types of investment funds, i.e., Equity Funds, Bond Funds, and Mixed Funds in Luxembourg. The exogenous shocks stem from hypothetical adverse scenarios that are similar to the Great Financial Crisis, the sovereign debt crisis, and the recent COVID-19 pandemic. Several stylized facts are documented for banks and the three types of investment funds during 2020-2023. First, the simulated shocks have significant first-round and higher-order effects on investment funds, in particular on Equity Funds. Moreover, Bond Funds display a stronger amplification factor than other types of investment funds. Second, the impact on Luxembourg banks is substantially muted. The overall bank capital depletion, measured by the total risk exposure amount, is low even in view of the tail risk metrics, which reflects the strong resilience of the Luxembourg banking sector as a whole. Finally, for both investment funds and banks, their vulnerabilities still reflect the procyclicality of the financial system. In view of these results, the joint modelling of banks and non-banks delivers clear benefits to the analytical capabilities of central banks and informs policymakers in developing the non-bank macroprudential toolkit of the future.

Résumé non-technique

La mise à l’épreuve de la résilience du système financier dans son ensemble (system-wide financial stress testing) est devenue un cadre essentiel pour évaluer la résilience du système financier, tant dans la littérature académique que dans la conduite de la politique macroprudentielle. Le procédé consiste à évaluer la capacité du système financier à absorber des chocs tout en maintenant opérationnelles ses fonctions essentielles. Compte tenu de la complexité croissante du système financier luxembourgeois et la diversité de ses acteurs, il est important de renforcer la surveillance du secteur financier au Luxembourg sous un angle systémique. Une telle perspective à l’échelle du système serait également appropriée pour d’autres systèmes financiers étrangers complexes.

Cette étude développe un cadre structurel pour les tests d’endurance à l’échelle du système, intégrant de multiples canaux de contagion et d’amplification qui interagissent via l’interaction du risque de liquidité et de solvabilité. Ce cadre permet d’identifier les vulnérabilités émanant des banques et des fonds d’investissement au Luxembourg. Il s’inspire du cadre de tests de résistance développé par la BCE en y intégrant d’une part la relation entre les flux et les performances, et d’autre part la gestion de la liquidité des fonds d’investissement avec à la fois l’effet de levier et les objectifs ciblés de trésorerie. En capturant simultanément les risques de marché, de crédit et de liquidité, le cadre adopté met en évidence les interactions entre liquidité et solvabilité, permettant des ajustements dynamiques du bilan, une intégration avancée des contraintes réglementaires et une formation endogène des prix de marché.

L’étude couvre la quasi-totalité des banques (hors succursales) et trois grandes catégories de fonds d’investissement au Luxembourg : les fonds actions, les fonds obligataires et les fonds mixtes. Les chocs exogènes proviennent de scénarios hypothétiques défavorables, similaires à ceux de la Grande Crise Financière, à la crise de la dette souveraine et à la récente pandémie de COVID-19. Plusieurs faits stylisés sont décrits pour les banques et les trois catégories de fonds d’investissement sur la période 2020-2023. Premièrement, les chocs simulés ont des effets de premier tour et d’ordre supérieur significatifs sur les fonds d’investissement, en particulier sur les fonds actions. En outre, les fonds obligataires présentent un facteur d’amplification plus élevé que les autres types de fonds. Deuxièmement, l’impact sur les banques luxembourgeoises est nettement atténué. L’épuisement global des fonds propres des banques, mesuré par le montant total d’exposition au risque, demeure faible même dans le cas de matérialisation d’un risque très sévère. Ceci reflète la robustesse du secteur bancaire luxembourgeois dans son ensemble. Enfin, pour les fonds d’investissement comme pour les banques, leurs vulnérabilités continuent de refléter la procyclicité du système financier. Au vu de ces résultats, la modélisation conjointe des banques et des entités financières non-bancaires apporte une réelle valeur ajoutée aux capacités d’analyse des banques centrales et éclaire les décideurs dans l’élaboration de futurs outils macroprudentiels pour le secteur des intermédiaires non-bancaires.

1. Introduction

System-wide financial stress testing has gained prominence in the academic and policy literature as a crucial framework for assessing the resilience of the financial system. It involves evaluating the capability of the financial system to absorb shocks while maintaining its critical functions. As suggested by the 2021-2024 IMF Luxembourg Article IV recommendation, it is important to step up the oversight of the financial sector in Luxembourg from a system-wide perspective. Specifically, the IMF recommended that the authorities involved in macroprudential policy should continue to enhance internal methodologies for system-wide liquidity stress testing, such as by incorporating higher-order effects. In response to the IMF, and in order to identify vulnerabilities arising from an increasingly intricate and complex financial system in Luxembourg, we develop a system-wide stress-testing framework for the financial sector through a dual channel of liquidity and solvency risks. Such a system-wide perspective would also be appropriate for other complex financial systems abroad.

Substantial research has been dedicated to assessing vulnerabilities of the wider financial system in the literature.[1] Recent studies underline the network structure of financial institutions, including non-bank intermediaries, and its role in the system risk propagation by using granular data. Greenwood, Landier and Thesmar (2015) develop a model in which fire sales propagate shocks across bank balance sheets. They describe the evolution of bank balance sheets following shocks to the value of banks' assets. For instance, a bank that experiences a negative shock is likely to sell assets in order to maintain its target leverage. However, if potential buyers are limited, then asset sales depress prices and impact other banks with common exposures. Fricke and Fricke (2021) extend the Greenwood, Landier and Thesmar (2015) fire sale model, by incorporating the flow-performance relationship as an additional funding shock. The Bank of England has developed its own system-wide stress simulation and publicly launched its system-wide exploratory scenario (SWES)[2] in June 2023 through several publications. Baranova et al. (2017) incorporate some important features of the financial system, including banks and non-banks, and describe how their actions may propagate and amplify stress. Farmer et al. (2020) propose a structural framework for the development of system-wide financial stress tests with multiple interacting contagion and amplification channels, as well as heterogeneous financial institutions. Recently, Sydow et al. (2024a) also propose an interconnected system-wide stress test analytics (ISA) model using a very large and granular data set for the euro area.[3] The model attempts to provide a holistic view of the entire system's dynamics by capturing both first-round and higher-order effects arising from direct and indirect exposures, as well as their interactions. Within a one-period model, they show how the combined endogenous reaction of banks and

[1] For a review, see Silva, Kimura and Sobreiro (2017).

[2] The SWES aims to improve the understanding of the behaviour of banks and non-bank financial institutions during stressed financial market conditions, and how such behaviour might interact to amplify shocks in financial markets that are core to financial stability in the UK.

[3] The mechanism described in Sydow et al. (2024a) assumes no flow-performance relationship and is solely driven by liquidity needs of financial institutions and the composition of their portfolios.

investment funds to an exogenous shock can amplify or dampen losses in the financial system compared to results from single-sector stress testing models. Budnik et al. (2024) provides an overview of stress-testing methodologies in Europe, with a focus on the advancements made by the ECB. Moreover, Sydow et al. (2024b) further extend the system-wide stress testing framework of the ECB by incorporating the insurance sector for a more thorough assessment of risks to financial stability. They assess the impact of liquidity and solvency shocks, and demonstrate how a combined endogenous reactions of banks, investment funds and insurance companies can further amplify losses in the financial system. In their framework, a flow-performance relationship is also used to derive scenario-conditional redemptions based on the initial price changes of funds caused by the exogenous market shock.

To assess the systemic risk from fund/bank connections in Luxembourg through a dual channel of liquidity and solvency risks, we follow the approach in Sydow et al. (2024a&b). Specifically, we incorporate the flow-performance relationship and the liquidity management with both leverage and cash targets for investment funds. Similarly to the ISA model, by capturing three different classes of risk (credit, liquidity and market risk), our framework highlights liquidity and solvency interactions, allowing for dynamic balance sheet adjustments, an advanced integration of regulatory constraints, and endogenous market price formation.

This paper considers almost all banks (excluding branches) and three main types of investment funds, i.e., Equity Funds, Bond Funds, and Mixed Funds in Luxembourg. As euro area banks made substantial efforts to reshape their business models in response to the challenges of the financial crisis and new regulatory requirements,[4] we investigate the channels of risk amplification for five main bank business models in Luxembourg. They are (i) Corporate Finance (CF), (ii) Covered Bonds Banking, Clearing, Treasury and Payment Services (CCTPS), (iii) Custodian Banking and Activities Linked to Investment Funds (CBALIF), (iv) Private Banking (PB) and (v) Universal, Retail and Commercial Banking (URCB). In addition, for each business model, the systemic effect is further broken down by banks' domicile type as per the Single Supervisory Mechanism's approach: domestic banks, EU foreign subsidiaries, and non-EU Foreign subsidiaries. Finally, regarding systemic risk indicators adopted, as in Sydow et al. (2024a), we propose the loss ratios for investment funds and capital depletion ratios for banks under exogenous shocks.

The loss ratio for a type of investment funds is the ratio of its loss to its net asset value (NAV), while the capital depletion ratio for a bank is the ratio of banks' capital depletion to its total risk exposure amount (REA).[5] As the framework incorporates bank solvency capital requirements with respect to REA, the capital depletion ratio is thus able to capture the bank credit risk loss. The capital depletion ratio for a group of banks is the REA weighted capital depletion ratios of those banks in the group. Besides these indicators,

[4] see ECB's Financial Stability Review, May & November 2016

[5] According to the rules of the Capital Requirements Regulation (CRR), banks must calculate a total risk exposure amount, which is the sum of their credit risk, their operational risk, their market risk and the risk of a credit valuation adjustment (CVA risk). For instance, the bank capital depletion in terms of REA is also used to address the high-order amplification effects in the ESRB report on climate-related risk and financial stability (July 2021).

the simple risk metrics of Value-at-Risk (VaR) and Expected Shortfall (ES) at 10% probability level for the simulated distribution of these loss ratios are provided. Moreover, an amplification factor is defined as the ES ratio of higher-order effects to first-round effects.

In order to assess the overall resilience of banks and investment funds, we do not specify economic triggers for the deterministic and stochastic exogenous shocks. Rather, we assume that they stem from hypothetical adverse shocks that could be similar to the Great Financial Crisis, the sovereign debt crisis and the recent COVID-19 pandemic. The initial exogenous shocks stem from a hypothetical market crash corresponding roughly to the first percentile of the monthly return distribution of the EA stock market index during 2003-2024. Driven by these initial exogenous shocks, the derived credit risk shocks and market risk shocks then affect investment funds' NAVs and banks' capital values. Importantly, the market risk, credit risk, and liquidity risk are endogenously integrated in our framework.

Several important facts are documented in this study. Based on end-2023 data, we find that the simulated shocks could have significant first-round and higher-order effects on the three types of investment funds, in particular on Equity funds. Bond Funds display a stronger amplification factor than other types of investment funds, as their ES for the higher-order effects almost triples that of the first-round effects. This amplification is mainly driven by the Bond Funds' high flow-performance elasticities. The results remain similar when we exclude the banking sector from our stress-testing framework, which reflects the limited influence of the Luxemburg banking sector on the dynamics of investment funds.

Furthermore, the impact of the simulated shocks on banks is substantially muted. Taking into account the initial high capital-to-REA ratios for all banks (e.g., around 23%), the ES of capital depletion ratio for the 10% tail is overall limited to around 0.58 percentage points, even if considering higher-order effects under a severely adverse scenario. This finding reflects the strong resilience of the Luxembourg banking sector as a whole. The bank amplification factors are similar across business models and domicile types, and much lower than those of the three types of investment funds. Nonetheless, Luxembourg domestic banks are relatively more affected than EU or non-EU foreign subsidiaries. For instance, while the initial capital-to-REA ratio is roughly 20% for domestic banks and 23% for EU foreign subsidiaries, the capital depletion ratio of domestic banks (measured by the ES at 10% level) is around 1.42 percentage point under the severely adverse scenario, compared to 0.38 p.p. for EU foreign subsidiaries. The stronger response of domestic banks might reflect the strong interconnectedness between those domestic banks and funds. At a more granular level, the overall bank capital depletion ratio is dominated by domestic banks in URCB, EU foreign subsidiaries in CBALIF, and non-EU foreign subsidiaries in CCTPS.

In order to investigate the evolution of vulnerabilities in banks and investment funds across time, we apply the same stochastic exogenous shocks to their year-end data from 2020 to 2023. Overall, for both investment funds and banks, vulnerabilities reflect the procyclicality of the financial system. Their activities tend to expand and contract in response to broader economic cycle. As such, their loss ratio distributions significantly worsened from 2020 to 2021, a period associated with the weak post-pandemic economic recovery. In turn, early 2022 was marked by accelerating inflation and supply-side bottlenecks and the Russian-Ukrainian war.

However, as the Federal Open Market Committee (FOMC) started the tightening process to help lower inflation in March 2022, and the Eurosystem initiated monetary policy normalization in July 2022 to bring high inflation back to its medium term objective, investment fund and bank vulnerabilities improved significantly towards the end of 2022. Nevertheless, the deterioration observed at the end of 2023 might reflect elevated macroeconomic uncertainty, mainly due to the continuation of global geopolitical tensions. Despite the cyclical variation, the profiles of vulnerabilities still reflect the different characteristics of banks and investment funds. At the end of 2023, the loss ratio distribution of investment funds approached its worst level of 2021. In contrast, Luxembourg banks showed increased resilience, with their overall loss ratio distribution remaining lower than that at the end 2021. The overall changes in bank vulnerability from 2020 to 2023 are driven by Luxembourg domestic banks, reflecting their linkages with investment funds.

The results also reveal that the loss ratio distribution of banks is mainly driven by market risk. Without considering the credit risk channel, the overall profile of bank capital depletion ratios under the same stochastic exogenous shocks is similar to the one obtained when considering the two channels.[6] The results for the overall bank capital depletion ratio are mostly driven by domestic banks. Non-Luxembourg intermediaries could provide significant liquidity support to banks in event of crisis materializing. This could considerably mitigate the effects of market risks on banks liquidity.

This paper is organized as follows. Section 2 describes the structural framework for system-wide stress tests. Section 3 describes the data. Section 4 defines parameter settings for the model. Section 5 presents the results. Section 6 conducts several robustness tests, while section 7 concludes.

2. Methodology

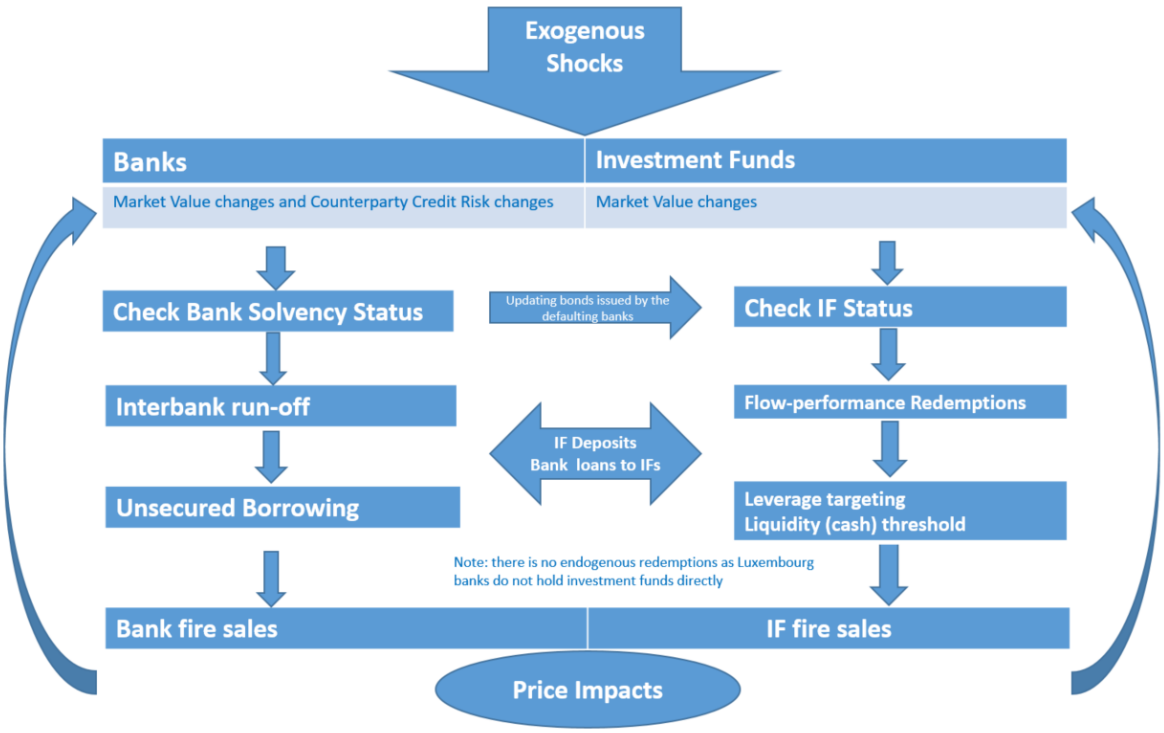
Luxembourg investment funds hold a significant part of their liquidity buffers under the form of demand deposits with Luxembourg banks. At the end of 2023, the deposits from Equity Funds, Bond Funds and Mixed Funds represented roughly the equivalent of respectively 13%, 9% and 30% of the total capital of Luxembourg banks. Given the size of the investment fund sector in Luxembourg, should investment funds experience large-scale redemptions, their actions may lead to liquidity stress in the banking system. Additionally, the sale of securities to meet investor redemptions may generate price corrections that could propagate stress to the rest of the financial system via indirect contagion in the form of mark-to-market losses. In light of these propagation channels, a thorough assessment of the resilience of the Luxembourg

[6] Given the overindebtedness of LU households, this conclusion might in practice be challenged by potential concerns around mortgage credit risk. However, in this paper, credit risk is modeled by a market factor dependent on investment fund returns and, therefore, such concerns are not directly considered. Nonetheless, a targeted stress test exercise focusing on mortgage credit risk could, in principle, be conducted using our framework.

financial system thus requires a system-wide perspective encompassing banks, investment funds, and their interlinkages.

We investigate how the combined endogenous reactions of banks and investment funds to exogenous shocks can amplify or dampen losses to the Luxembourg financial system, compared to what single-sector perspectives would suggest. Based on data available to the BCL, we follow the framework of Sydow et al. (2024a&b) by incorporating endogenous redemptions and investment fund managers' actions related to both leverage and cash ratios targets. We consider investment fund type-level data instead of a very large and granular dataset of securities held by funds. Figure 1 illustrates our model dynamics.

Figure 1: Model Dynamics



According to this setup, credit risk and market risk shocks affect investment funds' NAVs, bank securities, and bank credit risk exposures (e.g., bank loans to non-financial corporations and households). In reaction to a drop in investment funds' NAV, investors redeem their investment. These redemptions affect investment funds' balance sheets in such a manner that it may lead investment fund managers to take action to return to internal targets for leverage and cash ratios. In turn, the actions taken may result in the liquidation of tradable assets and changes in the amount of bank loans to investment funds and fund deposits at banks.

In parallel, the exogenous shock also leads to endogenous reactions from banks. Once a bank becomes distressed, it will withdraw liquidity (short-term exposures) from all its counterparty banks or investment funds, and all banks and investment funds withdraw their short-term exposures to the distressed banks as a precautionary measure. Additionally, banks experiencing liquidity stress would take remedial actions by curtailing their own short-term interbank lending and/or seeking interbank funding in the unsecured interbank market to the extent that their solvency allows. Finally, banks and investment funds address any remaining liquidity needs by selling tradable assets in accordance to their own liquidity management. The price impact from these asset fire sales leads, in turn, to marked-to-market losses for banks and investment funds with overlapping asset portfolios.

Furthermore, along this model dynamics, a set of parameters needs to be defined. Accordingly, several satellite models are also being investigated at the same time, for example, the bank credit risk model, the pricing model for bank's tradable securities, the flow-performance relationship model, and the price impact model at the aggregate level.

Overall, we present a stress-testing framework to model short-term effects of financial stress in a system of banks and investment funds. As for the channels of risk amplification, the joint asset fire sales of banks and investment funds would have the largest systemic effect in our model, and the redemption of fund shares turns out to be important.

2.1 Effects of bank credit risk[7]

We consider shocks directly on a bank's total credit risk, measured by the probability of default (PD), which describes the aggregate likelihood that a bank's obligors will default.[8] Thus, the values of relevant bank balance sheet items will be repriced according to the expected loss derived from the PD shocks. The change in expected loss for each bank is denoted as $\Delta EL = \Delta PD \times LGD \times E^{credit\ risk}$, where ΔPD represents the PD shock, the loss-given-default, LGD, describes the loss rate on the exposure in the event of default, and $E^{credit\ risk}$ denotes the total credit risk exposure.

The risk-weighted assets, or RWA can be also updated according to the Basel III capital requirement. RWA are calculated by the Basel risk weight functions for the derivation of supervisory capital charges for Unexpected Losses (UL). RWA are determined according to Basel Committee's formula: $RWA = 12.5 \times K \times E^{credit\ risk}$, where K is defined according to the capital requirement:

$$K = \left(LGD \times N \left[\frac{G\ (PD)}{\sqrt{(1 - R)}} + \sqrt{\frac{R}{(1 - R)}}\ G\ (0.999) \right] - PD \times LGD \right) \left(\frac{1}{1 - 1.5b} \right), \qquad (1)$$

[7] Bank credit risk is defined as the potential loss arising from a bank's borrower or counterparty failing to meet its obligations in accordance with the agreed terms.
[8] The exogenous PD shocks on specific credit risk balance sheet, e.g., loans to non-financial corporations, households and governments can be explored in a similar way.

where $G(PD)$ represents the inverse normal distribution with the probability of default, PD, as its argument. Here N(·) is the cumulative normal distribution, R denotes asset correlation and b is the maturity adjustment.

For each bank, we update its REA by the change of RWA under ΔPD, and capital by $\Delta EL + \alpha\text{Provisions}$, where α is the ratio of released provisions defined as the ratio of ΔEL to the original total credit risk exposure. The total assets and total credit risk exposures are also modified by the expected loss, ΔEL.

2.2 Dynamics of banks' tradable securities

The tradable securities of Luxembourg banks are categorized as financial assets held for trading at fair value through profit or loss according to IFRS 9. Thus, their values are driven by initial exogenous market valuation shocks and endogenous price impact shocks as well.

2.3 ***Banks' solvency status***

Following Sydow et al. (2024a), the default and distress thresholds in monetary units for each bank i is defined by multiplying the relevant capital requirements by its REA:

$$\tau_i^{default} = \chi^{default} * REA_i, \;\; \tau_i^{distress} = \chi^{distress} * REA_i \qquad (2)$$

where $\chi^{default} = \chi^{MC} + \chi^{P2P} + \chi^{sf\ AT1/T2}$, namely, the total Supervisory Review and Evaluation Process (SREP) capital requirement including uniform minimum CET1, χ^{MC}, the bank-specific Pillar 2 requirement, χ^{P2P}, and the shortfall of additional Tier-1 and Tier-2 capital, $\chi^{sf\ AT1/T2}$. The distress threshold $\tau_i^{distress}$ is higher than the default threshold $\tau_i^{default}$, and is given by $\tau_i^{distress} = (\chi^{default} + \chi^{CBR}) * REA_i$. The combined buffer requirement (CBR), χ^{CBR}, is the sum of the uniform capital conservation buffer (CCoB), the countercyclical capital buffer (CCyB) and the maximum of the structural risk related macroprudential capital requirements: systemic risk buffer (SyRB), buffer for global systemically important institutions (G-SII) and buffer for other systemically important institutions (O-SII): $\chi^{CBR} = \chi^{CCOB} + \chi^{CCyB} + \max(\chi^{SyRB}, \chi^{\text{O-SII}}, \chi^{\text{G-SII}})$. However, the SyRB and the G-SII do not apply to Luxembourg banks.

2.4 Dynamics of Investment Funds

First, once a bank becomes distressed, the NAVs of investment funds have to be updated accordingly if its issued securities are held by the investment funds. We assume that the value of securities issued by the defaulted banks drops to zero, while the securities issued by the distressed banks suffer a loss proportional to $(1 - \frac{default\ threshold}{distress\ threshold})$. In addition, investment funds withdraw cash/deposits from defaulted or distressed banks as a precautionary measure, and deposit these amounts proportionally in other banks according to the weights of the left deposits. Consequently, the total cash/deposits for each investment fund do not change. Furthermore, the defaulted or distressed banks withdraw their loans to investment funds.

However, we assume that investment funds can borrow from other banks, so total loans for each investment fund do not change. Accordingly, relevant bank balance-sheet items (including assets, liabilities, REA, default threshold and distress threshold, etc.) are also updated.

Next, we extend the fire-sale model introduced by Fricke and Fricke (2021) on investment fund indices by incorporating the flow-performance relationship with both leverage and cash targets. At the index level, we assume that there are three types of asset managers/assets (Bond Funds, Equity Funds and Mixed Funds), and all pre-shock variables have a time index of 0. For each investment fund index, $A_0 = E_0 + D_0$, where A corresponds to the asset, E to the equity (the net asset value, NAV) and D to the debt. We focus on bank loans and their own leverage target, meaning that other debts are not treated dynamically in this setting. As the funds' redeemable asset is not considered at the index level, the asset includes the tradable asset and the cash only: $A_0 = A_0^{trd} + C_0$, where A^{trd} is the tradable asset, C is the cash. In line with Fricke and Fricke (2021) and Greenwood, Landier and Thesmar (2015), we assume that asset managers target a fixed leverage ratio, $B = D_0/E_0$. Regarding the cash holdings, as in Sydow et al. (2024a), we assume that investment funds will keep at least a minimum fixed cash ratio for investment fund liquidity (redemptions) management given by $M = C_0/E_0$.

In the first step, we impose an negative shock, F, only on tradable assets, A^{trd}. Assuming that the shock does not wipe out all of the investment fund's equity, we update all variables sequentially.[9] $R_1 = F$, with R_1being the investment fund returns. This gives us the updated total assets: $A_1 = (A_0 - C_0)(1 + R_1) + C_0$, which yields an equivalent change in equity: $E_1 = E_0 + (A_0 - C_0)R_1$. The debt and cash remain unchanged: $D_1 = D_0$ and $C_1 = C_0$.

In the second step, investment fund flows in response to the fund's performance in the previous step: negative (positive) performance is followed by an outflow (inflow).[10] We assume a positive linear relationship between asset managers' performances and net flows: $\frac{\Delta E_2}{E_1} = \gamma^E R_1$, where ΔE_2 is the netflow, and γ^E is the flow-performance sensitivity parameter defined in the following equation:

$$flow_t = c + \gamma^E R_{t-1} + control\_variables_t + \varepsilon_{j,t}, \tag{3}$$

where $flow_t = \frac{FLOW_t}{NAV_{t-1}}$. $NAV_{j,t}$ is the net asset value of a fund at t, and $FLOW_t$ is the value in euros of the fund's net flow. The fund's market return valuation, R_t, is given: $R_t = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} - flow_t$. As in Fricke and Fricke (2021), the control variables include lagged flows and fund returns.

[9] This step follows the 'Check-IF-Status' by updating A and E considering the zero bond value issued by the defaulting Luxembourg banks.
[10] As discussed in Fricke and Fricke (2021), there is no documented evidence of a flow-performance relationship with regard to debt financing for asset managers in general.

The updated equity can be written as $E_2 = E_1(1 + \gamma^E R_1)$, and assets as $A_2 = A_1 + \Delta E_2$, and the adjusted return (before asset liquidation) as $R_2 = \frac{A_2 - A_0}{A_0}$. The debt and cash remain the same as in the first step: $D_2 = D_1$ and $C_2 = C_1$.

Liquidity management is addressed in the third step. As in Fricke and Fricke (2021), we assume that investment funds will take the full advantage of bank loans and adjust the value of debt with their target leverage as $D_3 = E_2 \mathrm{B}$, or, equivalently, $\Delta D_3 = E_2 \mathrm{B} - D_2$.[11] Regarding the cash target, following Sydow et al. (2024a), we assume that each investment fund has a target for cash holdings given by $C^{TG} = E_2 M,$ which yields $C_3 = \max\left(C^{TG}, C^{TG} + \min\left(\Delta E_2 + \Delta D_3, 0\right) + max(C_2 - C^{TG}, 0)\right)$, where $\Delta E_2 + \Delta D_3$ could be positive under a negative shock. The change of cash at this step is $\Delta C_3 = C_3 - C_2$.

Finally, the total assets to be liquidated by each investment fund are given by $\emptyset^{IF} = \Delta E_2 + \Delta D_3 - \Delta C_3$, and the total asset and equity are updated respectively by $A_3 = A_2 + \emptyset^{IF}$ and $E_3 = A_3 - D_3$. In addition, we assume that investment funds will allocate ΔD_3 and ΔC_3 to their banks in respective proportion to their weights of initial loans and deposits. The bank balance sheets are then adjusted accordingly.

2.5 Banks' liquidity status

We also consider the prudential liquidity regulation, the goal of which is to ensure that banks manage their liquidity risk adequately. The liquidity coverage ratio (LCR) constraint requires banks to hold an adequate stock of unencumbered High Quality Liquid Assets (HQLA) to meet their liquidity needs for a 30-calendar-day liquidity stress scenario. Following Sydow et al. (2024a), we assume the liquidity distress threshold as $\tau_i^{liquidity\ distress} = c_i^{out\ 30}$, where $c_i^{out\ 30}$ are the net cash outflows over one month under a stress scenario, and thus become the floor for unencumbered HQLA that banks must hold throughout the exercise. Any bank experiencing liquidity stress has to address the needs by curtailing their own interbank lending and/or seeking interbank funding to the extent that their solvency allows, as illustrated in the following steps.

2.6 Interbank run-offs

We assume that, for each Luxembourg bank, there is a synthetic non-Luxembourg counterparty bank for interbank loans. Banks suffer the loss on the long-term loans once a counterparty (the borrower) defaults. If a lender defaults, we assume that its long-term loans to borrowers do not change. The defaulted or distressed banks withdraw their short-term loans to all their counterparties. All banks withdraw their short-term loans to the distressed or defaulted banks as a precautionary measure. The defaulted or distressed banks are then excluded from the following model dynamics. As in Sydow et al. (2024a), banks in liquidity

[11] ΔD_3 can be further broken down as $\Delta D_3 = (A_0 - C_0)\gamma^E \mathrm{B} R_1^2 + (A_0 - C_0 + E_0\gamma^E)\mathrm{B} R_1 + BE_0 - D_0$. It is a non-linear function, thus, ΔD_3 could be positive even under a negative shock.

distress withdraw proportionally to close their gap of remaining liquidity needs until the iteration converges, that means, until their remaining liquidity needs cannot be cut further.

2.7 Unsecured borrowing

In case of further liquidity needs, we include the possibility for certain banks to access new unsecured borrowing. It is achieved by establishing new interbank lending relationships between the borrower with the largest need and the lender with the largest surplus. Interbank unsecured borrowing is, thus, created among banks until their remaining liquidity needs cannot be cut further. The amount that a bank borrows on the interbank market is capped by its solvency distress threshold with a credit constraint parameter suggested by Sydow et al. (2024a) as $u_i = \min\left(\left(\tau_i^{liquidity\ distress} - c_i\right)^+, \beta\left(k_i - \tau_i^{distress}\right)^+\right)$, where c_i and k_i are cash and capital for bank i.

2.8 Fire sales and price impacts

As a last resort, banks and funds proportionally start selling tradable assets to close liquidity gaps, and the endogenous shock is updated as follows:

$$F = L\left(\emptyset^{IF} + \emptyset^{LuxBank}\right), \tag{4}$$

where L is the price impact ratio, expressed in units of returns per euro of net sales. $\emptyset^{IF}$ and $\emptyset^{LuxBank}$ are the total assets to be liquidated for investment funds and banks respectively.

3. Data description

The sample covers 69 Luxembourg banks (excluding branches) and three types of Luxembourg investment funds on December 2023. As in IMF LU FSAP (2024), the 69 banks are classified into five business models. There are 14 banks in Corporate Finance (CF), 7 banks in Covered Bonds Banking, Clearing, Treasury and Payment Services (CCTPS), 11 banks in Custodian Banking and Activities Linked to Investment Funds (CBALIF), 29 banks in Private Banking (PB) and 8 banks in Universal, Retail and Commercial Banking (URCB). The aggregate capital-to-REA ratio for all banks is around 23%, and distributes across these business models respectively as 17%, 39%, 38%, 28% and 22% for CF, CCTPS, CBALIF, PB and URCB. Banks in our sample are also broken down by their domicile type as per the Single Supervisory Mechanism's approach (6 domestic banks, 29 EU foreign subsidiaries, and 34 non-EU foreign subsidiaries). The capital-to-REA ratio is roughly 20% for domestic banks, 23% for EU foreign subsidiary banks, and 27% for non-EU foreign subsidiary banks. The three types of investment funds are Bond Funds, Equity Funds, and Mixed Funds. The endogenous shocks on these three types of investment funds are driven by the price impact mechanism. We construct a database using several granular data sets for individual banks and three types of investment funds.[12] The database captures the network of bank-to-bank exposures as well

[12] Data for banks relies on FINREP, COREP, AnaCredit and BCL securities holding statistics reporting. Adjustments are also applied to distinguish among assets that are marked-to-market and unencumbered (both central bank eligible

as bank-to-investment fund exposures (based on AnaCredit, fund reporting and BCL's securities holding statistics), such as both short-term and long-term interbank loans, investment fund deposits at banks, bank loans to investment funds, and bank-issued debt securities held by investment funds.

In order to explore the structural change in Luxembourg's financial sector over time, we also build the database for banks and investment funds on December 2020, 2021 and 2022. This filtering leads to a sample of 63 banks available throughout this period. We focus on these 63 banks for comparison across time.

4. Model and Parameter Settings

We adopt a reduced-form model in order to explore the reaction of banks and investment funds to exogenous shocks, we assume the exogenous shocks stem from hypothetical macro-financial shocks. However, the specific financial triggers for such market crashes are not necessarily identified here.[13] The experiments we run can detect the overall vulnerability of the Luxembourg financial sector to potential adverse scenarios generated by empirical simulations. The credit risk and market risk shocks are driven by these exogenous shocks and immediately affect investment funds' NAVs and banks' equity capital values. To enable the contagion mechanism to operate through a dual channel of liquidity and solvency risk, the parameter settings are defined in Table 1.

and non-eligible). Data for funds comes primarily from BCL's securities holding statistics and internal fund classification data sets.

[13] The framework can be also used to assess the resilience of banks and investment funds under particular adverse scenario, for instance, shocks on interest rates and exchange rates.

Table 1: Parameters for the reduced-form model

		Corporate finance	Covered bonds banking, clearing, treasury and payment service	Custodian banking and activities linked to investment funds	Private banking	Universal, retail and commercial banking
		Betas for banks' tradable securities				
Adverse parameters	Holding Equities	0.80	0.05	0.14	0.28	0.63
	Holding Bonds	0.09	0.23	0.13	0.09	0.13
	Issued Bonds	0.04	0.14	0.69	0.33	0.18
Severely adverse parameters	Holding Equities	0.92	0.06	0.16	0.32	0.72
	Holding Bonds	0.10	0.26	0.15	0.10	0.15
	Issued Bonds	0.05	0.16	0.79	0.38	0.21
		Betas for bank credit risk				
Adverse parameters		-0.52	-0.13	-0.64	-0.04	-0.04
Severely adverse parameters		-0.60	-0.15	-0.74	-0.05	-0.05
		Price impact for seven days (per 1 bn of sales; in bps)				
		Bond fund	Equity fund	Mixed fund		
Adverse parameters		7.98	10.11	7.93		
Severely adverse parameters		9.17	11.62	9.12		
		Flow-performance elasticities				
		Bond fund	Equity fund	Mixed fund		
Adverse parameters		0.40	0.23	0.29		
Severely adverse parameters		0.46	0.26	0.33		
		Credit Constraint Parameters				
Adverse parameters		0.55				
Severely adverse parameters		0.25				

Source: IMF LU FSAP (2024) and authors' calculations.
Note: This table reports all parameters adopted in the reduced form model under both adverse scenario and severely adverse scenario. Price-impact parameters are calculated based on the parameters in IMF LU FSAP (2024) by taking the value-weighted parameters of assets included in these three investment funds respectively. Homogenous flow-performance elasticities are directly taken from IMF LU FSAP (2024).

The price impact parameters for the three types of investment funds considered are not easily identified because of the unavailability of granular data and inconsistences of methods and data used in the relevant literature. Greenwood, Landier and Thesmar (2015) assume a price impact of 1 basis point per billion asset sales for most of their asset classes. Fiedor and Fragkou (2021) use price impact parameters of 1 basis point per billion asset sales for normal liquidity periods, and 100 basis points per billion asset sales for severe illiquidity shock, for all asset classes in their macroprudential stress test of investment funds. However, Fukker et al. (2022) investigate the market price impact on a security-by-security basis from historical daily traded volumes and price returns. They show that the homogeneous estimation techniques, commonly employed for market impact, might lead to loss estimates that are more than twice as large as losses estimated with heterogeneous price impact parameters. For convenience, according to the impact parameters of several asset sales used in the context of IMF LU FSAP (2024),[14] we calculate the value-

[14] In this technical note, estimates for market depth of US securities rely on estimates from the IMF US FSAP (2020). Estimates for the sovereign debt of other major countries are taken from Cont and Schaanning (2017) and Coen, Lepore and Schaanning (2019). The market depth for other securities is estimated based either on ratios of equivalent types of securities, or estimated based on the ratio of the total outstanding of the value of securities in the market.

weighted price impact parameters for the three types of investment funds based on market caps of the assets held by each type of investment fund. As expected, Bond Funds prove to have much lower price impacts than Equity Funds, and Mixed Fund can reduce price impacts further by allowing investors to mitigate market risk by optimizing their portfolios. The asset sale period has been calibrated over a seven-day horizon. Moreover, 1.15 times the value of the adverse parameter is considered for the severely adverse scenario. Finally, we assume asymmetric price impacts under positive vs negative net assets to be liquidated. For net inflow, $\mathrm{L}^{\mathrm{netinflow}} = \mathrm{L}/3$, where L is our price impact parameter.

Regarding credit constraint parameters in interbank unsecured borrowing, as the mechanism is similar to a collateral requirement, we parametrize the credit constraint parameter as $1 - LGD$, and LGD is defined under the foundational internal ratings-based (F-IRB) approach for treatment of unsecured claims and non-recognized collateral.[15] We assume 55% and 25% for the adverse scenario and severely adverse one, respectively.

We adopt the flow-performance elasticities as in IMF LU FSAP (2024) which follows a benchmark regression model as in Coval and Stafford (2007) and Fricke and Fricke (2021). The model is estimated for the sample of regulated funds using monthly data from 2016 until 2023. The elasticities for a severely adverse scenario are defined by applying a 1.15x multiplier to the reference value in the adverse scenario.

As for credit risk for banks, financial theory (e.g., the structural approach by Merton, 1974, or the reduced form approach by Jarrow and Turnbull, 1995a&b) confirms that market and credit risks are intrinsically related to each other. In this context, a large number of empirical research studies have been dedicated to assessing their interaction (e.g., Jarrow and Turnbull, 2000, Böcker and Hillebrand, 2008, BIS, 2009, and Fiori and Iannotti, 2010). In this framework, we also assume that the bank credit risk is driven endogenously by a market factor that is represented by the NAV weighted market returns of these three types of investment funds, R_t^{IF}:

$$R_{j,t}^{LR} = c + \beta_j^{PD} R_t^{IF} + control\_variables_t + \varepsilon_{j,t}, \tag{5}$$

where $R_{j,t}^{LR}$ is the shock to a bank j's loss rate: $R_{j,t}^{LR} = \frac{LR_t - LR_{t-1}}{LR_{t-1}}$, and $LR = \mathrm{PD} \times LGD$, which can be proxied by $\frac{\text{exposure at default(EAD)}}{E^{credit\ risk}}$. As defined above, PD is the aggregate likelihood that a bank's obligors would default, and LGD denotes the loss rate on the exposure in the event of default. If we assume constant

[15] https://www.bis.org/basel_framework/chapter/CRE/32.htm. (32.6) Under the foundational approach, senior claims on sovereigns, banks, securities firms and other financial institutions (including insurance companies and any financial institutions in the corporate asset class) that are not secured by recognised collateral will be assigned a 45% LGD. Senior claims on other corporates that are not secured by recognised collateral will be assigned a 40% LGD. (32.7) All subordinated claims on corporates, sovereigns and banks will be assigned a 75% LGD. A subordinated loan is a facility that is expressly subordinated to another facility. At national discretion, supervisors may choose to employ a wider definition of subordination. This might include economic subordination, such as cases where the facility is unsecured and the bulk of the borrower's assets are used to secure other exposures.

LGD, $R_{j,t}^{LR}$ would be the relative change in the PD. Thus, β_j^{PD} measures the responsiveness of bank j's counterparty risk with respect to overall price impact shocks on the investment funds.

The macroeconomic control variables include EA short-term interest rates and interest rate spreads.[16] Given the constraints of data availability, we assume a homogenous beta for each business model and explore the betas by pooled regression in rolling window. The average negative betas over 3-year to 10-year rolling windows are then selected for adverse scenario, and 1.15 times the number is used for severely adverse scenario.

Finally, as regards the tradable securities of banks (bond securities/equity securities), we assume a homogenous beta for each bank business model as well.[17] We adopt a one-factor model for the dynamics of banks' tradable securities as follows:[18]

$$R_{j,t}^{tradable\ security} = c_j + \beta_j^{tradable\ security} R_t^{IF} + \varepsilon_{j,t}, \tag{6}$$

where $R_{j,t}^{tradable\ security}$ is the return of value-weighted tradable securities for business model j, and $\beta_j^{tradable\ security}$ measures pricing relationship with respect to the corresponding investment fund type R_t^{IF} (Bond Funds/Equity Funds). We estimate the betas based on monthly data using two years - ten years of data by rolling window and choose the average betas for adverse scenario, and 1.15 times the number for severely adverse scenario.

Overall, the adopted parameters capture well the characteristics of banking business models and types of investment funds. The beta of bank credit risk is much stronger in CF and CBALIF than in other business models, while in the case of banks' holding bonds, the beta is the highest in CCTPS. The betas of banks' issued bonds are mainly driven by individual banks, as only a few banks ever issued bonds that are held by these investment funds. As the values of holding equities are inconsequential to most of the banks in our sample, the variation of their betas across business models might not generate significant different impacts on the overall bank balance sheets. Regarding the price impact, the parameters are in the ranges used in the relevant literature, reflecting well the different depths of these markets. While there are no precise parameters even based on well-defined models, the reasonability and coherence of the comparative profiles of these parameters are substantially important for our stress testing. We have tested parameter values

[16] Short-term interest rate is represented by Euro generic government bond 3-month yield, and interest rate spread is Euro generic government bond 10-year yield minus Euro generic government bond 3-month yield.
[17] The betas at the bank level were estimated based on the relevant granular data from Bloomberg. However, because of the data issues, e.g., data availability, different data length, short sample period and missing values, the estimated betas at the bank level were considered not robust.
[18] The multi-factor pricing model could, in principle, be explored but data issues could also bring unreliable estimates if more factors are considered. Thus, a simple one-factor pricing model is preferred, and the most import factor is selected.

around the selected calibration and found that the derived risk indicators are still robust and stable within a reasonable range.

5. Results

In this section, in order to investigate the contagion mechanism between banks and investment funds, we first undertake the bank sensitivity analysis upon presumed credit risk and market risk shocks separately. Then, the resilience of the Luxembourg banking sector is investigated under both deterministic and stochastic shocks on the balance sheets of banks and investment funds in December 2023. Finally, we apply the same stochastic exogenous shocks to their year-end data from 2020 to 2023 to examine the evolution of bank and investment fund vulnerabilities across time.

5.1 Bank Sensitivity Analysis

In our reduced model, the bank market risk is driven endogenously by the shocks to returns of Bond Funds and Equity Funds, and the bank credit risk is also linked intrinsically to the weighted return of investment funds. Their betas are defined in Table 1. Figure 2 shows the capital depletion ratios for a range of shocks to returns of bond funds, equity funds, and investment funds; the results are calculated based on bank balance sheets of end-2023 for each business model and domicile type, respectively. The adverse parameters are used in this exercise. As defined in the introduction section, the capital depletion ratio for a bank is the ratio of banks' capital depletion to its REA. The capital depletion ratio for a business model or a domicile type is the REA weighted capital depletion ratios of the banks included in this model or domicile.

Some banks hold most of tradable assets as bonds, which leads us to expect that the shocks on their bond holdings would affect their capital substantially. As expected, the top left panel of Figure 2 shows that banks in CCTPS suffer most, and CBALIF and PB are more vulnerable than other business models. However, the profiles are not only driven by their betas, for example, with similar betas, CBALIF are more sensible than URCB, and PB is more noticeable than CF. In contrast, the differences in sensitivity across the domicile types are more easily discernible. It is important to note that Luxembourg domestic banks are the least sensible to the exogenous bond shocks among these three domicile types, and the higher sensitivity of non-EU foreign subsidiaries is actually driven by a few banks.

As for their equity holdings (middle row of Figure 2), the corresponding amounts are inconsequential to most of the banks in our sample. However, URCB is more sensitive than other business models, which could be explained by its comparatively higher beta and relatively more equities held by a few banks in this business model. The response of those same few banks might also explain the larger response of Luxembourg domestic banks among the three domicile types.

Turning to bank credit risk (last row of Figure 2), CF is considerably more sensitive than other business models, and both PB and CBALIF respond weakly in a similar manner, even with very different betas. It is also worth pointing out that, with the second most negative beta, CF capital depletion is not significant in terms of the REA, remaining below 0.7% even under extreme investment fund shocks up to -60%. The sensitivity rankings among domicile types is different to those under market risk shocks, with domestic banks responding relatively less.

Overall, even if the parameter settings are important drivers for bank sensitivity analysis, the heterogeneous composition of banks' balance sheets also reflects important structural differences across business models and domicile types. Bank market risk is dominated by bond holdings, while equity holdings still play an important role for a few banks. Nevertheless, the capital depletion ratios driven by bank credit risk are lower than those driven by bank market risk.

5.2 Deterministic exogenous shocks

We assume that the initial exogenous shocks stem from a severe market shock, equivalent to the GFC, the European debt crisis and recent Covid-19 pandemic. The market shocks to investment funds are generated by a specific market risk model, in which the market factor is represented by the EA market index from OECD,[19] and a market shock is associated with a drop of 20% in the index (which corresponds to the first percentile of its monthly return distribution over the period of 2003-2024) given by:

$$R_{j,t}^{IF} = c_j + \beta_j R_t^{EA} + \varepsilon_{j,t}, \tag{7}$$

where $R_{j,t}^{IF}$ is the monthly return of investment fund type j. Then, the deterministic shocks equal to β_j (-20%). Based on the monthly market returns of these three types of investment funds considered, the estimated deterministic exogenous shocks are roughly -2.4%, -11.6% and -5.7% for Bond Funds, Equity Funds and Mixed Funds, respectively. As described in the parameter setting, the market shocks and credit risk shocks to banks are driven by the market shocks to investment funds.

We report the results of our model following these deterministic shocks on the balance sheets of banks and investment funds in December 2023. As depicted in Figure 3, for both Bond Funds and Mixed Funds, the endogenous shocks driven by asset sales converge quickly over a month. However, it takes another two weeks for the shocks to die out for Equity Funds. This result also means that markets are impacted by these asset liquidations, triggering successive rounds of asset price revaluations and propagating shocks across the system. The process is also reflected in the dynamics of their market returns as Equity Funds suffer the largest decline. As expected, the price-impact parameters and flow-performance elasticities play an important role for the different profiles.

The loss ratios under these shocks are shown in Figure 4. The loss ratio for a type of investment funds is the ratio of its loss to its NAV. Considering higher-order effects, which propagate through Luxembourg

[19] The OECD Share price indices are calculated from the prices of common shares of companies traded on national or foreign stock exchanges. They are usually determined by the stock exchange, using the closing daily values for the monthly data, and normally expressed as simple arithmetic averages of the daily data.

banks and investment funds jointly, the NAVs of investment funds drop substantially. The impact for Bond Funds, Equity Funds and Mixed Funds respectively amounts to -7% (-10%), -28.5% (-36.5%) and -10.8% (-12.6%) of pre-shock NAV under the (severely) adverse scenario, and the ratio of the higher-order effect under (severely) adverse scenario to the first-round effect is about 2.95 (3.98), 2.45 (3.14), 1.91 (2.26) for Bond Funds, Equity Funds and Mixed Funds respectively. Although such scenarios were not observed in the past, these declines are still comparable with the dynamics of some observed market indices during the recent period of crisis (e.g., the GFC, the European debt crisis and recent Covid-19 pandemic). For example, the average price of the Bloomberg US Corporate Bond Index [20] dropped about 15% in less than half a year during 2008. The FTSE 100 experienced a sharp decline in March 2020 as the COVID-19 Pandemic led to global economic uncertainty. The index fell by about 34% from a peak in January to a trough in March 2020.[21]

We now turn to the capital depletion ratios for Luxembourg banks as depicted in Figure 5. Taking into account the initial high capital-to-REA ratios (e.g., around 23% as described in the data section), the capital depletion is overall limited even if considering higher-order effects under the severely adverse scenario. Indeed, when considering all banks, the capital depletion in this scenario is around 0.45 percentage points in terms of REA. This result reflects the strong resilience of the Luxembourg banking sector as a whole. Nevertheless, business model components denote some heterogeneous effects. The overall impact (including higher-order effect) is noticeable for URCB and CCTPS. However, it is interesting to note that CBALIF have the lowest capital depletion ratios even if activities related to this business model are directly linked to investment funds. As for the amplification powers, they are not substantially different across these business models. The ratio of the higher-order effect under (severely) adverse scenario to the first-round effect to is around 1.78 (2.60), 1.72 (2.54), 1.75 (2.59), 1.79 (2.3), 1.83 (2.65) for CF, CCTPS, CBALIF, PB and URCB respectively. Regarding domicile types, Luxembourg domestic banks are relatively more vulnerable to these exogenous shocks than EU or non-EU foreign subsidiary banks. For instance, the initial capital-to-REA ratio is roughly 20% for domestic banks and 23% EU foreign subsidiary banks; however, under the severely adverse scenario, in terms of REA, the capital depletion of domestic banks is around 1.1 percentage point, compared to around 0.3 percentage points for EU foreign subsidiaries. The stronger response for domestic banks might reflect the strong interconnectedness between domestic banks and investment funds. The amplification powers are also similar around 1.83 (2.65), 1.79 (2.61), 1.74 (2.56) for domestic banks, EU foreign subsidiary banks, and non-EU foreign subsidiary banks respectively. Next, the higher-order effects for both banks and investment funds are further investigated under stochastic exogenous shocks.

5.3 Stochastic exogenous shocks

[20] It is a sub-index of the Bloomberg US Aggregate Index composed only of investment-grade-rated bonds.
[21] https://www.standard.co.uk/business/business-news/ftse-100-losses-stock-market-crash-a4552761.html

To address the dependence structure of the innovations $\varepsilon_{j,t}$ in Equation 7, we use t-copula as it is able to capture non-linear dependencies across innovation processes. In order to allow for flexible marginal distributions, we do not specify these distributions but rather adopt a semi-parametric form for them. The marginal densities are estimated using a Gaussian kernel for the central part of the distribution, and a parametric Generalized Pareto distribution (GP) is used for the tails. Hence, the asymmetry can be captured directly by estimating the left and right tails separately. This approach is often referred to as the distribution of exceedances or peaks-over-threshold method (see McNeil 1999 and McNeil and Frey 2000 for more details). The stochastic shocks are generated by β_j (-20%) plus the simulated innovations, and are reported as positive values as depicted in Figure 6 using a blue color histogram for each type of investment funds. Table 2 presents the Value-at-Risk (VaR) and Expected Shortfall (ES) at 10% level for investment fund loss ratios under these stochastic exogenous shocks based on end-2023 data. The amplification factor is defined as the ES ratio of higher order effects to the first-round effects.

Table 2: VaR and ES for investment fund loss ratios under the stochastic exogenous shocks based on end-2023 data

	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	Bond Funds			Equity Funds			Mixed Funds		
First-round effects	3.76%	4.42%		15.26%	16.99%		7.40%	8.03%	
Higher-order effects (under adverse scenario parameters)	10.73%	12.43%	2.81	34.66%	37.23%	2.19	13.88%	14.96%	1.86
Higher-order effects (under severely adverse scenario parameters)	14.18%	16.25%	3.67	42.74%	45.24%	2.66	16.06%	17.27%	2.15

Source: authors' calculations.

As Figure 6 and Table 2 show, the impact on Equity Funds clearly surpasses those on Bond Funds and Mixed Funds across the entire distribution. However, focusing on the VaR and ES, it is noticeable that the higher order shocks on Bond Funds have an important impact in amplifying the first-round effects. The ES for Bond Funds under the adverse scenario almost triples its size compared to the first-round effects, increasing from 4.42% to 12.43%, a result partially driven by high flow-performance elasticities in this fund type.

Turning to the bank analysis under the stochastic exogenous shocks based on end-2023 data, and as depicted in Figure 7, we observe substantially more muted effects (both first and higher order effects) across the entire distribution. The overall bank capital depletion measured by the REA is low even in view of these tail risk metrics. However, it is worth noting that risk profiles are still very different across business models as shown in Figure 8 and Table 3. The tail risk is much stronger for CCTPS and URCB than for other business models. In addition, as shown in Figure 9, the overall bank capital depletion ratio seems to be dominated by domestic banks.

Table 3: VaR and ES for bank capital depletion ratios under the stochastic exogenous shocks based on end-2023 data broken down by business model

	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	All Banks			CF			CCTPS		
First-round effects	0.22%	0.24%		0.13%	0.14%		0.36%	0.41%	
Higher-order effects (under Adverse Scenario parameters)	0.38%	0.41%	1.70	0.22%	0.24%	1.69	0.60%	0.70%	1.68
Higher-order effects (under Severely Adverse Scenario parameters)	0.53%	0.58%	2.37	0.32%	0.34%	2.38	0.87%	1.00%	2.41
	CBALIF			PB			URCB		
First-round effects	0.09%	0.10%		0.09%	0.10%		0.38%	0.42%	
Higher-order effects (under Adverse Scenario parameters)	0.15%	0.18%	1.70	0.16%	0.18%	1.72	0.66%	0.72%	1.70
Higher-order effects (under Severely Adverse Scenario parameters)	0.22%	0.25%	2.44	0.23%	0.25%	2.46	0.92%	0.98%	2.33

Source: authors’ calculations.

Figure 10 and Table 4 further look at the interaction of bank domicile with bank business model. The overall bank capital depletion ratios are mostly driven by domestic banks in URCB, EU foreign subsidiaries in CBALIF and non-EU foreign subsidiaries in CCTPS. As for non-EU foreign subsidiaries in PB and URCB, their bank capital depletion ratios are trivial. Notably, amplification factors are similar across business models and domicile types: the amplification factor is of around 1.7 under the adverse scenario and 2.4 under the severely adverse scenario.

The exercise reflects the strong resilience of Luxembourg banking sector as a whole. Bank amplification factors are similar across business models and origins, and much lower than those of the three types of investment funds. The overall bank capital depletion ratios are dominated by domestic banks in URCB, EU foreign subsidiaries in CBALIF and non-EU foreign subsidiaries in CCTPS. As for investment funds, the first-round and higher-order effects on Equity Funds clearly exceed those on Bond Funds and Mixed Funds. However, the results for Bond Funds suggest significant amplification of first-round effects.

Table 4: VaR and ES for bank capital depletion ratios under the stochastic exogenous shocks based on end-2023 data broken down by domicile and business model

	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	Domestic banks			PB - Domestic banks			URCB - Domestic banks											
First-round effects	0.55%	0.61%		0.17%	0.19%		0.58%	0.65%										
Higher-order effects (under Adverse Scenario parameters)	0.96%	1.04%	1.70	0.29%	0.33%	1.70	1.02%	1.10%	1.70									
Higher-order effects (under Severely Adverse Scenario parameters)	1.33%	1.42%	2.33	0.42%	0.47%	2.44	1.42%	1.51%	2.33									
	EU foreign subsidiary banks			CF - EU foreign subsidiary banks			CCTPS - EU foreign subsidiary banks			CBALIF - EU foreign subsidiary banks			PB - EU foreign subsidiary banks			URCB - EU foreign subsidiary banks		
First-round effects	0.14%	0.16%		0.14%	0.16%		0.17%	0.20%		0.56%	0.64%		0.09%	0.11%		0.20%	0.22%	
Higher-order effects (under Adverse Scenario parameters)	0.25%	0.27%	1.70	0.25%	0.27%	1.69	0.29%	0.34%	1.68	0.96%	1.10%	1.70	0.16%	0.18%	1.72	0.34%	0.38%	1.70
Higher-order effects (under Severely Adverse Scenario parameters)	0.35%	0.38%	2.40	0.35%	0.38%	2.37	0.42%	0.49%	2.41	1.39%	1.57%	2.45	0.24%	0.26%	2.46	0.48%	0.52%	2.36
	Non-EU foreign subsidiary banks			CF - Non-EU foreign subsidiary banks			CCTPS - Non-EU foreign subsidiary banks			CBALIF - Non-EU foreign subsidiary banks			PB - Non-EU foreign subsidiary banks			URCB -Non-EU foreign subsidiary banks		
First-round effects	0.12%	0.14%		0.09%	0.10%		0.60%	0.70%		0.05%	0.06%		0.02%	0.02%		0.02%	0.02%	
Higher-order effects (under Adverse Scenario parameters)	0.20%	0.23%	1.69	0.16%	0.17%	1.70	1.02%	1.18%	1.68	0.09%	0.11%	1.70	0.03%	0.04%	1.71	0.03%	0.04%	1.65
Higher-order effects (under Severely Adverse Scenario parameters)	0.29%	0.33%	2.42	0.22%	0.25%	2.41	1.48%	1.70%	2.41	0.14%	0.15%	2.44	0.05%	0.05%	2.41	0.05%	0.05%	2.29

Source: authors' calculations.

5.4 Vulnerabilities over time

In order to investigate changes in the vulnerability of Luxembourg banking sector and investment fund sector, the initial analysis based on end-2023 data is extended to include end of year data for the period 2020-2022.

Figure 11 shows the time-series of investment funds loss ratios under the considered stochastic exogenous shocks for the period 2020-2023. Table 5 shows the VaR, ES and amplification factor for investment fund loss ratios across time. For Bond and Mixed Funds, there do not appear to be major changes in the distribution of these loss ratios over the considered horizon. However, Equity Funds seem to be the most sensitive to shocks. Moreover, higher-order effects are more prominent for Equity Funds than for other types of funds, while Bond Funds appear to amplify the effects of the first-round.

Table 5: VaR and ES for investment fund loss ratios under the stochastic exogenous shocks over time

	Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization		
	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	Bond Funds						Equity Funds						Mixed Funds					
2023	10.73%	12.43%	2.81	14.18%	16.25%	3.67	34.66%	37.23%	2.19	42.74%	45.24%	2.66	13.88%	14.96%	1.86	16.06%	17.27%	2.15
2022	9.89%	11.47%	2.59	12.70%	14.62%	3.31	31.49%	34.02%	2.00	38.16%	40.71%	2.40	13.29%	14.33%	1.78	15.29%	16.45%	2.05
2021	11.22%	12.96%	2.93	15.42%	17.58%	3.98	34.62%	37.15%	2.19	43.06%	45.51%	2.68	13.53%	14.58%	1.82	15.72%	16.90%	2.10
2020	10.64%	12.31%	2.78	14.25%	16.31%	3.69	28.56%	31.04%	1.83	33.61%	36.19%	2.13	12.79%	13.79%	1.72	14.54%	15.66%	1.95

Source: authors' calculations.

The investment funds loss is affected through three channels. First, the direct NAV channel. Under the same shocks, the higher NAV, the higher redemptions, and the higher second-round effects through the price impact. Second, the leverage target channel. If the leverage target ratio is high, with the decreased NAVs, the funds have to reduce their exposures to keep the ratio at its target, and thus are willing to sell assets to pay back the debt. Third, the cash target channel. If the cash target ratio is high, with the decreased NAVs, the funds have to cut more cash to keep the ratio at its target, and thus might release the pressure to sell assets. The investment fund loss ratio is finally determined by the overall effects, including the effect of the NAV as denominator of the ratio.

The internal structure of the three types of investment funds (i.e., NAVs, bank loans, and investment fund deposits) also captured the economic conditions in a timely manner, even under the same stochastic exogenous shocks and parameter settings. There seems to be a significant shift into the right tail (the worse) of the loss distributions in 2021, the period characterized by the weak post-pandemic economic recovery both in the euro area and globally, which was associated with accelerating inflation and supply-side bottlenecks. However, as the Federal Open Market Committee (FOMC) and the Eurosystem initiated monetary policy normalization in 2022 to bring high inflation back to its objective, the vulnerability of investment funds improved substantially. Nonetheless, the deterioration at the end of 2023 might reflect the macroeconomic uncertainty due to heightened global geopolitical tensions.

Figure 12 and Table 6 show the overall bank capital depletion ratios for the 63 banks under the stochastic exogenous shocks over the period covered by the sample. Similarly to investment funds, bank vulnerabilities reflect some procyclicality over this period. However, in contrast to investment funds, the rebound at end-2023 was mild compared to the level of capital depletion at the end of 2021. Regarding business model components as depicted in Figure 13, it is worth noting that the vulnerabilities for CBALIF improved consistently over time, while they deteriorated for CF, with the worst level observed at the end of 2023.

Table 6: VaR and ES for bank capital depletion ratios under the stochastic exogenous shocks across time

	Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization		
	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	All Banks						CF						CCTPS					
2023	0.38%	0.42%	1.70	0.53%	0.58%	2.37	0.22%	0.24%	1.69	0.32%	0.34%	2.38	0.64%	0.74%	1.68	0.92%	1.06%	2.41
2022	0.34%	0.37%	1.57	0.47%	0.51%	2.14	0.16%	0.18%	1.56	0.22%	0.24%	2.15	0.63%	0.73%	1.58	0.88%	1.02%	2.20
2021	0.43%	0.47%	1.74	0.62%	0.67%	2.49	0.19%	0.21%	1.74	0.28%	0.31%	2.51	0.97%	1.13%	1.79	1.47%	1.68%	2.67
2020	0.34%	0.38%	1.53	0.47%	0.52%	2.11	0.18%	0.20%	1.51	0.25%	0.27%	2.07	1.01%	1.17%	1.70	1.48%	1.71%	2.47
	CBALIF						PB						URCB					
2023	0.15%	0.18%	1.70	0.22%	0.26%	2.44	0.16%	0.18%	1.72	0.23%	0.25%	2.46	0.66%	0.72%	1.70	0.92%	0.98%	2.33
2022	0.20%	0.23%	1.58	0.28%	0.32%	2.21	0.16%	0.18%	1.60	0.22%	0.25%	2.22	0.58%	0.64%	1.56	0.79%	0.86%	2.10
2021	0.20%	0.23%	1.80	0.30%	0.35%	2.69	0.23%	0.25%	1.80	0.34%	0.38%	2.66	0.70%	0.76%	1.71	0.98%	1.05%	2.39
2020	0.27%	0.31%	1.69	0.39%	0.45%	2.46	0.20%	0.23%	1.63	0.29%	0.33%	2.32	0.45%	0.50%	1.44	0.60%	0.66%	1.90

Source: authors' calculations.

In addition, as shown in Figure 14, the banking vulnerabilities over the period are more important for Luxembourg domestic banks, while they improved consistently for Non-EU foreign subsidiary banks. Table 7 and Figures 15A-B further identify the components in each business model according to its origin. The overall vulnerability was still high at the end of 2023 for Domestic URCB banks, EU foreign subsidiary CBALIF banks, and Non-EU foreign subsidiary CCTPS banks. In contrasts, for Non-EU foreign CCTPS banks and Non-EU foreign CBALIF banks, their vulnerabilities decreased consistently over time.

Overall, the vulnerabilities of both investment funds and banks reflect the procyclicality of the financial system. Indeed, financial activities tend to expand and contract in response to the broader economic cycle. However, in contrast to investment funds, Luxembourg banks show increased resilience, as their overall loss ratios at the end of 2023 remained lower than their worst level at the end 2021. In particular, CBALIF banks show a consistent improvement over time. The findings might reflect the overall improvement on the asset allocation of their tradable assets, a hypothesis that is further explored in the following section.

Table 7: VaR and ES for banks capital depletion ratios under the stochastic exogenous shocks across time broken down by domicile and business model

	Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization			Adverse Scenario parametrization			Severely Adverse Scenario parametrization		
	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor	VaR 10%	ES 10%	Amplification Factor
	Domestic banks						EU foreign subsidiary banks						Non-EU foreign subsidiary banks					
2023	0.95%	1.04%	1.70	1.33%	1.42%	2.33	0.25%	0.27%	1.70	0.35%	0.39%	2.40	0.21%	0.23%	1.69	0.30%	0.33%	2.42
2022	0.87%	0.95%	1.56	1.18%	1.27%	2.09	0.20%	0.23%	1.57	0.28%	0.31%	2.16	0.23%	0.26%	1.58	0.32%	0.36%	2.20
2021	1.06%	1.15%	1.72	1.50%	1.61%	2.39	0.25%	0.28%	1.76	0.37%	0.40%	2.55	0.32%	0.37%	1.79	0.48%	0.55%	2.67
2020	0.67%	0.74%	1.44	0.89%	0.97%	1.91	0.22%	0.25%	1.55	0.31%	0.35%	2.15	0.38%	0.44%	1.69	0.55%	0.64%	2.44
	PB - Domestic banks						URCB - Domestic banks						CF - EU foreign subsidiary banks					
2023	0.27%	0.31%	1.71	0.39%	0.44%	2.45	1.02%	1.10%	1.70	1.42%	1.51%	2.33	0.25%	0.27%	1.69	0.35%	0.38%	2.37
2022	0.32%	0.36%	1.60	0.44%	0.50%	2.22	0.92%	1.00%	1.56	1.24%	1.34%	2.09	0.18%	0.20%	1.56	0.25%	0.27%	2.13
2021	0.32%	0.36%	1.60	0.44%	0.50%	2.22	0.92%	1.00%	1.56	1.24%	1.34%	2.09	0.18%	0.20%	1.56	0.25%	0.27%	2.13
2020	0.63%	0.72%	1.66	0.91%	1.04%	2.39	0.68%	0.75%	1.42	0.90%	0.98%	1.87	0.21%	0.23%	1.48	0.28%	0.31%	2.01
	CCTPS - EU foreign subsidiary banks						CBALIF - EU foreign subsidiary banks						PB - EU foreign subsidiary banks					
2023	0.32%	0.37%	1.68	0.46%	0.54%	2.41	1.00%	1.14%	1.70	1.44%	1.63%	2.45	0.16%	0.18%	1.72	0.24%	0.26%	2.46
2022	0.27%	0.32%	1.58	0.38%	0.44%	2.20	0.66%	0.76%	1.58	0.93%	1.07%	2.21	0.16%	0.18%	1.60	0.23%	0.25%	2.22
2021	0.27%	0.32%	1.58	0.38%	0.44%	2.20	0.66%	0.76%	1.58	0.93%	1.07%	2.21	0.16%	0.18%	1.60	0.23%	0.25%	2.22
2020	0.38%	0.44%	1.70	0.56%	0.65%	2.47	0.73%	0.84%	1.69	1.06%	1.22%	2.45	0.18%	0.20%	1.63	0.26%	0.29%	2.31
	URCB - EU foreign subsidiary banks						CF - Non-EU foreign subsidiary banks						CCTPS - Non-EU foreign subsidiary banks					
2023	0.34%	0.38%	1.70	0.48%	0.52%	2.36	0.16%	0.17%	1.70	0.23%	0.25%	2.41	1.02%	1.18%	1.68	1.48%	1.70%	2.41
2022	0.27%	0.30%	1.56	0.37%	0.40%	2.12	0.11%	0.12%	1.58	0.16%	0.17%	2.20	1.09%	1.26%	1.58	1.53%	1.76%	2.20
2021	0.27%	0.30%	1.56	0.37%	0.40%	2.12	0.11%	0.12%	1.58	0.16%	0.17%	2.20	1.09%	1.26%	1.58	1.53%	1.76%	2.20
2020	0.25%	0.28%	1.48	0.34%	0.38%	1.99	0.11%	0.13%	1.65	0.16%	0.18%	2.37	3.07%	3.57%	1.70	4.51%	5.19%	2.47
	CBALIF - Non-EU foreign subsidiary banks						PB - Non-EU foreign subsidiary banks						URCB -Non-EU foreign subsidiary banks					
2023	0.09%	0.11%	1.70	0.14%	0.15%	2.44	0.04%	0.04%	1.71	0.05%	0.05%	2.42	0.03%	0.04%	1.65	0.05%	0.05%	2.29
2022	0.16%	0.19%	1.59	0.23%	0.26%	2.21	0.04%	0.04%	1.58	0.06%	0.06%	2.19	0.02%	0.02%	1.53	0.03%	0.03%	2.06
2021	0.16%	0.19%	1.59	0.23%	0.26%	2.21	0.04%	0.04%	1.58	0.06%	0.06%	2.19	0.02%	0.02%	1.53	0.03%	0.03%	2.06
2020	0.24%	0.28%	1.69	0.36%	0.41%	2.46	0.08%	0.09%	1.53	0.11%	0.12%	2.10	0.03%	0.03%	1.43	0.03%	0.04%	1.90

Source: authors' calculations.

6. Robustness tests

In our framework, non-Luxembourg counterparty banks could also provide liquidity support in the interbank run-offs stage under exogenous shocks. In order to evaluate their liquidity role, we assume that the short-term loans granted by these non-Luxembourg counterparty banks are at zero. We find that the results are not different from the case that includes all non-Luxembourg counterparty banks.[22] Therefore, we conclude that non-Luxembourg counterparty banks can further provide sufficient liquidity support through interbank run-offs for any Luxembourg bank in liquidity distress, at least in case these foreign banks are not in liquidity distress themselves.

[22] To save the space, the results are not provided in this paper.

Moreover, when we exclude the banking sector from the stress-testing framework, the risk metrics for the three types of investment funds remains almost identical to those including the banking sector. This result reflects the limited influence of Luxemburg banking sector on the dynamics of investment funds.

Finally, in order to identify the relative importance of credit risk and market risk on the loss contribution of Luxembourg banks over time, we also exclude the credit risk channel from our model dynamics. As shown in Figure 16, even without considering the capital loss from the credit risk channel, the overall evolving profiles of bank capital depletion ratios under the same stochastic exogenous shocks are similar to those with both two channels, of course, with lesser magnitude.[23] It might partially reflect the significant structural changes with respect to bank securities during this period. Moreover, the overall bank capital depletion ratio is still driven by domestic banks over this period, reflecting their strong market risk interconnectedness between domestic banks and investment funds.

7. Conclusions

In order to identify vulnerabilities arising from increasingly interconnected banks and investment funds in Luxembourg, we propose a framework for system-wide financial stress-testing with multiple interacting contagion and amplification effect that act through a dual channel of liquidity and solvency risks. We assess the overall resilience of banks and investment funds to adverse external shocks by assuming that the deterministic and stochastic exogenous shocks stem from hypothetical market shocks. Market risk, credit risk and liquidity risk are analyzed. The suggested systemic risk metrics highlight the significant higher-order effects on investment funds, in particular on Equity Funds, and the strong resilience of the Luxembourg banking sector as a whole. Nevertheless, the vulnerabilities of both investment funds and banks seem to reflect the procyclicality of the financial system.

[23] The same findings are also documented for the business models and domicile types.

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Figure 2: Bank Sensitivity Analysis

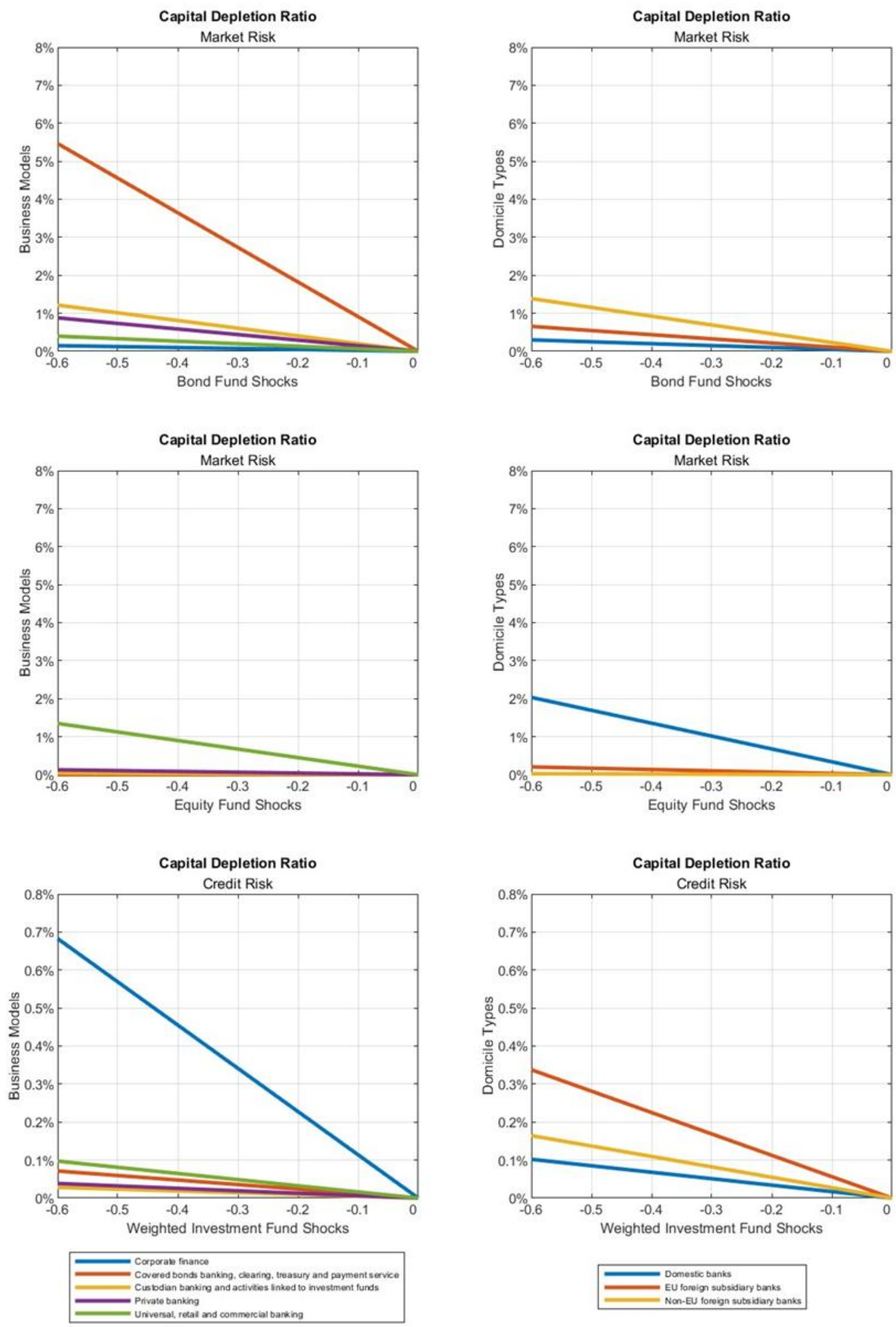


Figure 3: IF Shock Convergence under Deterministic Exogenous Shocks

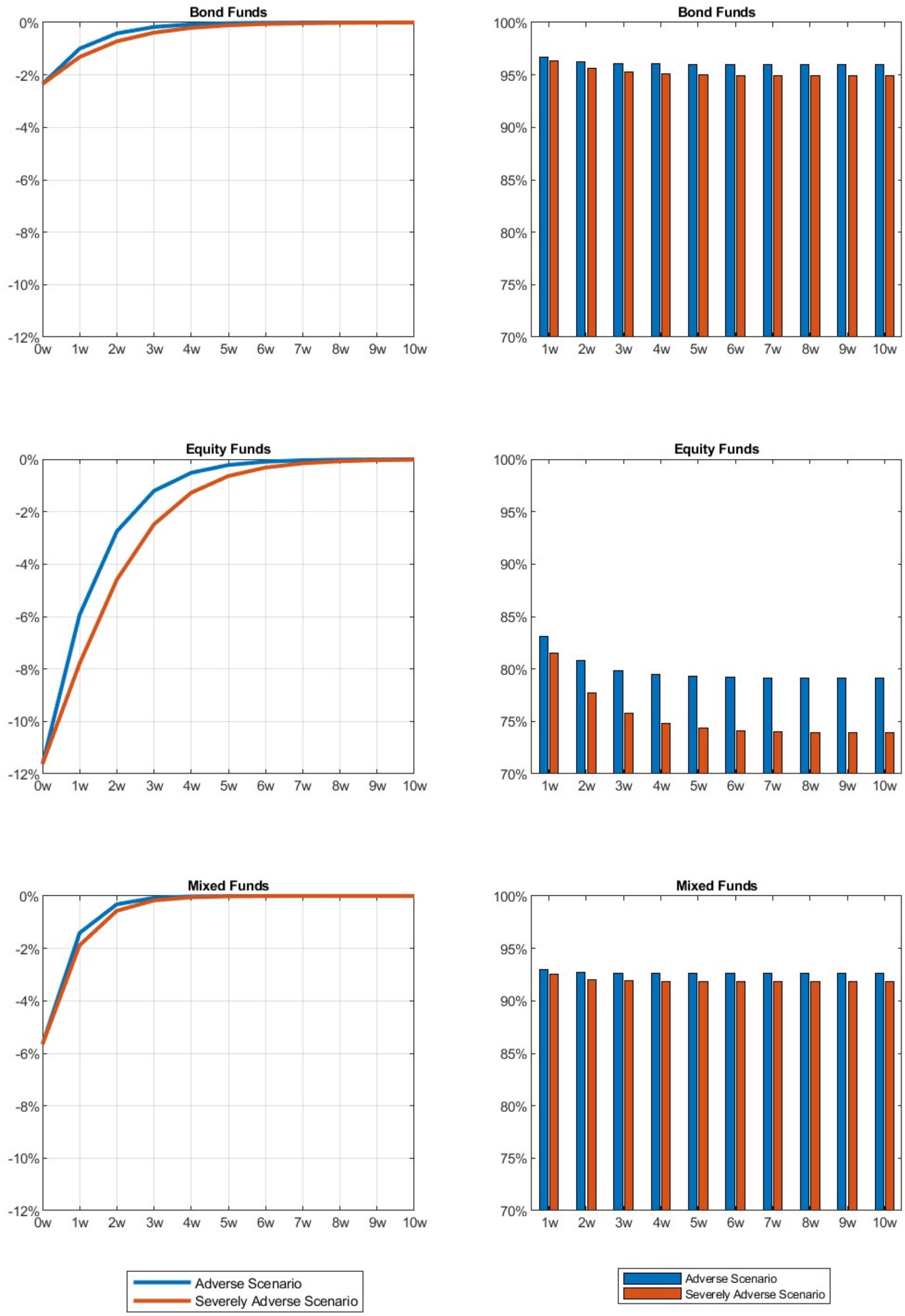


Figure 4: IF Loss Ratios under Deterministic Exogenous Shocks

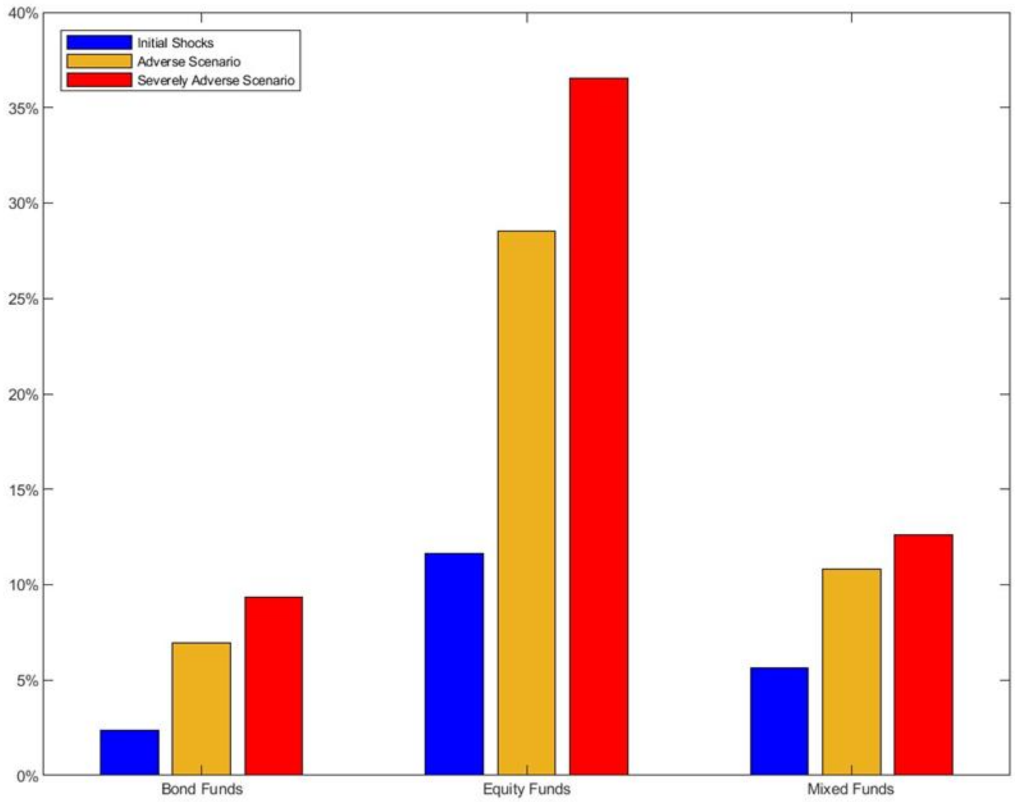


Figure 5: Bank Capital Depletion Ratios under Deterministic Exogenous Shocks

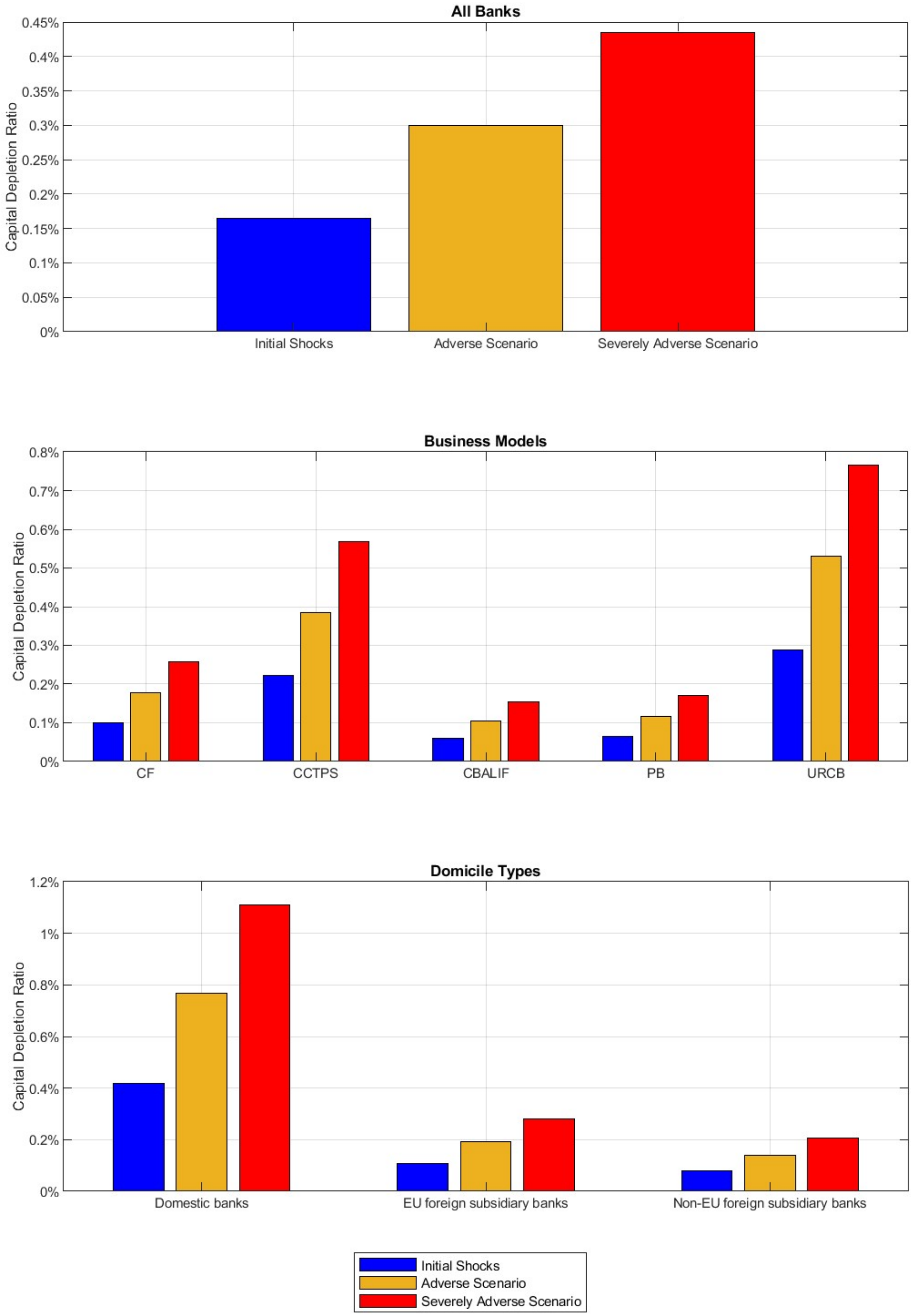


Figure 6: IF Loss Ratios under Stochastic Exogenous Shocks

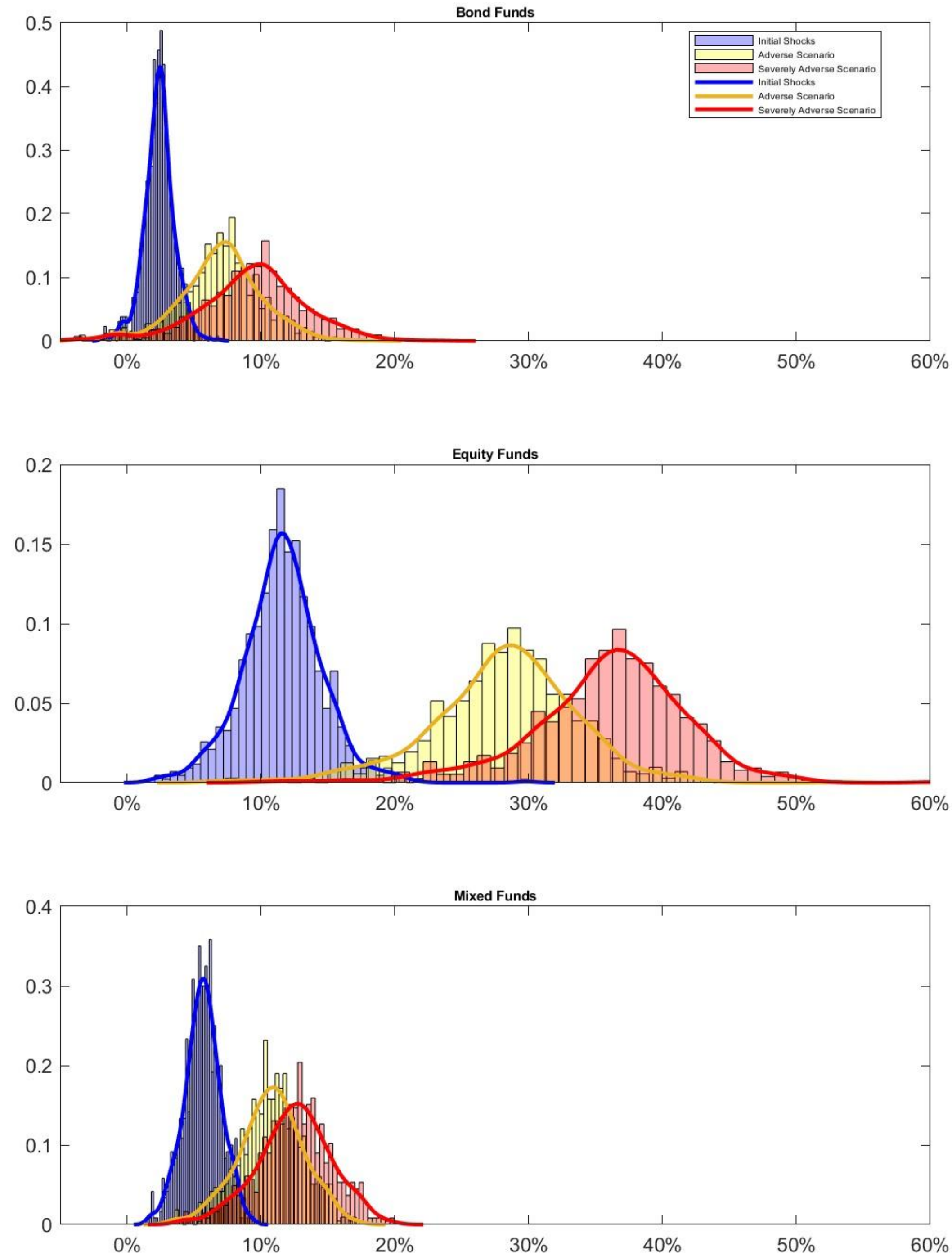


Figure 7: Bank Capital Depletion Ratios for All Banks under Stochastic Exogenous Shocks

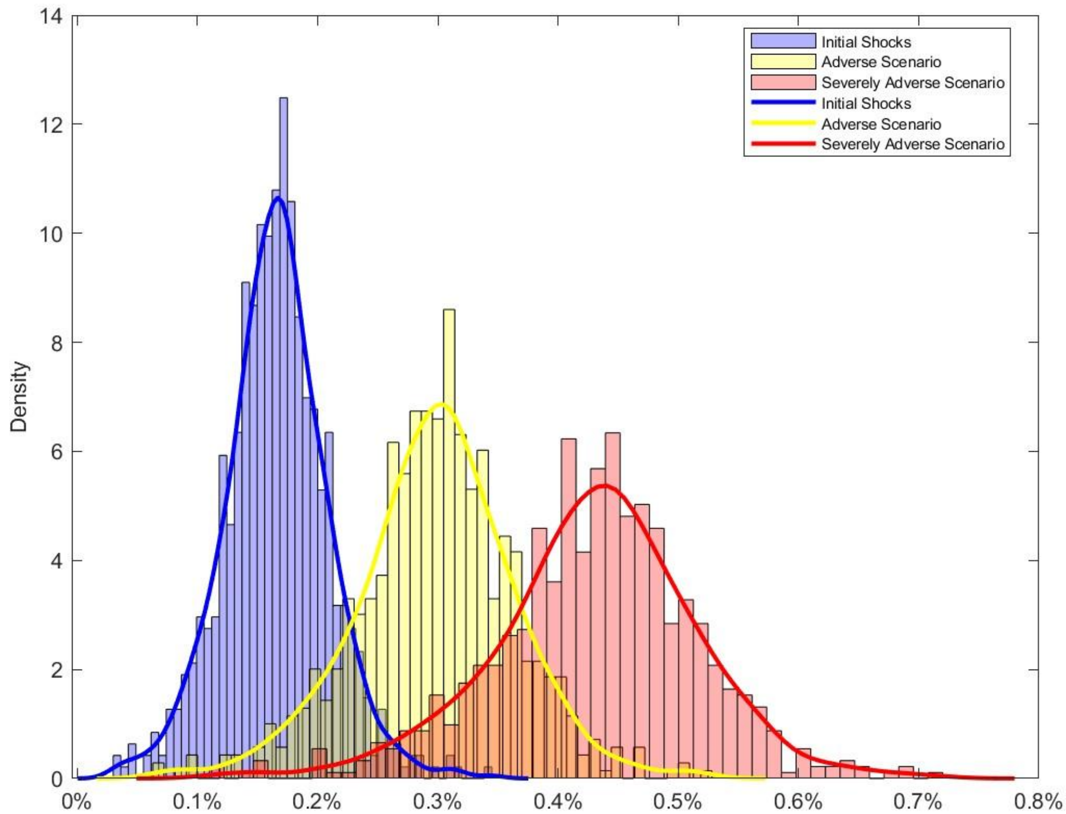


Figure 8: Bank Capital Depletion Ratios for Business Models under Stochastic Exogenous Shocks

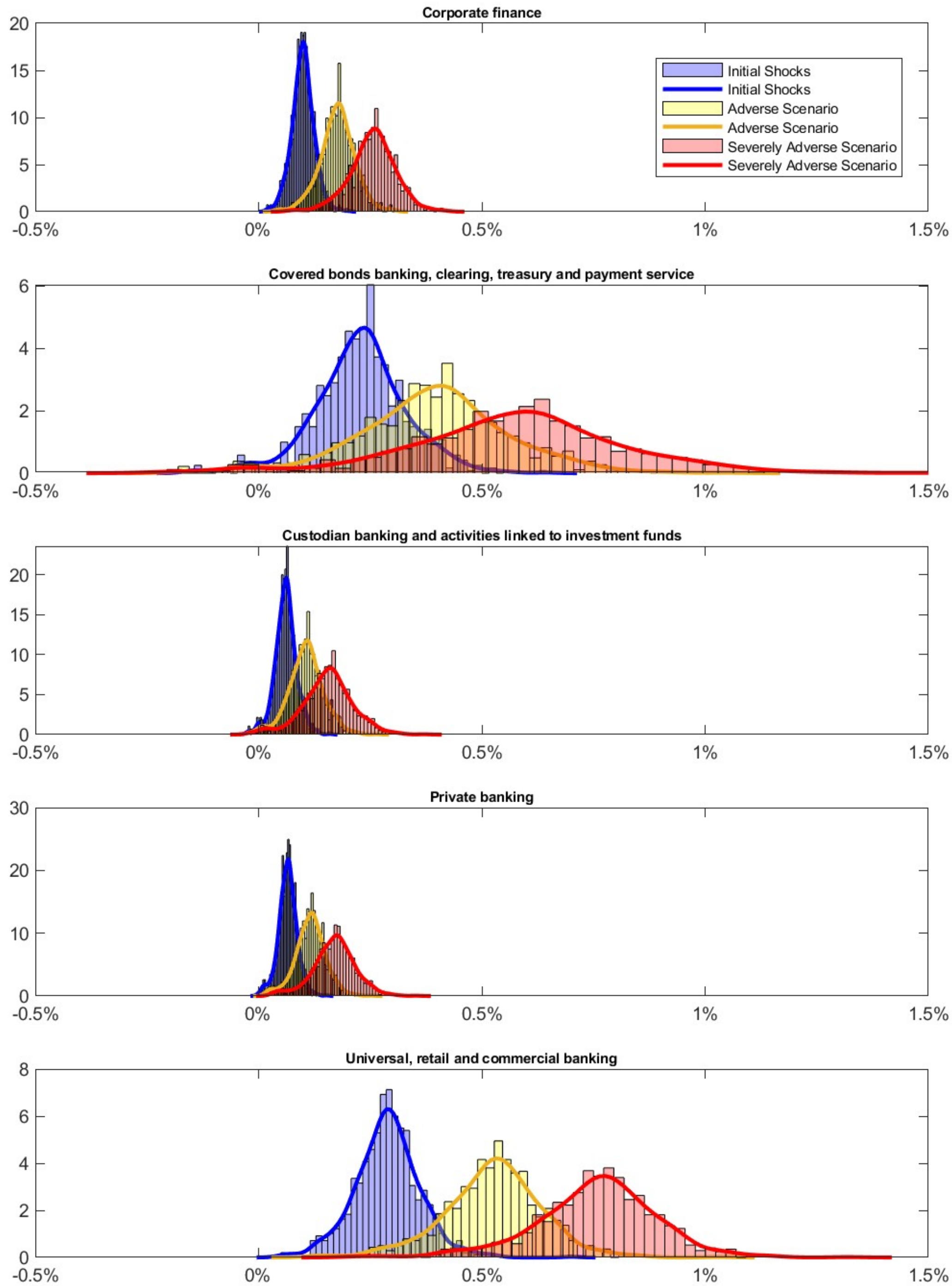


Figure 9: Bank Capital Depletion Ratios for Domicile Types under Stochastic Exogenous Shocks

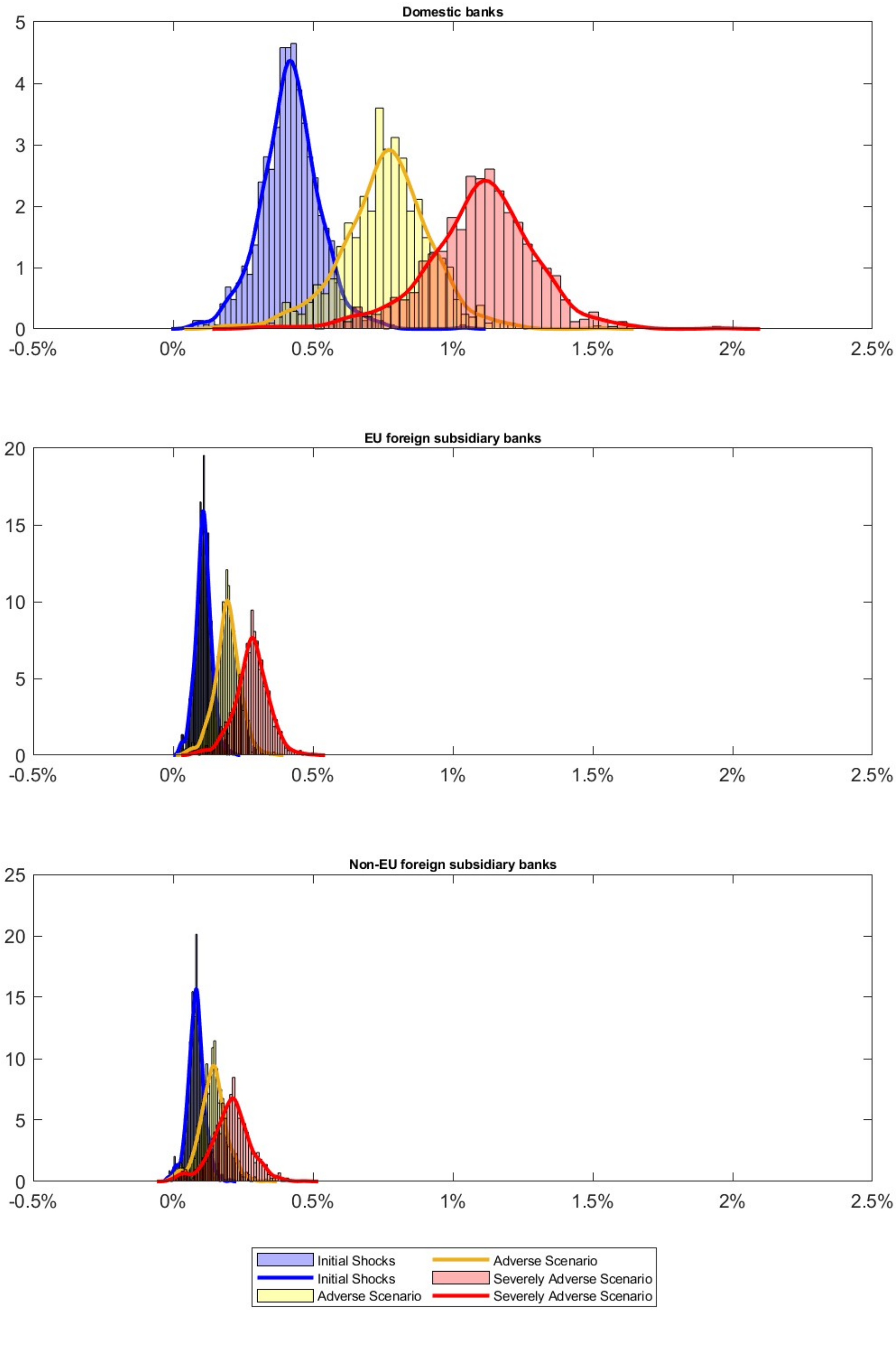


Figure 10: Bank Capital Depletion Ratios for Business Models and Domicile Types under Stochastic Exogenous Shocks

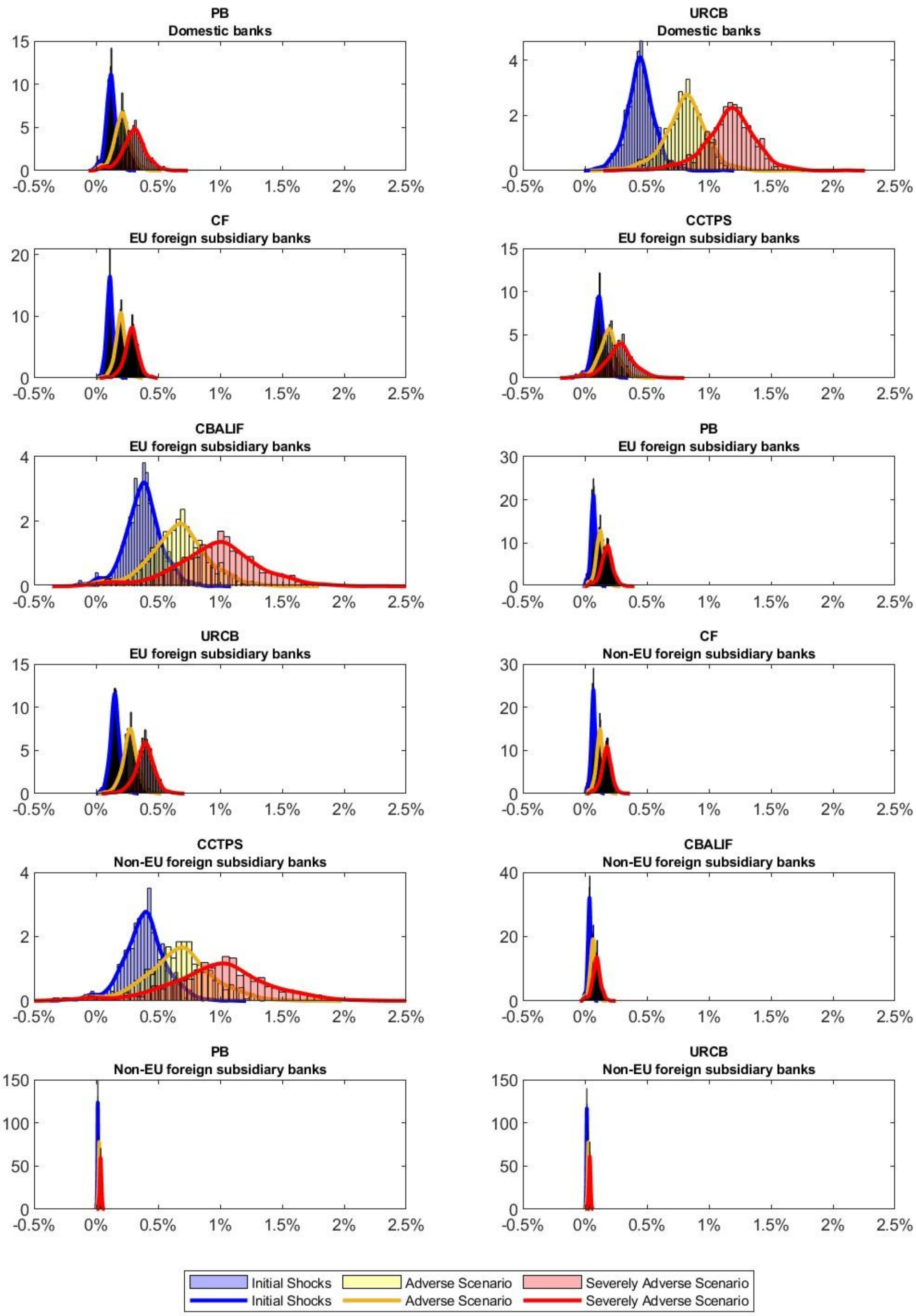


Figure 11: Time-Series IF Loss Ratios under Stochastic Exogenous Shocks

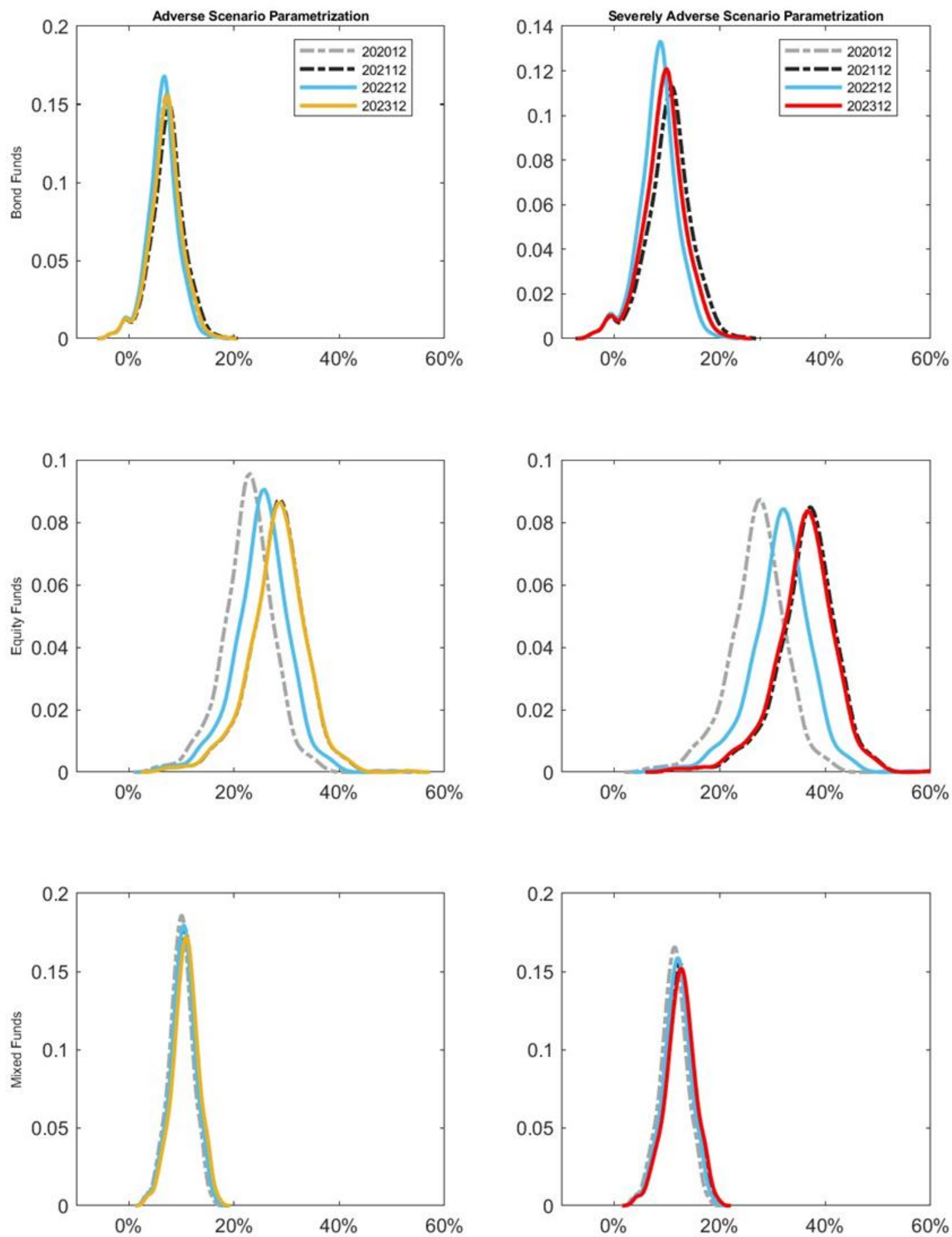


Figure 12: Time-Series Bank Capital Depletion Ratios for All Banks under Stochastic Exogenous Shocks

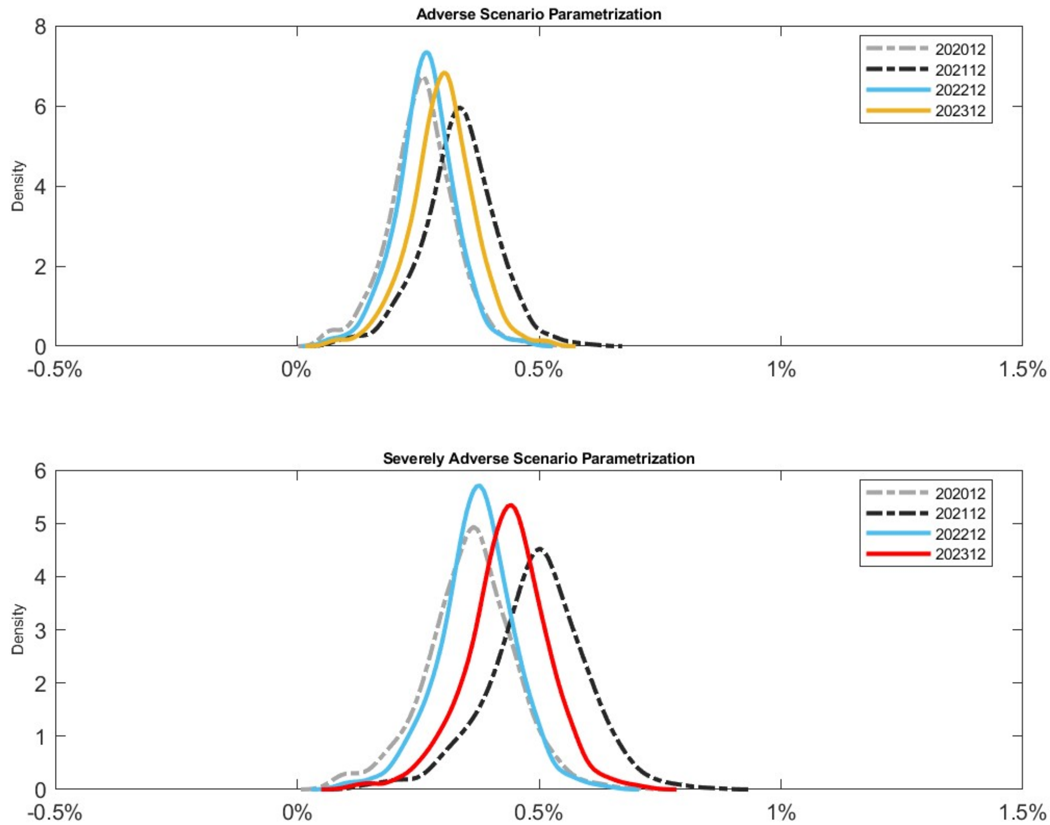


Figure 13: Time-Series Bank Capital Depletion Ratios for Business Models under Stochastic Exogenous Shocks

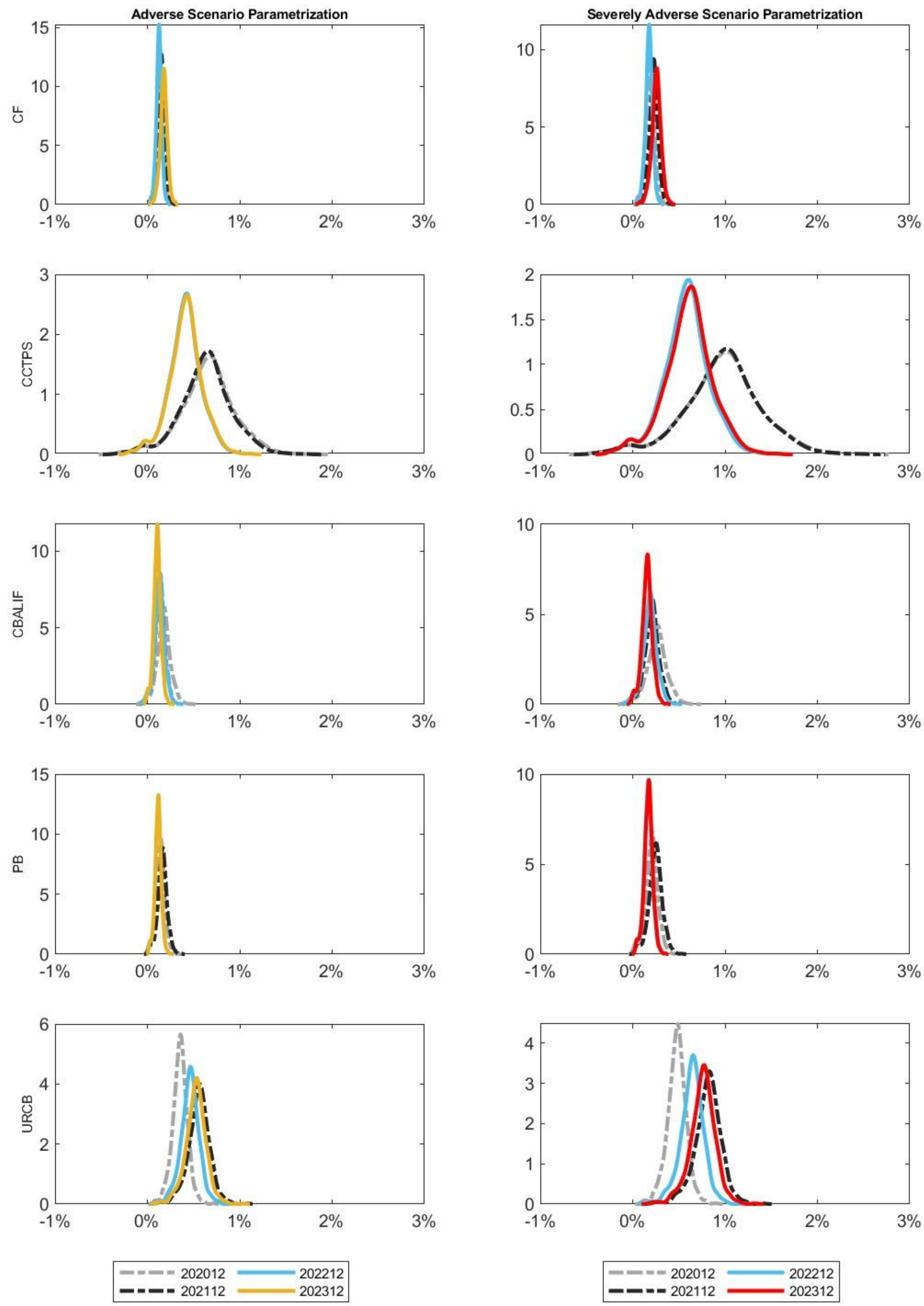


Figure 14: Time-Series Bank Capital Depletion Ratios for Domicile Types under Stochastic Exogenous Shocks

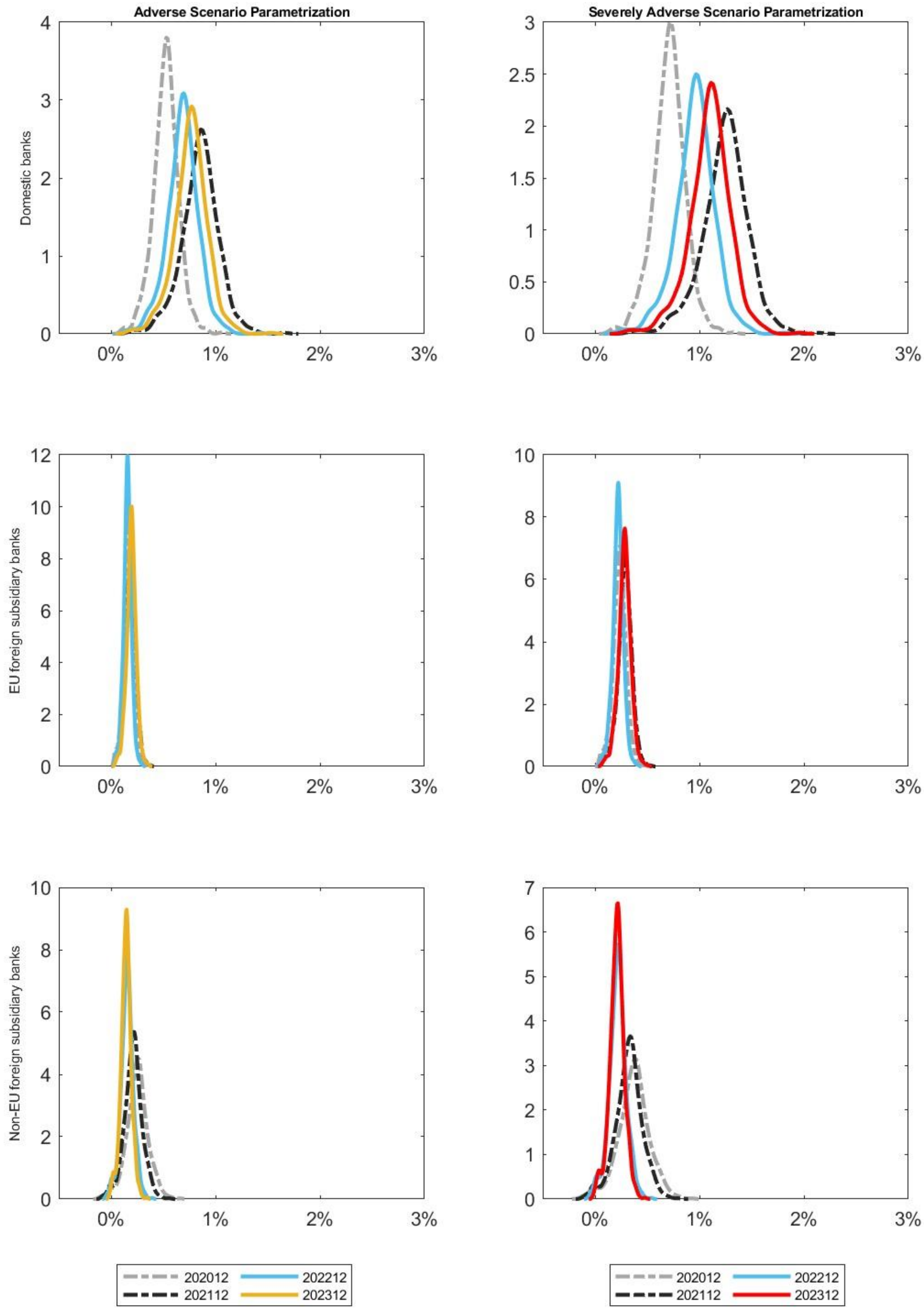


Figure 15A: Time-Series Bank Capital Depletion Ratios for Business Models and Domicile Types under Stochastic Exogenous Shocks - Adverse Scenario

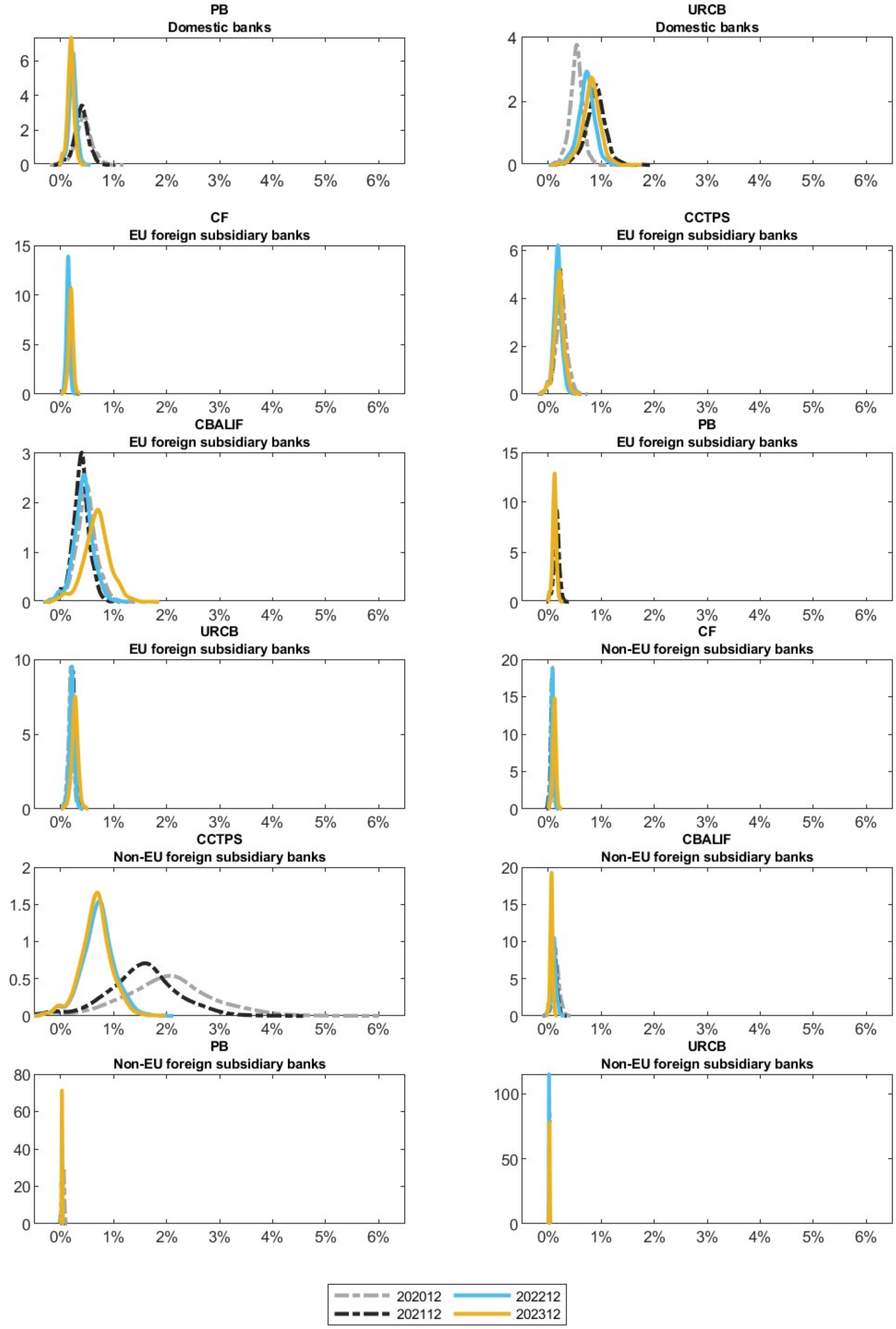


Figure 15B: Time-Series Bank Capital Depletion Ratios for Business Models and Domicile Types under Stochastic Exogenous Shocks - Severely Adverse Scenario

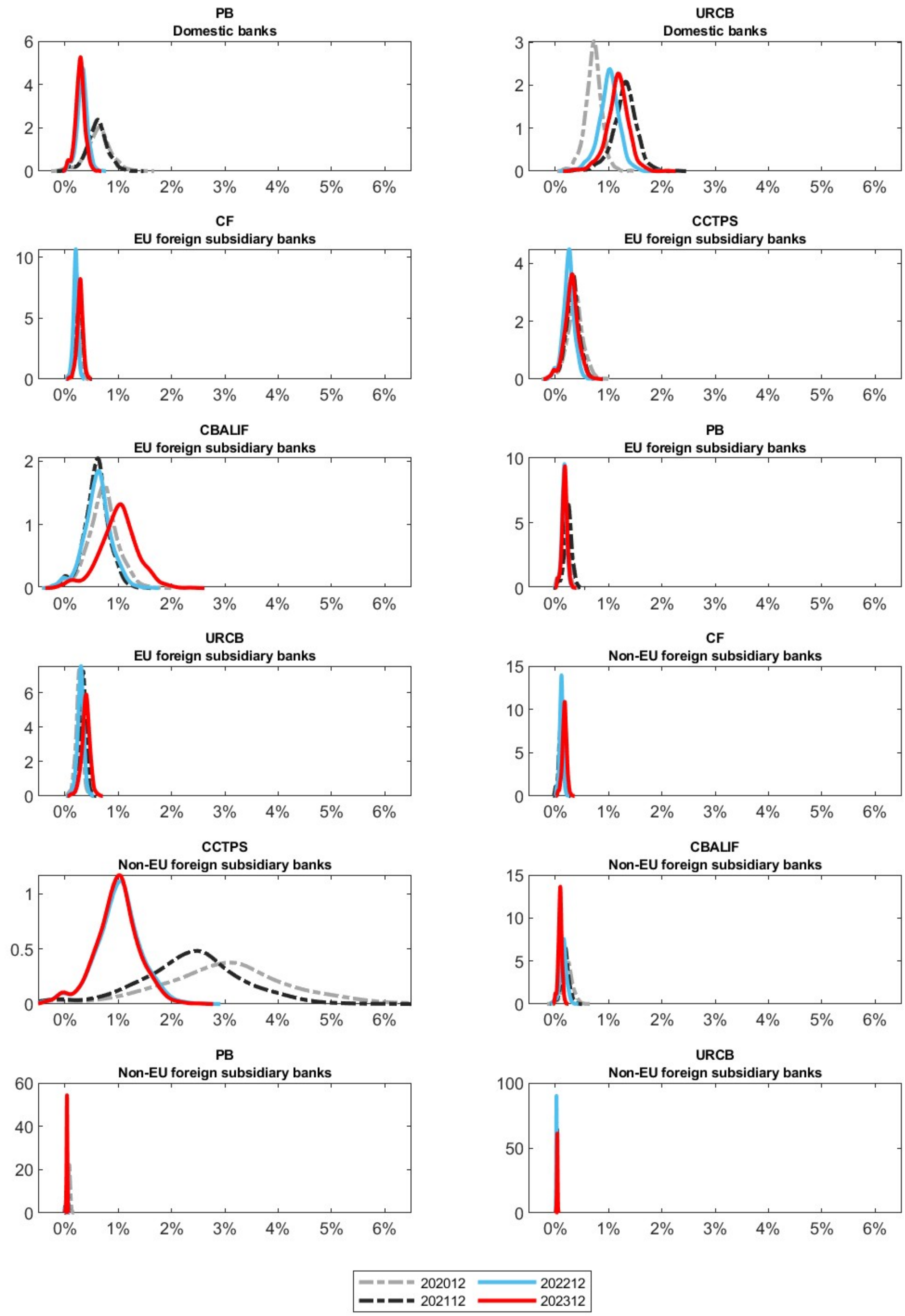
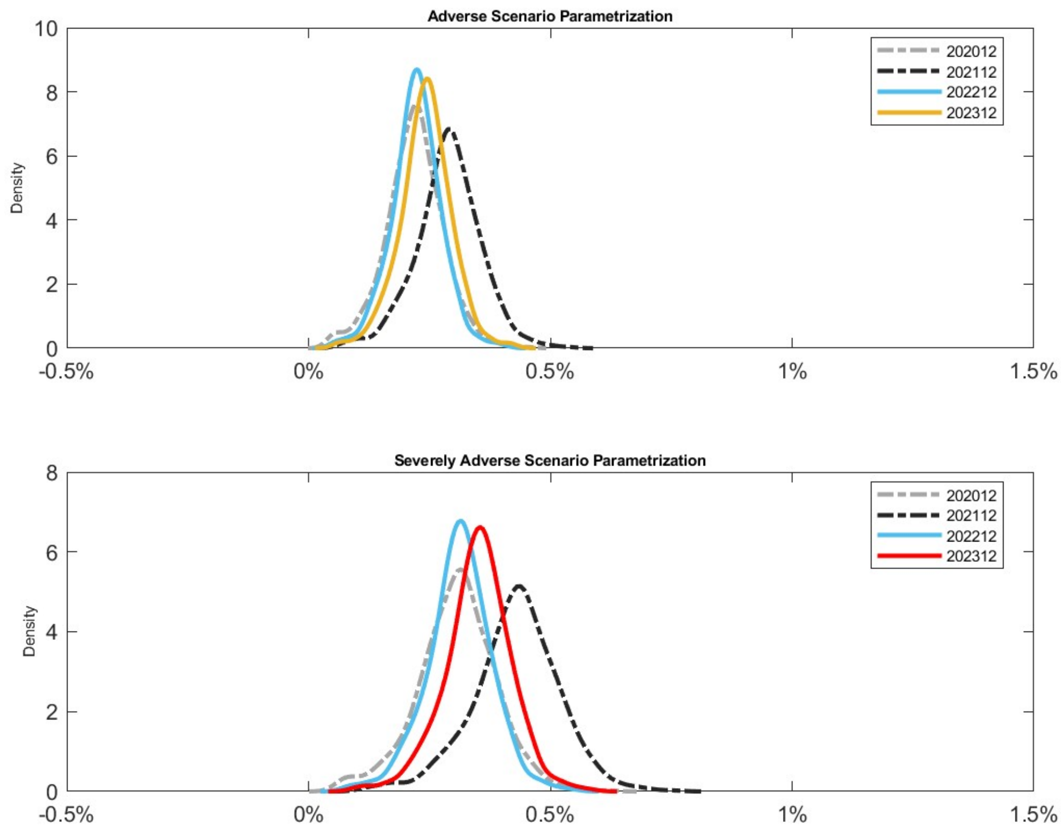


Figure 16: Robustness tests - Time-Series Bank Capital Depletion Ratios for All Banks under Stochastic Exogenous Market Risk Shocks



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