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DECOMPOSING SYSTEMIC RISK MEASURES BY BANK BUSINESS MODEL IN LUXEMBOURG

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Abstract

This paper introduces a forward-looking bank-level stress testing framework for a large-scale system to assess three forms of banking system vulnerability– bank capital fragility, bank capital adequacy and bank solvency. Results for Luxembourg are provided with a decomposition by bank business model and domicile type. The paper goes on to assess how these systemic risk indicators are linked to macroeconomic variables, and investigates their predictive power for Luxembourg's nominal GDP growth one year ahead. Several important findings are documented over 2003Q2 to 2023Q3. First, the systemic risk indicators responded to the main stock market crashes in a timely manner. However, contributions from different bank business models and domicile types varied over time. Second, association with key macroeconomic variables (interest rates, liquidity flow, euro area consumer confidence and business climate) depended on the different characteristics of systemic risk across bank business models. Third, the systemic risk indicators contributed to explaining nominal GDP growth one year ahead. However, the systemic risk component associated with search-for-yield behavior and fee & commission generating activities could also explain nominal GDP growth, suggesting that if banks became more dependent on these income sources, they could create financial stability issues in the long run. Overall, the framework provides a useful monitoring toolkit that tracks changes in forward-looking systemic risk and risk spillovers in the Luxembourg banking sector.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; systemic risk; macro-prudential policy; dynamic dependence; banking business model; financial stress index; coronavirus Covid-19; macro-financial linkages.

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Non-Technical Summary

High inflation, tightening financial conditions, geopolitical tensions, the lingering effects of Covid-19 pandemic and climate change still pose a great challenge to global financial stability. These challenges continue to test bank resilience, so it is important to monitor and identify potential vulnerabilities in the Luxembourg banking sector.

This paper proposes a forward-looking bank-level stress testing framework to assess three forms of banking system vulnerability: bank capital fragility, bank capital adequacy and bank solvency. The stress test simulates the effects of a severe stock market downturn on the resilience of individual banks, allowing for specific bank business models and domicile types. Bank capital fragility indicators capture the systemic risk tied to banks' equity capital. Bank capital adequacy indicators measure the expected bank capital shortage conditional on a severe market decline, allowing for prudential obligations to maintain equity capital above a certain share of total assets. Finally, bank solvency indicators assess credit risk with distress thresholds reflecting the maturity structure of the bank's debt portfolio. The paper goes on to assess how these systemic risk indicators are linked to macroeconomic variables, and investigates their predictive power for Luxembourg's nominal GDP growth one year ahead.

As this study considers almost all banks operating in Luxembourg, the proposed systemic risk indicators capture the evolution of vulnerabilities in the banking sector over more than 20 years.

Several stylized facts are documented for 2003Q1-2023Q3. First, these indicators captured the main market crashes in a timely manner (the Great Financial Crisis, the sovereign debt crisis and the recent Covid-19 pandemic). Bank vulnerability decreased significantly after the Covid-19 crisis and declined further once the Eurosystem started monetary policy normalisation in July 2022 to bring high inflation back to its medium term objective. Second, these systemic risk indicators are closely linked to interest rates, liquidity flow, euro area consumer confidence and business climate, although the level of association depends on the bank business model. Finally, estimated regressions provide evidence that systemic risk indicators can explain Luxembourg's nominal GDP growth one year ahead. However, the systemic risk component associated with search-for-yield behavior and fee & commission generating activities could also explain nominal GDP growth, suggesting that as banks became more dependent on these income sources they might increase financial stability risks in the long run. In view of these results, the framework might provide a valuable addition to the traditional toolkit for assessing time varying risks to the stability of the financial system.

Résumé non-technique

La stabilité du système financier mondiale continue de faire face à un ensemble de défis importants, à savoir la persistance d’une inflation élevée, le durcissement des conditions financières, la poursuite des tensions géopolitiques, les effets persistants induits par la pandémie liée à la Covid-19 et le changement climatique. Ces défis continuent de mettre à l'épreuve la résilience des banques, et il est donc important d'identifier et surveiller les vulnérabilités susceptibles d’affecter la solidité du secteur bancaire luxembourgeois.

L’étude propose un cadre prospectif de simulation de crise au niveau des banques afin d'évaluer trois formes de vulnérabilité du système bancaire : la fragilité des fonds propres, l'adéquation des fonds propres et la solvabilité bancaire. Le test de résistance simule les effets d'une forte baisse des marchés boursiers sur la résilience des banques individuelles, en tenant compte des modèles d'affaires et du type de banque (domestique ou étrangère). Les indicateurs de fragilité des fonds propres des banques adoptés sont censés capter le risque systémique ayant trait aux fonds propres des banques. Les indicateurs d'adéquation des fonds propres évaluent les besoins des fonds propres additionnels des banques induits par la matérialisation d’un choc sévère des marchés financiers, en tenant compte des obligations prudentielles visant à maintenir les fonds propres au-dessus d'une certaine proportion du total des actifs. Enfin, les indicateurs de solvabilité bancaire évaluent le risque de crédit avec des seuils de détresse tenant compte de la structure des échéances du portefeuille de dettes de la banque. L’étude évalue ensuite la manière dont ces indicateurs de risque systémique sont liés aux variables macroéconomiques et analyse leur capacité prédictive de la croissance nominale du PIB du Luxembourg sur un horizon d'un an.

Dans la mesure où cette étude porte sur la quasi-totalité des banques opérant au Luxembourg, les indicateurs de risque systémique proposés reflètent adéquatement l'évolution des vulnérabilités du secteur bancaire sur plus de 20 ans.

Plusieurs faits stylisés sont documentés pour la période allant du premier trimestre 2003 au troisième trimestre 2023. Tout d'abord, ces indicateurs permettent de refléter précisément les principaux krachs boursiers (la grande crise financière, la crise de la dette souveraine et la récente pandémie liée à la Covid-19). Tout d’abord, la vulnérabilité des banques a diminué de manière significative après la crise liée la pandémie et s'est réduite davantage une fois que l'Eurosystème a débuté la normalisation de sa politique monétaire à partir de juillet 2022 pour ramener l'inflation vers son objectif de moyen terme. Par ailleurs, ces indicateurs de risque systémique sont étroitement liés aux taux d'intérêt, aux flux de liquidités, à la confiance des consommateurs de la zone euro et au contexte économique, bien que le niveau d'association dépende du modèle d'affaires de la banque. Enfin, les régressions estimées montrent que les indicateurs de risque systémique peuvent expliquer la croissance du PIB nominal du Luxembourg sur un horizon d'un an. Cependant, la composante du risque systémique associée au comportement de recherche de rendement et aux activités génératrices de commissions pourrait également expliquer la croissance du PIB nominal, suggérant ainsi que les banques, en devenant plus dépendantes de ces sources de revenus, sont susceptibles d'accroître les risques pour la stabilité financière à long terme. Au vu de ces résultats, ce cadre d'analyse

pourrait constituer un complément utile aux outils traditionnels pour une évaluation de l'évolution temporelle des risques pour la stabilité du système financier.

1. Introduction

Weak economic growth, geopolitical tensions, the lingering effects of the Covid-19 pandemic and climate change related risks still pose challenges to global financial stability (IMF Global Financial Stability Report, October 2023). Even though acute stress in the banking system has subsided, risks to euro area financial stability remain elevated, especially in a period characterized by tight financial and credit conditions, weak economic prospects, and the ongoing correction in real estate markets (ECB Financial Stability Review, November 2023). These challenges continue to test banks' resilience, making it important to monitor and identify potential vulnerabilities in the Luxembourg banking sector.

To this end, this paper proposes a forward-looking bank-level stress testing framework for a large-scale system to assess three forms of banking system vulnerability: bank capital fragility, bank capital adequacy and bank solvency.[1] Regarding bank capital fragility, the indicators in this study capture the systemic risk of banks' equity capital with distress-thresholds based on the lower tail of the distribution of bank equity returns. Baron, Verner, and Xiong (2021) find that a large decline in bank equity returns is associated with an increased likelihood and severity of deposit runs, non-performing loans, bank failures, and likelihood of government interventions, as well as more severe recessions. Instead, the bank capital adequacy indicators measure the expected capital shortage of banks conditional on a severe market decline, while accounting for prudential obligations to maintain bank equity capital above a certain share of total assets. Finally, the bank solvency indicators, which are based on Merton's model, detect the credit risk with distress thresholds reflecting the maturity structure of debt obligations.

Since the 2007-2009 US subprime mortgage crisis, academics and national authorities alike have stepped up their efforts to improve the ability to identify and assess systemic risk for macroprudential policy purposes. These efforts lead to the development of a large number of systemic risk measures (see e.g., Bisias et al., 2012 and Cesare and Picco, 2018 for a review). This study develops systemic risk indicators (SRIs) and their corresponding conditional systemic risk indicators (CoSRIs), capturing the effects of potential stock market crashes, from traditional state-of-the-art risk metrics (i.e., Expected Shortfall, Expected Loss and Probability of Distress) and a set of systemic risk measures (i.e., CoVaR or CoES in the work of Adrian and Brunnermeier 2016, Expected Capital Shortage under a market crisis introduced by Brownlees and Engle 2017, Banking Stability Index[2] and Probability of Cascade Effects presented by Segoviano and Goodhart 2006 and 2009 and Lehar 2005). In addition, the forward-looking risk assessment framework is based on two high-dimensional dynamic multivariate models, namely the dynamic multivariate copula approach applied to banks' equity capital and the Multi-Merton's model applied to banks' assets. SRIs and their corresponding CoSRIs are constructed and simulated forward from the multivariate distributions built on marginal distributions and a dependence structure with presumed distress

[1] A top-down (macro) stress test on these bottom-up systemic risk indicators can be further explored as in Rouabah and Theal (2010) and Guarda, Rouabah and Theal (2011).

[2] The Banking Stability Index measures the expected number of banks that will become distressed conditional on any one bank having become distressed.

thresholds. As this study considers almost all banks (excluding branches) in Luxembourg, the proposed systemic risk measures can track vulnerabilities in the Luxembourg financial sector over time.

Furthermore, euro area banks made substantial efforts to reshape their business models (see ECB's Financial Stability Review, May & November 2016) in response to the challenges posed by the persistently low interest rates and increased financial regulation and supervision. The Covid-19 crisis also brought new challenges and opportunities for the banking industry. In view of these trends, it is important to understand the effects of business model characteristics on banks' overall riskiness, especially under the current high-inflation environment. Thus, this paper also explores the potential banking system vulnerabilities in terms of bank capital fragility, bank capital adequacy and bank solvency for five main business models in Luxembourg: Retail and Commercial Banking (RCB), Private Banking (PB), Corporate Finance (CF), Custodian Banking and Activities Linked to Investment Funds (CBALIF) and Clearing, Treasury and Payment Services (CTPS). In addition, for each business model, banking systemic risk is further broken down by banks' domicile types as per the Single Supervisory Mechanism's approach: domestic banks, EU foreign subsidiary banks and non-EU Foreign subsidiary banks.

Additionally, this paper explicitly analyses the linkages between macroeconomic variables and the systemic risk measures.[3] By identifying the main macroeconomic variables more closely associated with vulnerabilities in the banking sector and its business models, the proposed approach explicitly pinpoints the economic and financial variables that may be of interest for authorities to safeguard financial stability. Finally, following Allen et al. (2012), this paper also investigates whether the systemic risk indicators have additional explanatory power for annual growth in nominal GDP up to 12 months ahead, and identifies the contribution from each business model accordingly.

Several important facts are documented in this study for the period spanning 2003Q1-2023Q3. In general, these banking vulnerability measures captured the main market crashes in a timely manner. SRIs and CoSRIs for the Luxembourg banking sector decreased significantly after the Covid-19 outbreak and they declined further since the Eurosystem started normalizing policy rates to contain high inflation in July 2022. CoSRIs were on average higher than their corresponding SRIs, and their decoupling starting from 2005 captured the banking vulnerability to potential market crashes even prior to the GFC. Systemic risk was dominated by domestic banks in RCB, by EU Foreign subsidiaries in PB and CF, and by non-EU foreign subsidiaries in CBALIF. The three types of banking vulnerability measures reflected different characteristics of systemic risk across bank business models.

First, the proposed bank capital fragility measures derived from banks' equity capital provides important insights on the recent developments of Luxembourg's banking sector. It reveals that the overall risk profiles followed the main market crashes in a timely way. However, the contributions to systemic risk varied substantially across business models. The systemic risk was dominated by RCB, PB and CF, and CF was

[3] The panel regression analysis of the impact of business models on banking stability or profitability in the context of the EU banking sector is ignored in the paper as similar topics have been explored widely in the literature.

squeezed harder by the Covid-19 outbreak, notably as reflected in its banking stability index. The expected shortfall of CBALIF culminated at the Covid-19 outbreak, whereas the systemic risk measures of CTPS also captured its business events around the end of 2018. The cascade effects in PB were stronger and deeper than those in other business models. In contrast, the Covid-19 pandemic had the strongest spillover effects on CF, and spillover risks were less volatile in CTPS.

Second, as for bank capital adequacy, the expected capital shortage under a market crisis declined quickly after it peaked around mid-2008, mainly driven by the EU banking deleveraging process. However, it kept rising slowly since mid-2016, decreased temporarily after the Covid-19 outbreak, and finally dropped substantially since the Eurosystem started rate hikes in July 2022. Among all business models, the contributions to the expected capital shortage from CTPS were trivial. From 2010, PB became more important for bank capital adequacy than other business models as the capital shortage of RCB was apparently under control after the GFC, and the contributions from CF also declined over time. In contrast, the expected capital shortage of CBALIF increased persistently (even more so during the Covid-19 pandemic), and only improved sharply from 2022 owing to mergers and acquisitions in CBALIF.

Third, regarding bank solvency, the total risk profiles of expected loss and probability of distress tracked closely the GFC, the European debt crisis and the Covid-19 pandemic, peaking during the Covid-19 outbreak, albeit to a lesser extent compared to the level observed during the GFC. Among the business models, the credit risk of RCB stabilized after the GFC and only deteriorated during recent Covid-19 pandemic. The PB business model was hit substantially by the GFC and the European debt crisis, while the indicators for the CF business model also captured some risks noticeably around 2006 and 2015-2017, with its solvency risk deteriorating consistently since the Covid-19 outbreak. In contrast, the credit risk of CBALIF and CTPS increased over time and peaked during the Covid-19 pandemic. Furthermore, the overall cascade effects declined after the GFC and the European debt crisis. Nevertheless, under the pressure of the low interest rate environment with low bank profitability and low growth, the banking industry took on risk taking behavior that gradually raised spillover risk starting in 2014. This trend was temporarily interrupted during the Covid-19 pandemic by the Eurosystem's prompt monetary policy response, namely the new pandemic emergency purchase programme (PEPP), and assorted supervisory actions. Since 2022, the cascade effects fell substantially towards the end of 2023. The spillover risk was considerably higher in PB and CBALIF than in the other business models. The higher conditional spillover risk around 2015-2017 in all business models was mainly driven by the high asset correlation during this period.

As for the forward or long-term solvency risk conditional on not defaulting on short-term debt, it was substantially different from, and much lower than, the short-term solvency risk. The forward systemic risk was dominated by RCB, PB and CF business models with less contribution from RCB on average while still mirroring the main market crises closely. The forward risk increased over time from 2014 and peaked around the beginning of 2022, and risk dependence and cascade effects remained high until the beginning of 2022, mainly driven by the CF business model.

Furthermore, macroeconomic variables captured different characteristics of these banking vulnerabilities, and the key macroeconomic determinants also varied across the business models. For example, high interest rates predicted an improvement in bank capital adequacy and short-term bank solvency in CTPS, long-term bank solvency in CF and CBALIF, however, a deterioration in bank capital fragility in PB and CF, and long-term bank solvency in CTPs in the following month. These systemic risk indicators are largely driven by interest rates, liquidity flow, consumer confidence and business climate in the EA.

Finally, the predictive regressions show that the systemic risk indicators for bank fragility can explain nominal GDP growth in Luxembourg in the following year. The systemic risk measures driven by PB and RCB could offer an early warning to alert regulars to the risk of slower growth in nominal GDP. In contrast, for capital adequacy and bank solvency, debt structure or debt rollover revealed that CF may have been driven by search-for-yield behavior, and CBALIF and CTPS by fee & commission generating activities in the low-interest rate environment. This finding suggests that such business models may carry financial stability implications in the long run.

The remainder of this paper is organized as follows. Section 2 describes three types of models and their associated systemic risk indicators to identify the potential banking vulnerabilities with respect to bank capital fragility, bank capital adequacy and bank solvency. Section 3 describes the data. Section 4 explores the systemic risk measures for the banking sector in Luxembourg. Section 5 investigates the macroeconomic variables most closely associated with these banking systemic risk indicators using a set of linear regressions. Section 6 examines the predictive power of these systemic risk indicators on future growth in nominal GDP. Finally, Section 7 assesses survivor bias and Section 8 concludes and discusses some potential macro-prudential policy considerations.

2. Methodology

To assess the systemic risk of the banking sector in Luxembourg, this paper explores banking stability under stock market crash conditions, considering bank capital fragility, bank capital adequacy, and bank solvency. The SRIs and their corresponding CoSRIs are constructed from relevant stress testing and systemic risk models conditional on stock market crashes. The shocks are assumed to stem from the euro area stock market index.[4] Three types of models are selected based on several benchmark models in the literature with some extensions.

2.1 Dynamic copula model on equity - bank capital fragility

A t-Copula is applied to the returns of book-value of Luxembourg banks' equity and returns of market indexes. The conditional systemic risk indicators under market crashes can be constructed by simulating from multivariate distributions built on marginal distributions and a dependence structure. In order to track the evolution of systemic risk in the Luxembourg banking sector over time, banks no longer operating in

[4] Other shocks can also be considered in this framework.

Luxembourg are also considered. Thus, the number of dimensions in the dataset is high, and the lengths of the available data are different, being particularly short for some banks.

In addition, forecasting returns in the short-term is challenging based on historical data, therefore, expected short-term returns are usually assumed as zero in the standard market risk management. For simplicity, similarly as in the RiskMetrics framework, this study considers the Exponentially Weighted Moving Average (EWMA) model with one decay parameter to deal with the information field and heteroscedasticity in both market returns and bank equity returns.[5] Assuming one parameter can avoid much noise driven by estimation errors when the decay factor is estimated respectively for each bank on data of varying and limited length. The decay factor can be fixed as proposed by RiskMetrics (see J.P. Morgan/Reuters, 1996). However, there is no optimal way to fix the decay factor. Therefore, in this paper, all the univariate models are first estimated, and then the median of these parameter estimates are selected to forecast the heteroscedasticity in these returns.

To address the dependence structure of the innovations, as in Engle, Jondeau and Rockinger (2015), the dynamic conditional t-copula is adopted.[6] It is able to capture the possible non-linear dependencies across innovation processes very well, and is attractive from the statistical and computational viewpoints for a large dimensional system.[7] The joint distribution modeled by the dynamic conditional t-copula is defined as follows:

$$C(\eta_{1,t}, \eta_{2,t}, \dots, \eta_{n,t}; R_t, v_t) = T_{R_t, v_t}\left(t_{v_t}^{-1}(\eta_{1,t}), t_{v_t}^{-1}(\eta_{2,t}), \dots, t_{v_t}^{-1}(\eta_{n,t})\right), \tag{1}$$

where $\eta_{j,t} = \mathrm{F}(z_{j,t})$ for $j = 1,2,\dots,n$, and $z_{j,t}$ are the standardized residuals from the marginal dynamic processes. R_t is the copula correlation matrix, and v_t is the degree of freedom. $t_{v_t}^{-1}(\eta_{j,t})$ denotes the inverse of the t cumulative distribution function. In this study, R_t is assumed to be dynamic process through time and v_t is assumed to be constant for simplicity.

[5] A univariate AR (6) - GARCH (1, 1) model was also tested for each bank equity return series. However, because of the varying and short data series length, the derived systemic risk indicators look noisier than those from EWMA with one decay factor.

[6] See Patton (2012) for the definition of a general conditional copula.

[7] The t-copula generalizes the normal copula by allowing for non-zero dependence in the extreme tails. This type of dependence is measured by τ^U upper tail dependence, and τ^L lower tail dependence:

$$\tau^L = \lim_{\zeta\to 0}\Pr[\eta_1 \le \zeta | \eta_2 \le \zeta] = \lim_{\zeta\to 0}\Pr[\eta_2 \le \zeta | \eta_1 \le \zeta] = \lim_{\zeta\to 0}(\frac{C(\zeta,\zeta)}{\zeta}, \text{ and}$$

$$\tau^U = \lim_{\zeta\to 1}\Pr[\eta_1 > \delta | \eta_2 > \delta] = \lim_{\zeta\to 1}\Pr[\eta_2 > \delta | \eta_1 > \delta] = \lim_{\zeta\to 1}(\frac{1-2\delta+C(\delta,\delta)}{1-\delta}).$$

Two random variables exhibit lower tail dependence, for instance, if $\tau^L > 0$. The normal copula imposes that this probability is zero. The two parameters of the t-copula, ρ_t and v_t, jointly determine the amount of dependence between the variables in the extremes. Since it is a symmetric copula, the dependence between the variables during extreme appreciations is restricted to be the same as during extreme depreciations, and is given by: $\tau_t^U = \tau_t^L = 2 - 2T_{v_{t+1}}(\sqrt{v_t+1}\sqrt{\frac{1-\rho_t}{1+\rho_t}})$.

Misspecification of marginal distributions can lead to significant biases in the estimation of the dependence structure. However, estimating a marginal distribution based on relatively short historical data series is extremely difficult. Thus, a homogenous marginal distribution is assumed for all banks by pooling all standardized residuals, $z_{j,t}$.[8] In order to allow for flexible marginal distributions, this study does not specify the marginal distribution, but adopts a semi-parametric form for the marginal distribution $\mathrm{F}(z)$ as in McNeil (1999) and McNeil and Frey (2000). The marginal density is estimated using a Gaussian kernel for the central part of the distribution mass, and a parametric Generalized Pareto distribution for the two tails. Consequently, the asymmetry can be examined 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.

Engle (2002) proposes a class of models – Dynamic Conditional Correlation (DCC) – that preserves the ease of estimation of Bollerslev's (1990) constant correlation model while allowing the correlations to change over time. These types of dynamic processes can also be extended into t-copulas. Since the considered time series data is relatively short and its dimension is relatively high, the simplest copula correlation dynamics considered empirically is the symmetric scalar model where the entire copula correlation matrix reverts to a long-run average correlation and is only driven by two parameters:[9]

$$Q_t = \left(1 - \alpha^{copula} - \beta^{copula}\right)\bar{Q} + \alpha^{copula}(\tilde{z}_{t-1}\tilde{z}'_{t-1}) + \beta^{copula}Q_{t-1}, \tag{2}$$

Where $\alpha^{copula} \geq 0,\ \beta^{copula} \geq 0,\ \alpha^{copula} + \beta^{copula} \leq 1$, and $\tilde{z}_{j,t} = t_{v_t}^{-1}(\eta_{j,t} = \mathrm{F}_j\left(z_{j,t}\right))$. $Q_t = \left|q_{ij,t}\right|$ is the auxiliary matrix driving the copula correlation dynamics, the nuisance parameters $\bar{Q} = E[\tilde{z}_t\tilde{z}'_t]$ with sample analog $\bar{Q} = T^{-1}\sum_{t=1}^{T}[\tilde{z}_t\tilde{z}'_t]$, so that R_t is a matrix of copula correlations $q_{ij,t}$ with ones on the diagonal, and $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$.

In this dynamic t-copula application, a two-step algorithm is adopted for convenience. This means that R_t is first estimated from the dynamic Gaussian copula,[10] and then v_t degrees of freedom are recovered from the t-copula with R_t fixed from the first step. For large dimensional problems, the dynamic Gaussian copula

[8] The semi-parametric form for the marginal distribution $\mathrm{F}_j(z_{j,t})$ was also explored for each bank. However, the marginal distributions based on relatively short historical data were seriously misspecified, and the simulated systemic risk indicators revealed many outliers. In contrast, assuming a homogenous marginal distributions effectively removes these outliers and does not change the overall profiles of these systemic risk indicators.

[9] The simple exponential smoothing model is also tested for the copula correlation dynamics in which the entire copula correlation matrix is driven only by a decay factor. The profiles of the systemic risk indicators were somehow similar to those from the DCC model. It could be an alternative good model for updating easily these indicators by a fixed parameter, however, without reverting to a long run average copula correlation.

[10] The dynamic multivariate Gaussian copula is defined similarly to the t-copula as follows:

$$C\left(\eta_{1,t}, \eta_{2,t}, \ldots, \eta_{n,t}; R_t^{Gaussian}\right) = \Phi_{R_t^{Gaussian}}\left(\Phi^{-1}\left(\eta_{1,t}\right), \Phi^{-1}\left(\eta_{2,t}\right), \ldots, \Phi^{-1}\left(\eta_{n,t}\right)\right),$$

where $\eta_{j,t} = \mathrm{F}_j(z_{j,t})$ for $j = 1,2,\ldots,n$, and $z_{j,t} \sim iid(0,1)$ are the innovations from the marginal dynamics introduced in the previous section. $R_t^{Gaussian}$ is the Gaussian copula correlation matrix. The copula correlation dynamics is similarly driven by the two parameters listed above for the t-copula. However, $\tilde{z}_{j,t} = \Phi^{-1}(\eta_{j,t} = \mathrm{F}_j\left(z_{j,t}\right))$.

can be estimated by maximizing the composite log-likelihood by summing the log-likelihoods of pairs of assets as in Engle et al. (2021). However, since the bank time series data used in this study have very different lengths, the parameters estimated by the composite log-likelihood method can also be seriously biased. Thus, this study uses a convenient estimation approach called the MacGyver method as in Engle (2007). It first estimates all the bivariate models and then selects the median of these parameter estimates in creating and forecasting copula correlations.

By using conditional dynamic copulas, it is relatively straightforward to construct and simulate from multivariate distributions built on marginal distributions and a dependence structure. The dynamics in both variance and copula correlation offers multi-step-ahead predictions of portfolio returns simultaneously. The one-step-ahead simulation is explored in this paper, and the SRIs and CoSRIs are obtained by these simulated returns of all banks and market index.[11] The risk indicators to measure the bank capital fragility are as follows:

a. Weighted Expected Shortfall (ES) and Conditional Expected Shortfall (CoES). For a banking system consisting of N banks, the equity-value-weighted ES and CoES over all banks are defined similarly as in Adrian and Brunnermeier (2016):

$$\mathrm{ES}_{\mathrm{q,t+1}}^{\mathrm{Bank\ sys}} = \sum_{\mathrm{j}}^{\mathrm{n}} \frac{\mathrm{Size}_{\mathrm{Euro,t}}^{\mathrm{Bank^j}}}{\mathrm{TotalSize}_{\mathrm{Euro,t}}^{\mathrm{Bank\ sys}}} \mathrm{ES}_{\mathrm{q,t+1}}^{\mathrm{Bank^j}}, \text{ and}$$

$$Co\mathrm{ES}_{\mathrm{q,t+1}}^{\mathrm{Bank\ sys|market}} = \sum_{\mathrm{j}}^{\mathrm{n}} \frac{\mathrm{Size}_{\mathrm{Euro,t}}^{\mathrm{Bank^j}}}{\mathrm{TotalSize}_{\mathrm{Euro,t}}^{\mathrm{Bank\ sys}}} \mathrm{CoES}_{\mathrm{q,t+1}}^{\mathrm{Bank^j|market}}, \tag{3}$$

where, $\mathrm{Size}_{\mathrm{Euro,t}}^{\mathrm{Bank^j}}$ is the equity value of bank j at time t, and $\mathrm{TotalSize}_{\mathrm{Euro,t}}^{\mathrm{Bank\ sys}}$ is the total equity value of the n banks at time t. $\mathrm{CoES}_{\mathrm{q,t+1}}^{\mathrm{Bank^j|market}} = -\mathrm{E_t}\left(\mathrm{R}_{\mathrm{t+1}}^{\mathrm{Bank^j}} \middle| \mathrm{R}_{\mathrm{t+1}}^{\mathrm{Bank^j}} \leq \mathrm{CoVaR}_{\mathrm{q,t+1}}^{\mathrm{Bank^j|market}}\right)$ and $\mathrm{CoVaR}_{\mathrm{q,t+1}}^{\mathrm{Bank^j|market}}$ is value-at-risk (VaR) of bank j's return, $\mathrm{R}_{\mathrm{t+1}}^{\mathrm{Bank^j}}$, at a confidence level q conditional on some market events at time $\mathrm{t}+1$. The negative sign is added because ES are usually defined as a positive number. The market events in tail are defined as the set of $\mathrm{R}_{\mathrm{t+1}}^{\mathrm{market}}$ events falling below its $\mathrm{VaR}_{\mathrm{q,t+1}}^{\mathrm{market}}$ level. In this study, $\mathrm{q} = 0.05$ is selected for both market returns and banks returns.

b. Expected Shortfall in Euro (ES Euro) and Conditional Expected Shortfall in Euro (CoES Euro). These measures are the sum of ES in Euro and CoES in Euro over all banks: $\sum_{\mathrm{j}}^{\mathrm{N}} \mathrm{Size}_{\mathrm{Euro,t}}^{\mathrm{Bank^j}} \mathrm{ES}_{\mathrm{q,t+1}}^{\mathrm{Bank^j}}$ and $\sum_{\mathrm{j}}^{\mathrm{n}} \mathrm{Size}_{\mathrm{Euro,t}}^{\mathrm{Bank^j}} \mathrm{CoES}_{\mathrm{q,t+1}}^{\mathrm{Bank^j|market}}$, respectively.

c. Weighted Probability of Distress (PD) and Conditional Probability of Distress (CoPD). Baron, Verner, and Xiong (2021) suggest that large bank equity declines provide a useful signal of banking crises in real-time. This study defines an identical distress threshold, -15% of the log equity returns, for all banks.

[11] The multi-month ahead conditional systemic risk measures can also be estimated from the simulated multi-step-ahead returns in a similar manner.

It represents approximately the 1% quantile of the log equity returns for Luxembourg banks throughout the sample period. The PD is the probability that simulated banks returns fall below the distress threshold, and CoPD is the PD conditional on market crashes. The market crashes are defined as the 5% quantile of simulated market returns. Similarly, the aggregate risk measures are the equity-value-weighted PD and CoPD over all banks.

d. Banking Stability Index (SI) and Conditional Banking Stability Index (CoSI). Proposed by Segoviano and Goodhart (2006 and 2009), SI measures the expected number of banks that will become distressed conditional on any one bank having become distressed. The measure can be written in a system made of three banks i, j, and k as $\frac{\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{i}}} \le \mathrm{D}\right)+\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{j}}} \le \mathrm{D}\right)+\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{k}}} \le \mathrm{D}\right)}{1-\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{i}}} \ge \mathrm{D} \cap \mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{j}}} \ge \mathrm{D} \cap \mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{k}}} \ge \mathrm{D}\right)}$ and CoSI is the corresponding SI conditional on some market events:

$$\mathrm{CoSI}_{q,t+1}^{\mathrm{Bank\ sys|market}} = \frac{\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{i}}} \le \mathrm{D}\middle|\mathrm{C}(\mathrm{R}_{t+1}^{\mathrm{market}})\right)+\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{j}}} \le \mathrm{D}\middle|\mathrm{C}(\mathrm{R}_{t+1}^{\mathrm{market}})\right)+\ \mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{i}}} \le \mathrm{D}\middle|\mathrm{C}(\mathrm{R}_{t+1}^{\mathrm{market}})\right)}{1-\mathrm{P}\left(\mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{i}}} \ge \mathrm{D} \cap \mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{j}}} \ge \mathrm{D} \cap \mathrm{R}_{t+1}^{\mathrm{Bank}^{\mathrm{k}}} \ge \mathrm{D}\middle|\mathrm{C}(\mathrm{R}_{t+1}^{\mathrm{market}})\right)}, \tag{4}$$

where $\mathrm{C}(\mathrm{R}_{t+1}^{\mathrm{market}})$ denotes the market events, and the distress threshold, D, is defined as -15% of the log equity returns for all banks. Market crashes are defined as the 5% quantile of simulated market returns. When SI or $\mathrm{CoSI} = 1$, the linkages across banks are minimal. These measures could also be interpreted as a measure of contagion.

e. Probability of Cascade Effects (PCE) and Conditional Probability of Cascade Effects (CoPCE). Based on another popular systemic risk indicator measuring the spillover effects in banking system presented by Segoviano and Goodhart (2006 and 2009) and Lehar (2005), the PCE measures the probability that at least a proportion (e.g., 5%, 10%) of the total number of banks or total equity value of banks becomes distressed. CoPCE is the corresponding PCE conditional on some market crashes. Thus, the CoPCE measure shows the likelihood that a market shock is propagated to the banking industry. The distress thresholds are defined as -15% of the log equity returns for all banks, and the market crashes are defined as the 5% quantile of simulated market returns. For each type of business model, this study also considers at least one or two banks for PCE or CoPCE besides a proportion of the total number of banks.

2.2 *The conditional expected capital shortage – bank capital adequacy*

The expected capital shortage under a market crisis was introduced by Brownlees and Engle (2017). Consider a panel of financial institutions indexed by $i = 1, \ldots, n$ observed at times $t = 1, \ldots, T$. For each financial institution, D_i and W_i denote, respectively, the book-value of its debt and the market- or book-value of its equity. Assuming that prudential management would restrict each institution to maintain equity as a fraction k of its total assets, the expected capital shortage can be defined as:

$$CS_{it+h|t} = -kD_{it} + (1-k)W_{it}MES_{it+h|t}\left(VaR_q^{R_m\,t+h:t}\right), \tag{5}$$

where $MES_{it+h|t}\left(VaR_q^{R_{m\,t+h:t}}\right) = E_t(exp(R_{it+h:t})|R_{m\,t+h:t} < -VaR_q^{R_{m\,t+h:t}})$ is the tail expectation of the firm equity returns conditional on the systemic event expressed by $VaR_q^{R_{m\,t+h:t}}$ at $q\% - quantile$ of the conditional probability distribution of $R_{m\,t+h:t}$, and the return of total equity is denoted as the log return. The conditional capital shortfall measure of systemic risk – SRISK described by Brownlees and Engle (2017) in the financial system or a subsection of a financial system is

$$SRISK_t = \sum_{i=1}^{I} \max(0, CS_{it}), \tag{6}$$

SRISK is a function of a firm's size, leverage, and its expected equity loss given a market downturn. It can be thought of as the total amount of capital that the government would have to provide to bailout the financial system or its component in the case of a crisis. As for $MES_{it+h|t}\left(VaR_q^{R_{m\,t+h:t}}\right)$, which depends on modeling a dynamic distribution, Brownlees and Engle (2017) propose several models only for a bivariate distribution. In this paper, the dynamic high-dimensional multivariate distribution modeled by the time-varying t-copula provides a more flexible way to assess the aggregated systemic risk of expected capital shortage under multiple adverse scenarios.

SRISK is considered to proxy bank capital adequacy at the prudential ratios k = 8%, 12%, 22% and 33%, respectively. The market crashes are defined by the fixed threshold corresponding to the 5% quantile of market returns over the whole sample period.

2.3 Multi-Merton's model - bank solvency

As Luxembourg bank subsidiaries are not publicly quoted, an alternative approach has to be followed to calculate bank solvency PDs. By the mark-to-market accounting rule, the values on the balance sheet can still track the changes of market conditions in a timely way, and some systemic risk measurements can be applied on the book-value data directly.[12] In an application to Brazilian and Mexican banks, Souto et al. (2009) and Blavy and Souto (2009), respectively, show that the book-based Merton's credit risk measures are highly correlated with market-based Merton's credit risk measures. This suggests that banks' financial statements are a crucial piece of information when forming market expectations about the probability of

[12] The so-called fair value or mark-to-market accounting has the advantage of reflecting the market and relevant value of the balance sheets of financial institutions and therefore of allowing regulators, investors and other users of accounting information to better assess the risk profile of financial institutions. Luxembourg financial institutions are allowed to publish their annual and consolidated accounts according to Luxembourg Banking GAAP, IFRS, or mixed of both regimes. IFRS requires certain assets and liabilities – in particular certain financial items – to be measured using the fair value or mark-to-market accounting basis. The Luxembourg law of 16 March 2006 has transposed the fair values and modernization directives into Luxembourg law, and enables, among others, the use of certain provisions of IFRS as adopted by the EU. As regards to the prudential financial reports to the CSSF, financial institutions are required to submit a periodical financial report based on IFRS.

bank distress. This approach is followed here, however, by using the Multi-Merton's model as in Lehar (2005) for a large-scale system.[13]

The asset values of Luxembourg banks are assumed to follow a geometric Brownian motion with a vector of drifts and a covariance that is multi-normal distributed, and the threshold determined by the book-value of debt. The expected loss can be simulated from Multi-Merton's model in the risk-neutral framework. In order to capture the changes of risks in a more timely way, the covariance of asset returns is estimated using EWMA model in which the mean return is neglected as in Lehar (2005)[14] as follows:

$$Cov_t = (1-\lambda)\left(R^A_{t-1}{R^{A}}'_{t-1}\right) + \lambda cov_{t-1}, \tag{7}$$

Where R^A_{t-1} is a vector of log returns of total assets of banks at time $t-1$. The EWMA model is used in the RiskMetrics framework and is a standard tool in market risk management. The choice of the decay factor λ is of critical importance for the EWMA model. However, it is hard to estimate the lambda as the data series is comparatively short and thus, causes a lack of convergence. There is no optimal way to fix the decay factor as discussed in the literature (e.g., Mentel and Brożyna 2014 and Bollen 2015). A higher λ is used to obtain average long-term volatility and, accordingly, a lower λ can be applied to examine volatility within shorter periods. As it is discussed in the previous section, the time series data for Luxembourg banks is relatively short and the dimensionality is high. Thus, a convenient estimation approach called the MacGyver method as in Engle (2007) is also used here. First, all the bivariate models are estimated and then the median of these parameter estimates is selected in creating and forecasting covariance.

2.31 One single debt obligation

The total asset values of banks can be simulated in a risk-neural framework as

$$V_i^s(t) = V_i(0) * \left(rt + W_i^s - \frac{1}{2}\sigma_{ii}^2 t\right), \tag{8}$$

where σ_{ii}^2 is the ith diagonal element of the annualized Σ , and W_i^s is simulated from the multivariate normal distribution with $E[X(t)] = 0_{n,1}$ and $Var[X(t)] = t\Sigma$. A bank is assumed to be in distress if the value of the assets falls below the value of its debt within the next year. Following the KMV approach

[13] The GARCH option-pricing models are difficult to estimate because of the high-dimensionality and the short data length.

[14] The study also tested the BEKK model for covariance dynamics in which the entire covariance matrix is driven by two parameters. The profiles of systemic risk indicators are similar to those by the EWMA model. However, for large dimensional problems with very different data lengths, it is not easy to estimate the two parameters with the nuisance parameters of target sample mean.

devised by Bohn and Crosbie (2003), the distress barrier for one single debt obligation is composed of the short term debt plus half of the long term debt.

2.32 Maturity structure of debt obligations

The previous model considers only a single debt maturity. However, debt maturity influences both credit risk and liquidity risk, the two major sources of bank default risk. He and Xiong (2012a) state that the debt maturities of lenders (e.g. investment banks) on short-term debt are spread across time and rolled over to avoid bank-run risk if all debt contracts expire at the same time. A more direct channel of how liquidity and credit risk can jointly cause default is theoretically shown by He and Xiong (2012b). This single debt maturity is an important drawback for a central bank or a supervisor interested in assessing and tracking bank solvency. Geske (1977) and Delianedis and Geske (2003) consider a multi-period debt payment framework to which they apply compound option theory. This enables to account for the influence of the time structure of debt on the estimated PD. In the simulation framework, this study can also explore the short-term PDs and forward or long-term PDs conditional on not defaulting on the short-term debt.

Assuming that a bank has long-term debt, M_2 , which matures at date T_2 , and short-term debt, M_1, which matures at date T_1, if at date T_1 the value of the bank is greater than M_1 plus the market value of the long term debt at T_1, then the bank is not bankrupt and can refinance. In the simulation framework, the short-run PD at T_1 can be first evaluated, then conditional on not defaulting at date T_1, the forward PD at T_2 can also be estimated. However, in order to compare the short-run PD with the forward PD over the same specified period, this study defines $T_1 = 1\ year$, and $T_2^d = T_1 + 1\ year$. The distress-barrier at T_1 is the short-term debt plus the discounted value of the long term debt, while the distress-barrier at T_2^d is the value of long-term debt at T_2^d discounted by the long-term interest rate. Thus, similarly to the one-year short-term PD, the forward or long-term PD can also be interpreted as one-year PD conditional on not defaulting at date T_1.

In addition, it is assumed that a synthetic market index 'bank' follows a geometric Brownian motion. However, its threshold is supposed to be the VaR at 5% of market returns over the whole sample. The risk indicators to measure bank solvency in both the short-term and the long-term can be derived from the risk-neutral framework of Multi-Merton's model as follows:

a. Expected Loss (EL) and Conditional Expected Loss (CoEL). The EL^i is the put option or the present value of expected loss for bank i, and $CoEL^i$ is its EL conditional on some market crashes. The aggregate risk measures are the sum of EL^i and $CoEL^i$ over all banks.

b. Weighted Probability of Distress (PD) and Conditional Probability of Distress (CoPD). The aggregate risk measures are the asset-value-weighted PD and CoPD over all banks experiencing the solvency distress.

c. Weighted Risk Premium (RP) and Conditional Risk Premium (CoRP). In Merton's model, for bank i, the RP^i is the credit spread required to compensate for the expected loss: $-\frac{1}{T}\ln(1-\frac{EL^i}{Be^{rT}})$, with B standing for the distress barrier, and time represented by T, while the $CoRP^i$ is its RP^i conditional on some market crashes. The aggregate measures are the asset-value-weighted RP and CoRP over all banks.

d. Banking Stability Index (SI) and Conditional Banking Stability Index (CoSI). These measures are defined similarly as in the section of bank capital fragility. However, the distress threshold is the solvency distress barrier or value of its debt.

e. Probability of Cascade Effects (PCE) and Conditional Probability of Cascade Effects (CoPCE). The probability of cascade effects (PCE) measures the probability that at least a proportion (e.g., 5%, 10%) of the total number of banks or total asset value of banks experiences solvency distress. CoPCE is the corresponding PCE conditional on some market crashes. For each type of business models, this study considers at least one to two banks for PCE or CoPCE in addition to a proportion of the total number of banks.

3. Data description

All banks (excluding branches) operating during the sample period in Luxembourg, with observations for more than 6 quarters, are considered in this paper. The database contains quarterly balance-sheet information from March 2003 to September 2023. There are 133 banks (excluding branches) meeting the length criterion, of which information on the business model is available for 82 banks (including 69 banks that were still in operation in September 2023). It is the maximum sample size of Luxembourg banks ever considered, and these 82 banks include almost all banks (excluding branches) in Luxemburg since 2019. This study focuses on the 82 banks to identify three aspects of Luxembourg banking vulnerabilities in view of business models, and also assesses the potential survivor bias based on all 133 banks.

These 82 banks are categorized into five business models according to the CSSF[15]: 11 banks in Retail and Commercial Banking (RCB), 35 banks in Private Banking (PB), 20 banks in Corporate Finance (CF), 13 banks in Custodian Banking and Activities Linked to Investment Funds (CBALIF) and 3 banks in Clearing, Treasury and Payment Services (CTPS). For all selected banks, short-term debt includes demand and time deposits of up to one-year maturity, short-term funding, and repos, while the long-term debt includes time deposits of over one-year maturity and other long-term funding. A bank's equity or capital is defined as the difference between its total assets and total debts. In order to explore market crashes, the data set also includes OECD market indexes of a number of systemic important countries and the EA19 index. As

[15] The identification of Luxembourg's bank business models is ignored in this paper because relevant EU research papers have already categorized EU banks by different cluster models.

quarterly data frequency is not enough to estimate the dynamic models sufficiently, bank quarterly balance-sheet data is converted into monthly data by linear interpolation.[16]

Figure 1 shows the quarterly cumulative returns and leverage ratios of all banks and five bank business models during the period from 2003Q2 to 2023Q3. The equity returns and debt-to-equity ratios are equity-value weighted, whereas asset returns and debt-to-asset ratios are asset-value weighted. Overall, the assets of all considered banks grew marginally during this period. In contrast, their equity capital increased substantially, in particular, after the GFC driven by the EU banking deleveraging process as shown by both leverage ratios. Deleveraging reflected a more efficient allocation of financial resources in the Luxembourg banking sector. Among five business models, both equity and assets of CBALIF increased substantially over time, especially around mid-2018, and only deteriorated temporally due to the Covid-19 pandemic starting on March 2020 but recovered quickly since the end of 2020. However, assets of CBALIF declined sharply from January 2022 owing to the mergers and acquisitions in CBALIF. In addition, CF somehow successfully improved its equity capital by cutting more debt than both PB and RCB. As for CTPS, its assets grew more slowly than those of CBALIF. Nevertheless, its asset structure changed considerably. Its equity capital kept rising until mid-2018 while its leverage ratios bounced back sharply mainly because of the large business expansion in CTPS. It is important to note that the Eurosystem started rate hikes to help lower inflation in July 2022 and, since then, the leverage ratios declined further towards the end of 2023.

Figure 2 depicts the interquartile ranges of volatilities and correlations with the EA market returns in the sample period. As volatilities and correlations were estimated by using a simple exponential smoother on the covariances with a decay factor of 0.92, they can be compared directly across banks' equity returns and asset returns. Overall, equity volatilities were much higher than asset volatilities, and both followed closely the main market crashes (e.g., the GFC and the European debt crisis). However, asset volatilities also increased during the Chinese stock market turbulence of 2015–2016. Furthermore, the idiosyncratic risks were reflected differently across these five business models. For example, asset volatility of CF reflected the Covid-19 pandemic substantially, the assets of CBALIF were impacted by the China-US trade war since 2018, and the equity of CTPS reflected its business expansion events whereas its asset and equity were still affected by the Covid-19 pandemic.

Regarding the correlations with the EA market returns, the profiles of asset correlations were similar across the business models. The correlations increased around the GFC and the Chinese stock market turbulence. Nevertheless, while facing the Covid-19 pandemic, except for CF, the correlations with the EA market returns declined sharply reflecting their diversified asset allocation. As for equity correlations, they captured these market events in a timely way as well. However, the interquartile ranges were much narrower during the Covid-19 pandemic than around the GFC, except for CBALIF in which the correlations were also driven by its own business model characteristics. This may be a reflection of the overall challenges to bank

[16] The monthly data from the BCL statistical table S1.1 is not used as some balance sheet items are not reported for the non-quarter end month.

profitability and growth under the deteriorating macro environment. Nevertheless, similar to the leverage ratios, volatilities and correlations for all banks dropped further towards the end of 2023.

4. Economic application

To capture volatility clustering, the EWMA model with one decay parameter of 0.9159 is fitted to the equity returns of both markets and Luxembourg banks.[17] Overall, the EWMA was able to pick up the strong persistence in squared returns. The skewness and kurtosis of the pooled standardized residuals also proved the need of certain semi-parametric forms for the distribution. As for the dynamic copula, this study estimates all bivariate models, and by the MacGyver method, selects the median of these parameter estimates which exclude certain outliers in creating and forecasting copula correlations. The dependence-updating parameter, α^{copula}, is 0.021, and the autoregressive parameter, β^{copula}, is 0.829 with persistence of 0.85. The degrees of freedoms are around 11. Thus, the copula dependence of the equity returns is still highly dynamic. As for the covariance of asset returns in the Multi-Merton's model, the MacGyver method yields λ= 0.9125. In addition, a range of parameters around the selected ones is also tested, it is proved that the derived risk indicators are robust and stable to a reasonable range of parameters.

4.1 Bank capital fragility

Figure 3A shows four SRIs of bank capital fragility and their corresponding CoSRIs, including their business model components. Overall, the total risk profiles followed the main market crashes in a timely way, and CoSRIs were on average higher than their corresponding SRIs. However, the different contributions to systemic risk from business models were remarkable. The systemic risk was overall dominated by RCB, PB and CF, and CBALIF also weighed heavily in the SI. For both RCB and PB, the bank capital fragility improved significantly over time since the GFC, and only deteriorated mildly with the onset of the Covid-19 pandemic in early 2020. On average, they were impacted by market crashes more strongly than other business models. It is interesting to notice that the weighted PDs of CF were not very high after the GFC. However, CF was apparently squeezed by the Covid-19 outbreak, notably as reflected in its SI. Finally, the CoES and CoES Euro of CBALIF peaked during the Covid-19 outbreak, whereas the systemic risk measures of CTPS mainly captured its business events around the end of 2018.

Figure 3B further identifies their domicile components in each business model. The systemic risk was mostly driven by non-EU foreign subsidiaries in CBALIF and CTPS, and was dominated by EU foreign subsidiaries in CF. However, the non-EU foreign subsidiaries in CF also played an important role since the Covid-19 outbreak, particularly reflected in the banking stability index. Domestic retail and commercial banks were more vulnerable as indicated by the capital fragility indicators than domestic private banks, and

[17] This study also tested several values of decay factor between 0.90 and 0.99. The results are overall similar and robust.

domestic private banks were squeezed substantially by the Covid-19 pandemic. In contrast, the EU Foreign subsidiaries suffered more distress in PB than in RCB business model during the whole period.

Figure 4 depicts cascade scenarios or spillover effects measured by the probabilities that at least 5% or 10% of banks or bank equity, and at least one or two banks in each business model, become distressed. The CoPCE is its corresponding PCE conditional on some market crashes. Overall, the cascade effects for the 10% scenario were much lower than those of at least 5%, and were almost flat around zero except during the GFC. Because of the value-weighted effect, the CoPCE of at least 5% of bank equity also captured the business event of CTPS around the end of 2018, while the CoPCE of at least 5% of banks showed that the spillover effects were comparatively strong during the GFC, the European debt crisis, the Chinese stock market turbulence and the Covid-19 pandemic.

Turning to their business model components, the spillover effects in RCB were overall the highest measured by the bank equity capital. In contrast, the spillover effects of at least one or two banks yielded more interesting findings. First, the cascade effects in PB were stronger and deeper than in other business models. They declined over time since the GFC, however, still kept rising since the outbreak of COVID-19 pandemic. Second, the Covid-19 pandemic had the strongest spillover effects in CF. In addition, the cascade effects in both RCB and CBALIF were less volatile in the scenario of at least one bank, which might be partially driven by the dynamic efficient allocation of financial resources. Nevertheless, at the level of at least two distressed banks, their CoPCE still significantly captured the contagion effects during the GFC, the European debt crisis and the Covid-19 pandemic. Finally, spillover effects in CTPS were minor, however, they were highly sensitive to their own business events in 2018 and the Covid-19 pandemic.

4.2 Bank capital adequacy

Figure 5A depicts SRISK and its business model components for Luxembourg banks at the prudential ratios k = 8%, 12%, 22% and 33%, respectively. The market crashes are defined as a fixed threshold of 5% quantile of market returns over the whole sample period. Overall, the total SRISK increased starting in 2004, maintained a higher level since the middle of 2005 and declined quickly after it peaked around mid-2008, mainly driven by the EU banking deleveraging process as shown by both leverage ratios in Figure 1. The expected capital shortage kept rising slowly since mid-2016, and improved significantly under the support by the Eurosystem's prompt monetary policy and supervisory actions after the Covid-19 outbreak. It deteriorated again since the mid-2020 because of the increasing challenges created by a weakened economic outlook. Nevertheless, it fell substantially since the Eurosystem started rate hikes to help lower inflation in July 2022.

Figure 5B provided further details on the business model breakdown of SRISK. The contributions from CTPS were trivial. Since 2010, PB played a more important role in RISK than other business models as the expected capital shortage of RCB was apparently under control after the GFC. The SRISK from CF declined over time, in particular, as shown at k = 12% and 22%. In contrast, it is worth noting that the SRISK of

CBALIF increased persistently over time (even more so during the Covid-19 pandemic), and only improved sharply from January 2022 owing to mergers and acquisitions in CBALIF.

As for their domicile components in each business model, the SRISK, in particular, at k = 12%, was mostly driven by the domestic banks in RCB, by the EU Foreign subsidiaries in PB, CF and CTPS, and only by the non-EU foreign subsidiaries in CBALIF.

4.3 Bank solvency

Figure 6A shows four SRIs for bank solvency from Merton's framework and their corresponding CoSRIs, including their business model components. The distress barrier for one single debt obligation is the sum of the short-term debt and half of the long term debt. Overall, the total risk profiles as shown by EL, PD and RP tracked noticeably the GFC, the European debt crisis and the Covid-19 pandemic, peaking during the Covid-19 outbreak at a level only lower than the one during the GFC. However, the SI – which measures the expected number of banks that will become distressed conditional on any one bank having become distressed – was muted during the Covid-19 pandemic. Besides around the GFC, it also peaked at the beginning of 2017 coinciding with the edge-up of stress in sovereign bond markets (e.g., ECB's Financial Stability Review, November 2017). Furthermore, CoSRIs were higher than their corresponding SRIs, except during the period of 2011-2014 and in 2020 immediately after the Covid-19 outbreak, corresponding to the comparatively low asset correlation with the market as shown in Figure 2. The divergence between CoSRIs and their corresponding SRIs starting from 2005 captured the banking vulnerability to potential market crashes even before the GFC.

It is worth noting that risk profiles of business models were still very different. Regarding EL, PD and RP, the solvency risk of RCB stabilized after the GFC and only deteriorated during recent Covid-19 pandemic. The PB business model was substantially hit by the GFC and the European debt crisis, whereas CF also showed some risks noticeably around 2006 and 2015-2017. In contrast, except in the case of banking stability index, the solvency risk of CBALIF and CTPS increased over time and culminated at the onset of the Covid-19 pandemic in early 2020. Risk dependence as measured by SI was mainly dominated by PB and CBALIF, and was muted during the Covid-19 pandemic, except for CF and CTPS.

Figure 6B depicts the domicile breakdown of the bank solvency SRIs for each business model. In contrast to bank capital fragility, solvency risk was mainly driven by EU foreign subsidiaries in CTPS. For both RCB and PB, the domestic banks performed well after the GFC, and since then solvency risk was almost dominated by EU foreign subsidiaries. However, the contribution from both domestic banks and non-EU foreign subsidiaries to the risk dependence is not negligible in PB.

Figure 7 shows the solvency cascade effects measured by the probabilities that at least 5% or 10% of banks or bank assets, and at least one or two banks become distressed, respectively. Overall, the cascade effects declined after the GFC and the European debt crisis. However, under the pressure of an economic environment characterized by the low interest rate environment with low profitability and low growth, the induced risk taking behaviors in the banking industry raised the spillover risk slowly since 2014. The trend was interrupted during the Covid-19 pandemic by the Eurosystem's prompt monetary policy and supervisory actions. Since 2022, the cascade effects fell substantially towards the end of 2023. Because of the value-weighted effect, the PCE in bank assets was much lower than that in the number of banks.

As for their business model components, the spillover effects in RCB bank assets concentrated more or less on the GFC, whereas they were scattered throughout this period for PB. Contagion risk within CTPS was nearly absent. The PCE in CF bank assets also captured risk events around 2006 and 2016, whereas the spillover risk in CBALIF increased markedly since 2010 and peaked during the Covid-19 pandemic. The spillover effects in the number of banks in distress generally conformed to those in bank assets. However, it showed that the spillover risk was much higher in PB and CBALIF than in other business models, and it was non-negligible in CTPS if considering the at least one bank in distress scenario. Furthermore, the overall higher conditional spillover risk around 2015-2017 was mainly driven by the high asset correlation as shown in Figure 2.

As shown in Figures 8A-B, short-term SRIs and their corresponding CoSRIs were on average higher than those considered in the case of a single debt obligation, as the distress barrier includes short-term debts and discounted long-term debts. Nevertheless, their risk profiles look similar to those under the assumption of a single debt obligation. As for the short-term cascade effects depicted in Figure 9, some spillover effects exceeded those under the single debt obligation case. For example, the spillover effects of at least 10% of PB bank assets being in distress were material during the 2014-2022 period. Additionally, from 2018 onwards, spillover risk of at least one or two CF banks being in distress did not abate as much as it did as per Figure 7. Thus, the short-term SRIs cannot be simply substituted by indicators derived from one single debt obligation.

As in Delianedis and Geske (2003), the simulation framework in this study further provides a set of forward or long-term SRIs and their corresponding CoSRIs conditional on not defaulting on the short-term debt. In general, as shown in Figures 10A-B, the long-term SRIs were substantially different from the short-term SRIs. The forward solvency risk indicators were dominated by RCB, PB and CF with less contribution from RCB on average, still mirroring the main market crises in a timely way. However, their risk profiles were somehow different from, and much lower than, those of the short-term. The forward risk dominated by PB and CF increased over time since 2014 and peaked around the beginning of 2022. The risk contribution from RCB was somewhat stable over time. It is also worth pointing out that the weighted PDs of CBALIF jumped up during the Covid-19 pandemic, while the forward risk of CTPS was around zero over the whole sample period. In contrast to the short-term solvency risk indicators, the forward risk contribution from domestic private banks was negligible throughout this period.

Finally, as shown in Figure 11, the overall cascade effects of at least 5% of banks (or bank assets) being in distress were substantially lower than those under the short-term case. However, they remained elevated from 2014 until the beginning of 2022. In the case of banks assets, spillover risk peaked around 2008-2012 for RCB, 2016-2022 for PB, and 2005-2007 for CF respectively. As for the cascade effects measured by at least one bank being in distress, spillover risk in both RCB and PB did not abate significantly after the European debt crisis. Additionally, it increased dramatically in CF since 2014 as it did in the case of at least two banks being in distress.

5. Economic variables and forward-looking systemic risk measures

In an effort to better understand the systemic risk measures of Luxembourg banks discussed in this paper, both SRIs and CoSRIs are regressed on various macroeconomic variables as follows:

$$SRI_t = c + \alpha_j SRI_{t-1} + \sum_{n=1}^{N} \gamma_{j,k} Macrofactors_{n,t-1} + \varepsilon_{j,t}. \tag{9}$$

There is no recognized theory to identify the determinants of these systemic risk measures. The macroeconomic variables include several euro area variables, which are reasonable metrics of the state of the Luxembourg economy, as well as measures of market uncertainty and liquidity risk. More precisely, the set of explanatory variables considered in this paper contains:

- Short-term interest rates: Euro generic government bond 3-month yield
- Interest rate spreads: Euro generic government bond 10-year yield minus Euro generic government bond 3-month yield
- Liquidity spreads: 3M Euribor rates - 3M Germany T-bill rates[18]
- Business climate indicator: European Commission euro area business climate indicator
- Consumer confidence sentiment: European Commission euro area consumer confidence indicator
- Log VSTOXX volatility index
- One-year log returns of OECD stock market price index

All macroeconomic variables are sourced from Bloomberg, Eurostat, OECD and ECB. In order to compare the explanatory power of these macroeconomic variables for the systemic risk indicators, all systemic risk indicators and macroeconomic control variables are standardized by their respective means and standard deviations.

For the sake of brevity, as reported in Table 1, this paper only shows the results in percentage of the relevant representative indicators: weighted PDs and CoPDs for bank capital fragility and bank solvency, and SRISK with k=0.12 for bank capital adequacy. Regressions are run with Newey-West robust standard errors using

[18] This spread represents the European equivalent of the TED spread, which is the difference between the interest rates on interbank loans and on short-term government debt (“T-bills”). Market participants look at this difference as a proxy for short-term liquidity risk. Clearly, it cannot be excluded that the proxy also captures some credit risk, and one could even argue an implicit government guarantee. However, the correlation between this measure and other proxies for liquidity also used in the literature, such as Euribor-OIS 3M spread, is almost 94%.

a Bartlett kernel. The discussion focuses on the distribution of these macroeconomic variables in explanation of the characteristics of these selected systemic risk indicators.

Considering overall systemic risk, liquidity and business climate were the key macroeconomic determinants of the expected capital shortage. Business climate might reveal the procyclicality of leverage in the expected capital shortage by encouraging risk taking or triggering sharp pull-backs. The negative sign of liquidity spread reflected the following-up deleveraging effects on the expected capital shortage, especially after it peaked around mid-2008.

As for bank capital fragility, the weighted PDs were driven significantly by both short-term interest rates and liquidity spreads. It suggests that under high short-term interest rates and liquidity spreads, bank capital fragility would deteriorate in the next period. However, when a single debt obligation is considered as in the bank solvency indicator, business climate and consumer confidence sentiment became the key macroeconomic determinants. It is worth noticing that the maturity structure of debt obligations enables these systemic risk indicators to identify more significant macroeconomic variables than in the single debt obligation instance. Besides consumer confidence sentiment and business climate, liquidity spreads were also statistically significant for both short-term and long-term PDs. In general, high liquidity spreads and poor business climate accompanied with high consumer sentiment predicted high bank solvency risk in the following month. In addition, the macroeconomic determinants of CoPDs were similar as those of PDs. However, CoPDs also captured market returns or volatilities significantly as they are constructed conditioning on market crashes.

Turning to their business model components, the key macroeconomic determinants also varied across these business models. There were more significant macroeconomic variables in CF and CTPS for bank capital adequacy than in other business models. Conversely, for bank capital fragility, the regressions for the PB and CF business models yielded more statistically significant macroeconomic variables than for other business models. As for bank solvency in the case of a single debt obligation, the regressions for CBALIF picked up more significant determinants. In addition, monetary policy affected banking vulnerabilities differently across the business models as well. High short-term interest rates predicted an improvement in bank capital adequacy and short-term bank solvency in CTPS, long-term bank solvency in CF and CBALIF, however, a deterioration in bank capital fragility in PB and CF, and long-term bank solvency in CTPs in the following month.

Overall, these macroeconomic variables captured different characteristics of these banking vulnerabilities, and the key macroeconomic determinants also varied across the business models. The predictive regressions suggest that the key macroeconomic determinants of these systemic risk indicators include interest rates, liquidity flow, consumer confidence and business climate in the EA.

6. Explanatory power of systemic risk for future growth in nominal GDP

This section further investigates the predictive power of these systemic risk indicators for future growth in nominal GDP. As in Allen et al. (2012), this study estimates the following n-month-ahead multivariate predictive regression of the SRIs and CoSRIs on the annual growth rate of Luxembourg's nominal GDP after controlling for a set of macroeconomic and financial variables as well as one-month to twelve-month lags of the nominal GDP growth:

$$GDP_{GrowthRate_{t+n}} = \alpha + \beta SRI_t + \sum_{n=1}^{N} \gamma_n Macrofactors_{n,t} + \sum_{i=1}^{12} \lambda_i GDP_{GrowthRate_{t-i+1}} + \varepsilon_{j,t}, \qquad (10)$$

where SRI_t denotes a systemic risk indicator.[19] A monthly rate of GDP growth is generated by a linear interpolation of seasonally adjusted quarterly nominal GDP data assuming a constant month-to-month GDP growth rate within each quarter. The EA macroeconomic control variables include short-term interest rates, interest rate spreads, business climate indicator, and consumer confidence sentiment. As this study focuses on the impact of the systemic risk measures on Luxembourg's nominal GDP growth directly, liquidity spreads, market return and its volatility are not considered among the macroeconomic control variables.[20]

In order to compare the impacts on nominal GDP growth across these systemic risk indicators, all systemic risk indicators and macroeconomic control variables are standardized by their respective means and standard deviations. This study only considers a few relevant indicators for GDP growth rate (i.e., ES Euro and CoES Euro for bank capital fragility, EL and CoEL for bank solvency, and SRISK with the prudential capital fraction k=0.12 for bank capital adequacy[21]). Regressions are run with Newey-West robust standard errors using a Bartlett kernel in the period of 2003Q3 - 2023Q3. The estimated coefficients for these systemic risk indicators are shown in Figure 12.

For all banks, after controlling for four important macroeconomic variables, the bank capital fragility indicators for all banks contributed significantly to explain nominal GDP growth in the latter months of the following year. The negative sign was significant for all business models except CBALIF. In contrast, the coefficients on SRISK for k=0.12 were significantly positive only in CF up to 12 months in advance. This suggests that the bank capital adequacy indicators capture different aspects of banking vulnerabilities from

[19] The correlation among the systemic risk indicators of business models is still mild for each type of banking vulnerability measure. However, in order to interpret these coefficients precisely across business models and three types of banking vulnerabilities, the predictive regression does not include all systemic risk indicators of business models simultaneously. Nevertheless, for a robust test, all systemic risk indicators of business models are included in the predictive regression, the results are roughly consistent with the findings in the paper.
[20] For a robustness test, the log of VSTOXX volatility index is included in the macroeconomic control variables, the results are overall still consistent in ranking. This paper does not consider the market return as a control variable as it is a fundamental market factor and moderately correlated with the interpolated monthly nominal GDP growth in Luxembourg (the correlation coefficient is around 60% for the period from 2003Q2 to 2023Q3).
[21] The profile of SRISK is greatly affected by the selected the prudential capital fraction k. At k=0.08, its business model components, as shown in Figure 5B, showed up only in certain periods or were trivial throughout the whole period. However, the expected capital shortage at a higher k might not be realistic for forecasting the GDP growth.

the bank capital fragility, which does not capture the leverage effect directly. As shown in Figure 5B, the SRISK of RCB for k=0.12 was mostly dominated by domestic banks, and declined quickly after it peaked around mid-2008, and the SRISK profile of CF actually followed the banking deleveraging process closely. The positive coefficients in CF might reflect the search-for-yield behavior in the low-interest rate environment which might push up the GDP growth at the cost of the buildup of its expected capital shortage under potential market crises.

As for the bank solvency measured by a single debt maturity, solvency risk indicators for all banks were negative, however, not significant. The coefficients on EL in both RCB and PB were significantly negative some months in advance, whereas those in CTPS were significantly positive after 3 months in the following year. The predictive power of the short-term bank solvency indicators was slightly stronger than those in the bank solvency with a single debt obligation. The solvency risk indicators for all banks were significantly negative only in the latter months of the following year. However, regarding the long-term bank solvency, EL for all banks were actually positively significant up to 3 months in advance. Only the coefficients in RCB were significantly negative up to 8 months in the future, whereas those in CF, CBALIF and CTPS were all positively significant some months in advance. In general, the positive impacts of long-term bank solvency indicators on nominal GDP growth might reveal the effective adaptation of bank business models by lengthening debt maturity to search for yield and enhance fee and commission based activities.

Overall, the systemic risk indicators as well as their bank business model components for bank fragility predicted nominal GDP growth in the following year. This is consistent with the findings in Baron, Verner, and Xiong (2021) that large declines in bank equity returns are associated with an increased likelihood of future economic downturns. Considering all banks, the short-term bank solvency indicators anticipated nominal GDP growth some months in advance, whereas the bank capital adequacy measure did not have a robust, significant explanatory power. In addition, for both bank fragility and bank solvency, the systemic risk measures driven by PB and RCB would offer an early warning to alert regulars to the risk of slower growth in nominal GDP.[22] In contrast, as it was reflected in the debt structure or debt rollover for capital adequacy and bank solvency, CF driven by the search-for-yield behavior, and CBALIF and CTPS driven by fee & commission generating activities typically in the low-interest rate environment predicted nominal GDP growth.[23] It is worth highlighting the potential financial stability implications of an increased focus on the search-for-yield behavior, the refinancing of debt and fee & commission generating activities (e.g., ECB's Financial Stability Review, November 2016 − Special features and November 2020).

7. Survivor bias and risk assessment

[22] The expected capital shortfall for RCB and PB with other prudential capital fractions significantly predicted a decline in nominal GDP growth for some months in the following year.

[23] For a robustness test, the predictive regression is also explored during the period from 2003Q2 to 2019Q4 before the Covid-19 outbreak, the results are roughly consistent with the findings in the paper.

These 82 banks, for which business model information is available, include almost all banks (excluding branches) in Luxemburg since 2019. However, their systemic risk measures might not track well the evolution of vulnerabilities in the Luxembourg banking sector in the past. This section further explores the same three aspects of Luxembourg banking vulnerabilities based on all 133 banks as shown in Appendix Figures 1-5.

Overall, the risk profiles based on the 133 banks were similar to those based on the 82 banks. However, the level of non-value-weighted SRIs or CoSRIs of all banks were comparatively higher during the GFC and the European sovereign debt crisis. The overall systemic risk measures, in particular the CoSRIs, also captured extra risk around the European debt crisis and the built-up of bank vulnerability even before the GFC. Regarding cascade effects, the PCE and CoPCE of all banks captured more vulnerable banks, which did not operate afterward. Nevertheless, the systemic risk measures based on 82 banks are still capable to identify well these three aspects of Luxembourg banking vulnerabilities in view of business models.

8. Conclusions and macro-prudential policy implications

This paper proposes a forward-looking bank-level stress testing framework to identify three aspects of potential banking vulnerabilities – bank capital fragility, bank capital adequacy and bank solvency. The suggested systemic risk indicators reflected the main market crashes (e.g., the GFC, the European debt crisis and the recent Covid-19 pandemic). However, the contribution to systemic risk varied across business models. These systemic risk indicators were found to be closely associated with developments in interest rates, liquidity flow, consumer confidence and business climate in the EA. Regression results also provided evidence that the systemic risk indicators could explain nominal GDP growth one year ahead. However, the systemic risk component associated with search-for-yield behavior and fee & commission generating activities also appeared to be able explain nominal GDP growth. These findings suggest that such business models could raise financial stability issues in the long run.

The framework proposed in this paper provides a possible addition to the financial stability toolkit for assessing risks in a large-scale banking system. In addition, this study provides the basis for a monitoring toolkit that can track changes in systemic risk in the banking sector as a whole, with a view to identify the build-up of vulnerabilities. Given that this paper's approach explicitly links the systemic risk measures with the state of the economy, it can help to facilitate a more informed assessment of the appropriate policy response to rising stress in the banking sector with regard to specific business models.

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Figure 1: Bank Data Descriptions

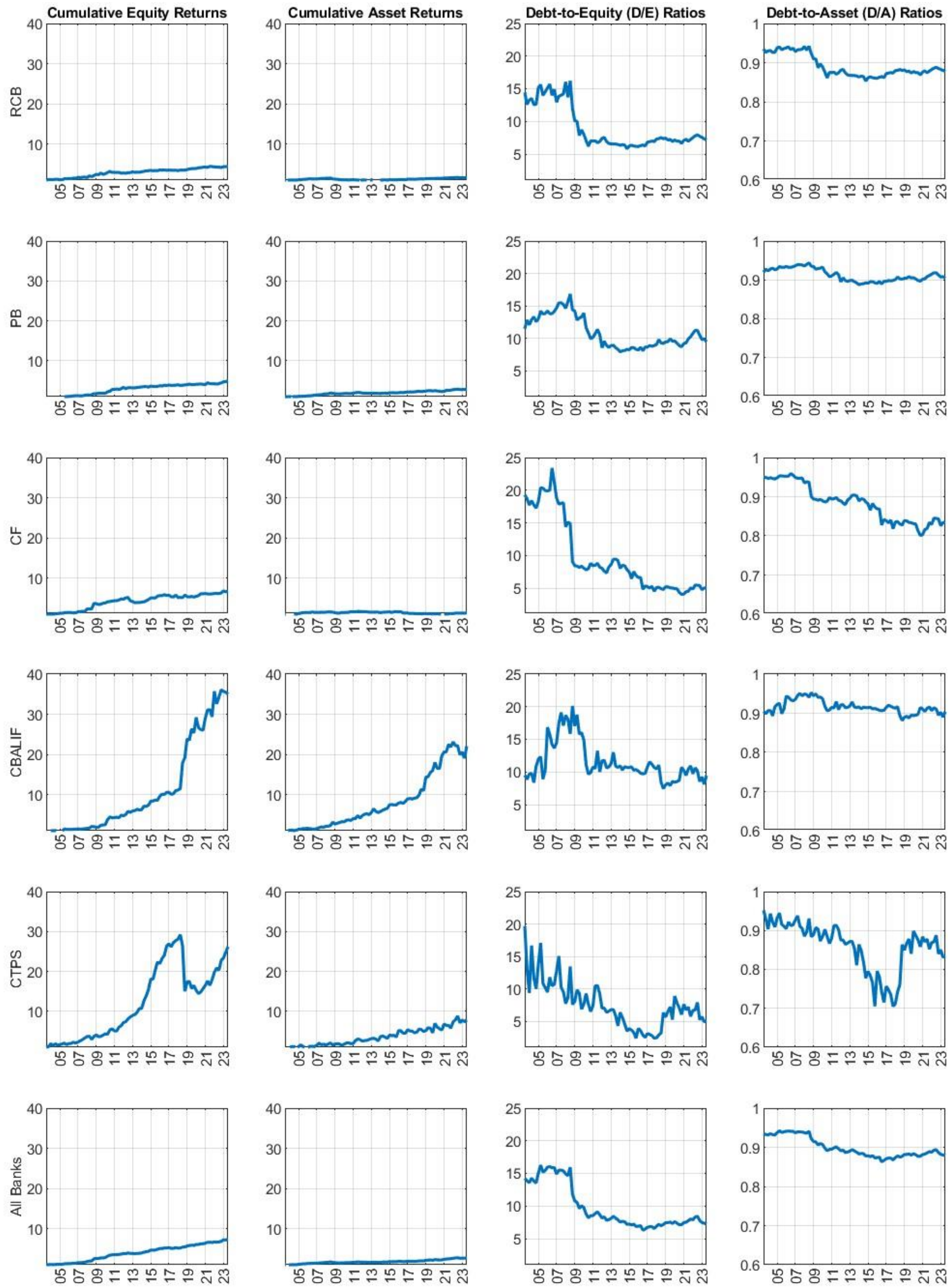


Figure 2: Correlations and Volatilities - EWMA Statistics at λ = 0.92

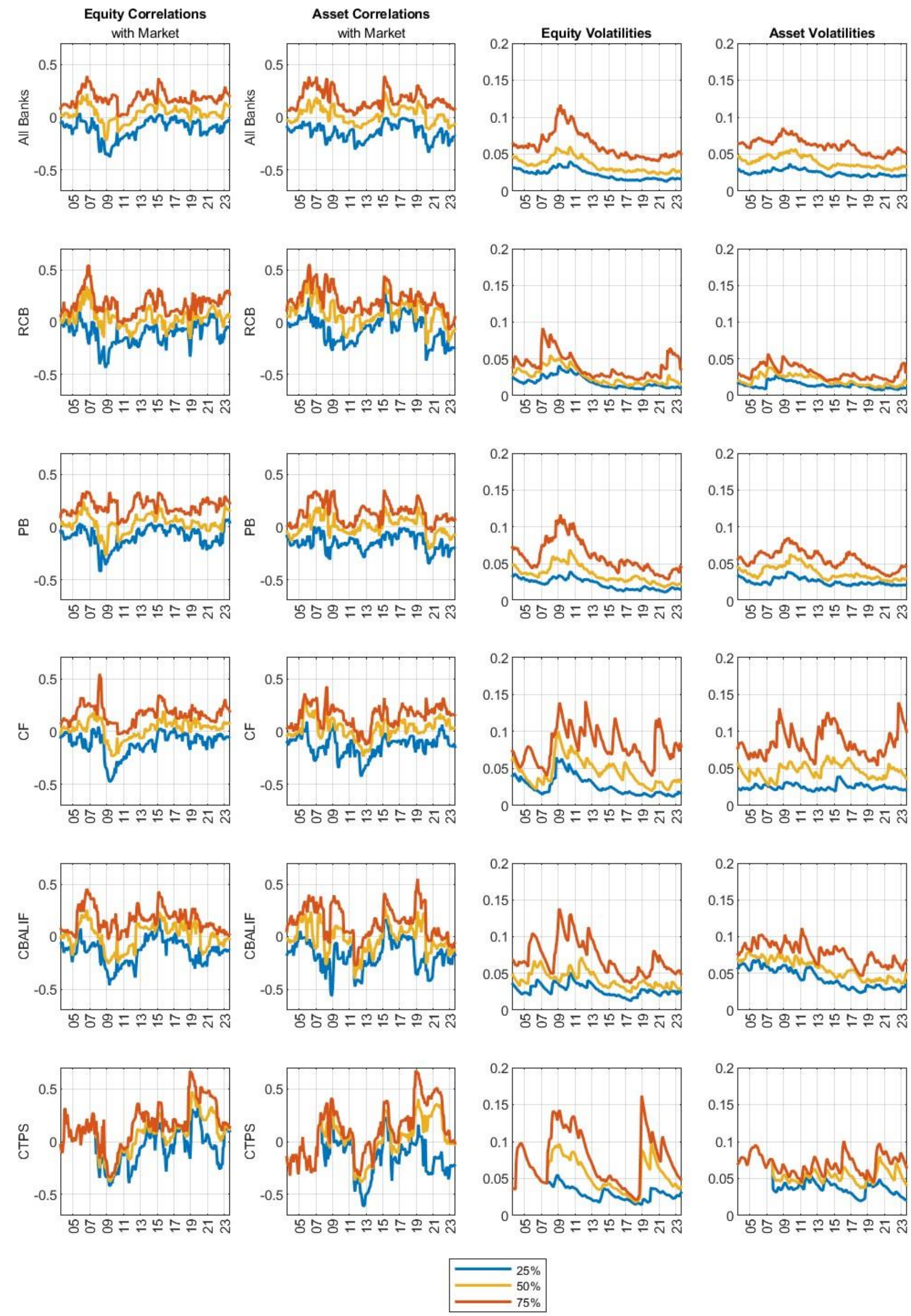


Figure 3A: ***Bank Capital Fragility*** **- Systemic Risk Indicators**

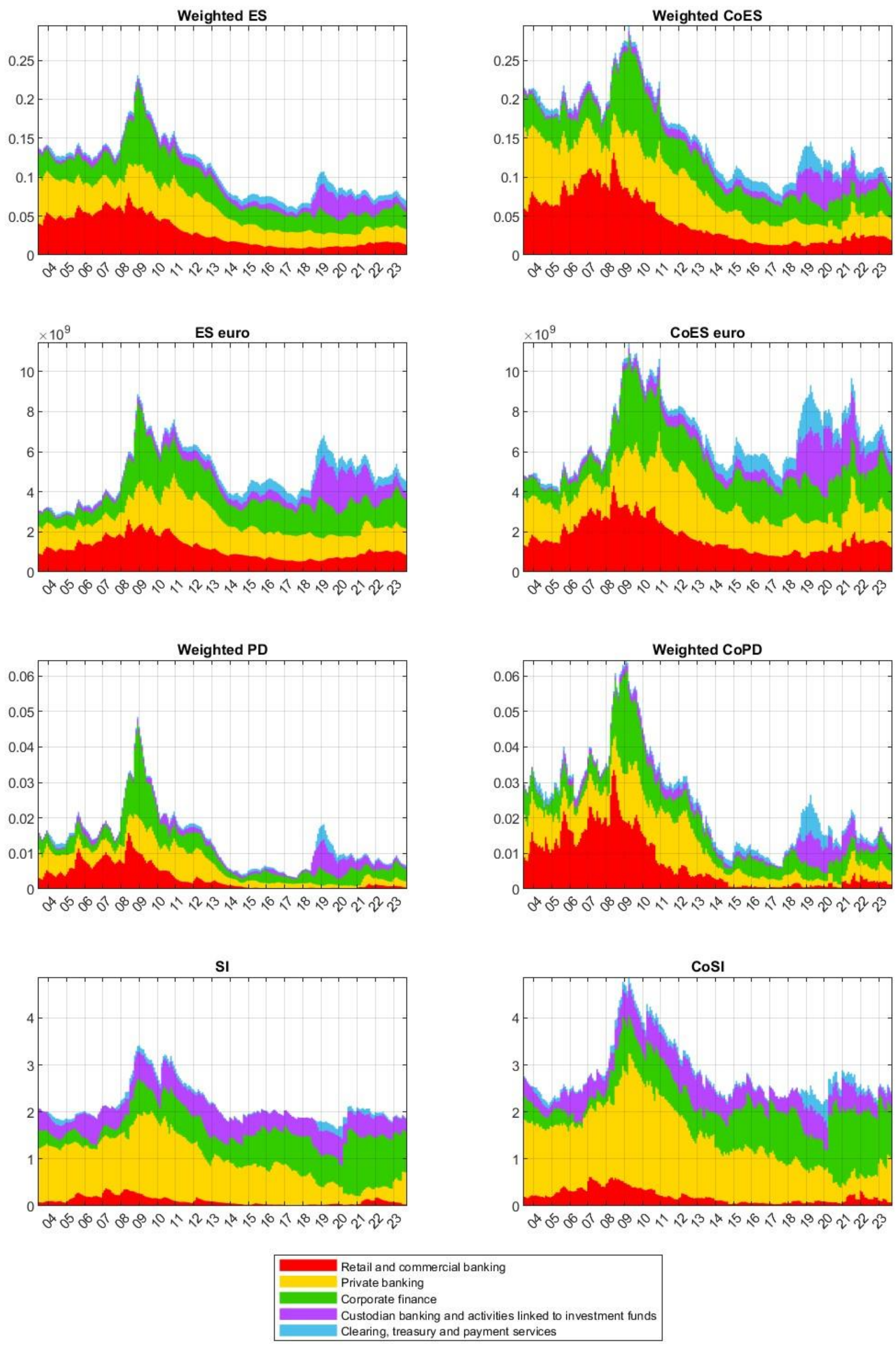


Figure 3B: ***Bank Capital Fragility*** **- Systemic Risk Indicators**

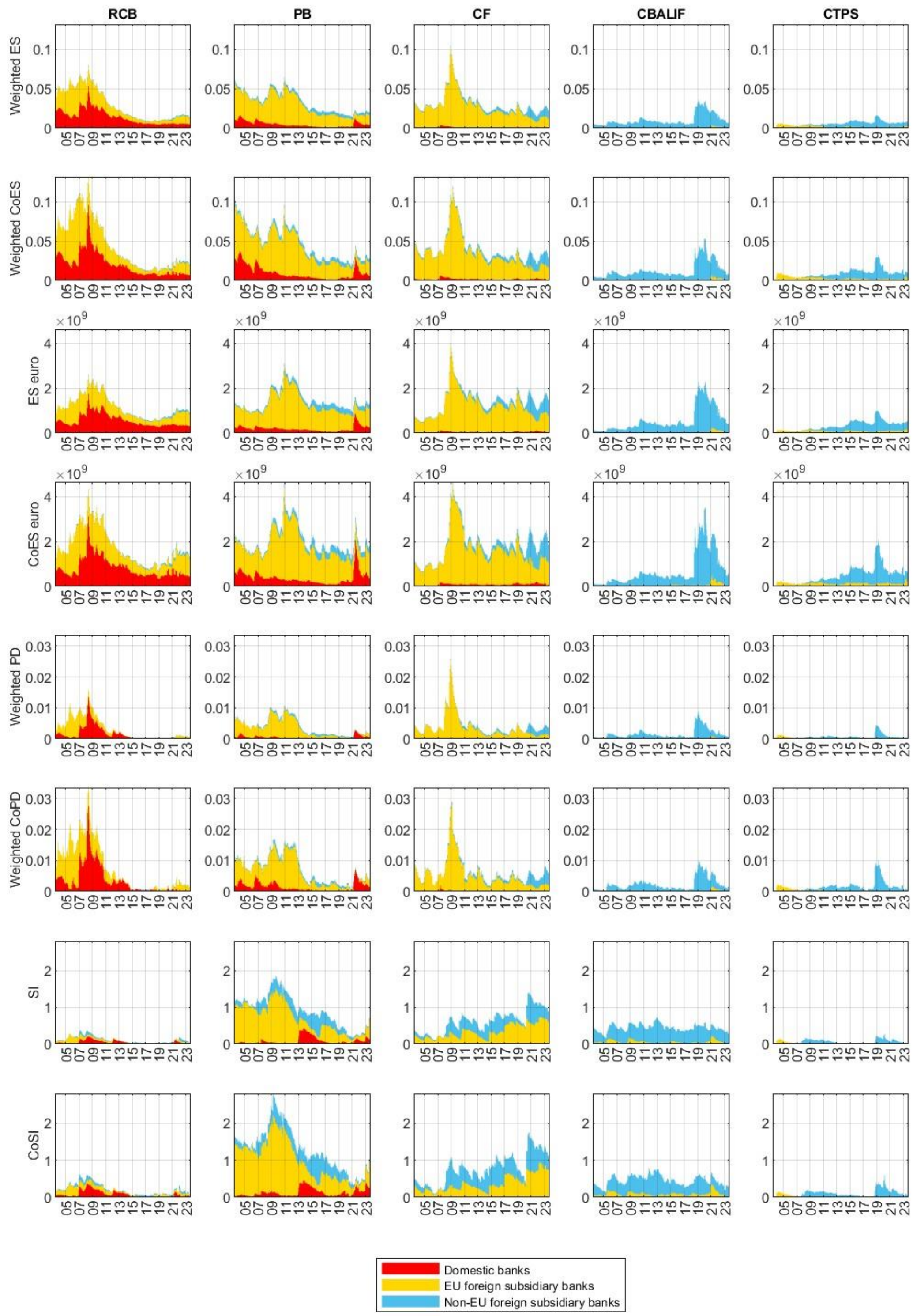


Figure 4: Bank Capital Fragility - Probability of Cascade Effects

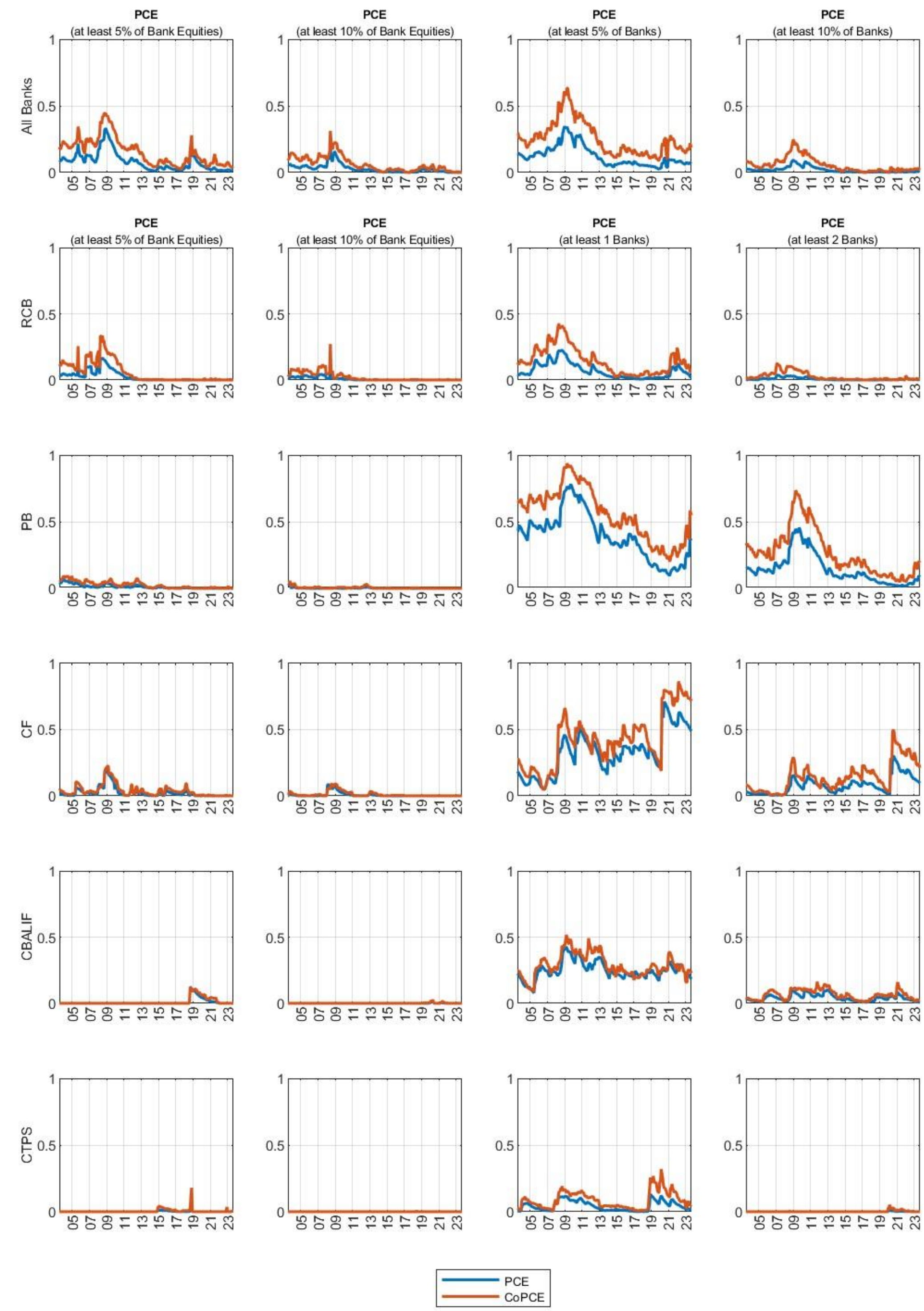


Figure 5A: Bank Capital Adequacy - Conditional Expected Capital Shortage (SRISK)

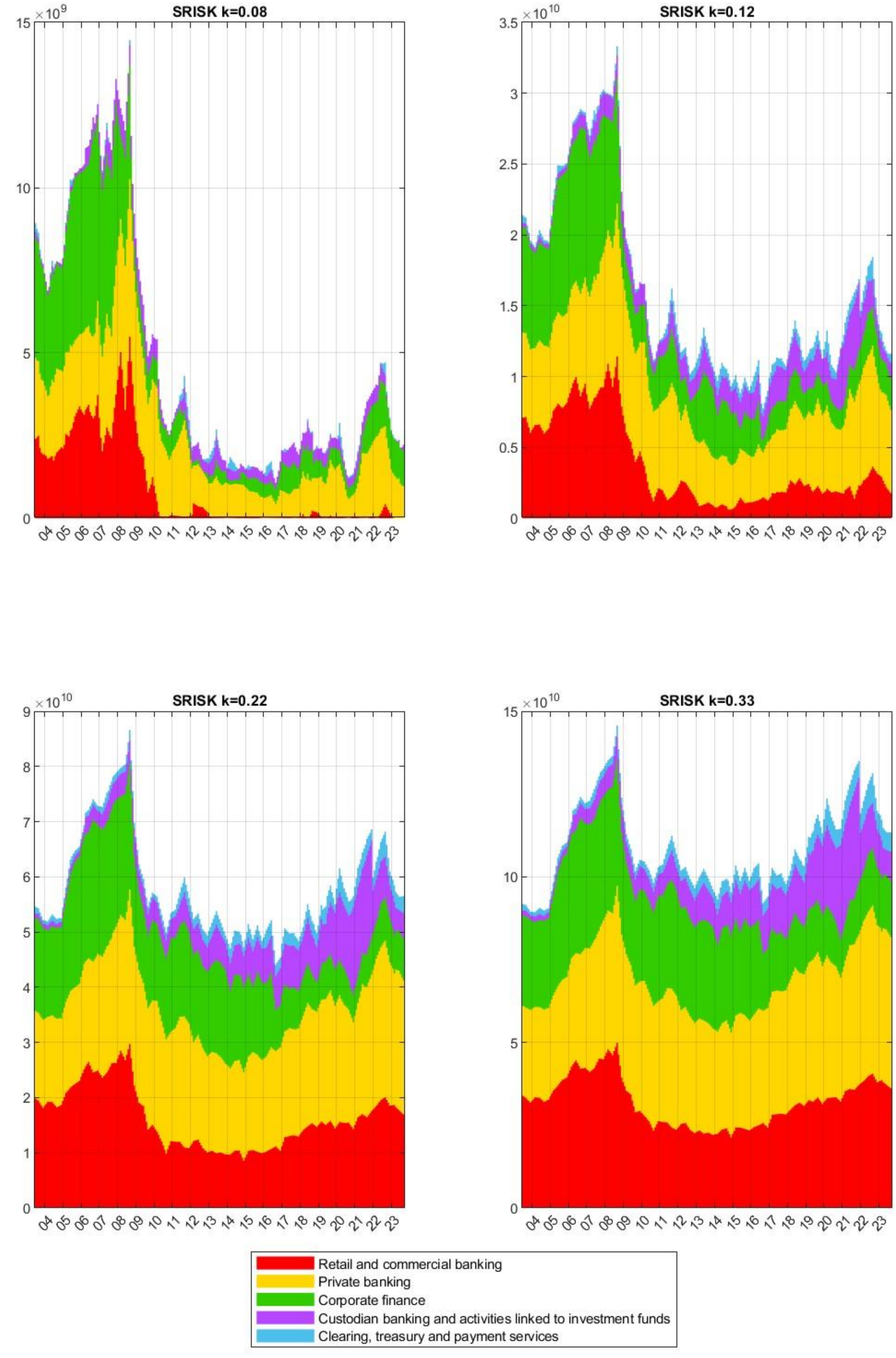


Figure 5B: Bank Capital Adequacy - Conditional Expected Capital Shortage (SRISK)

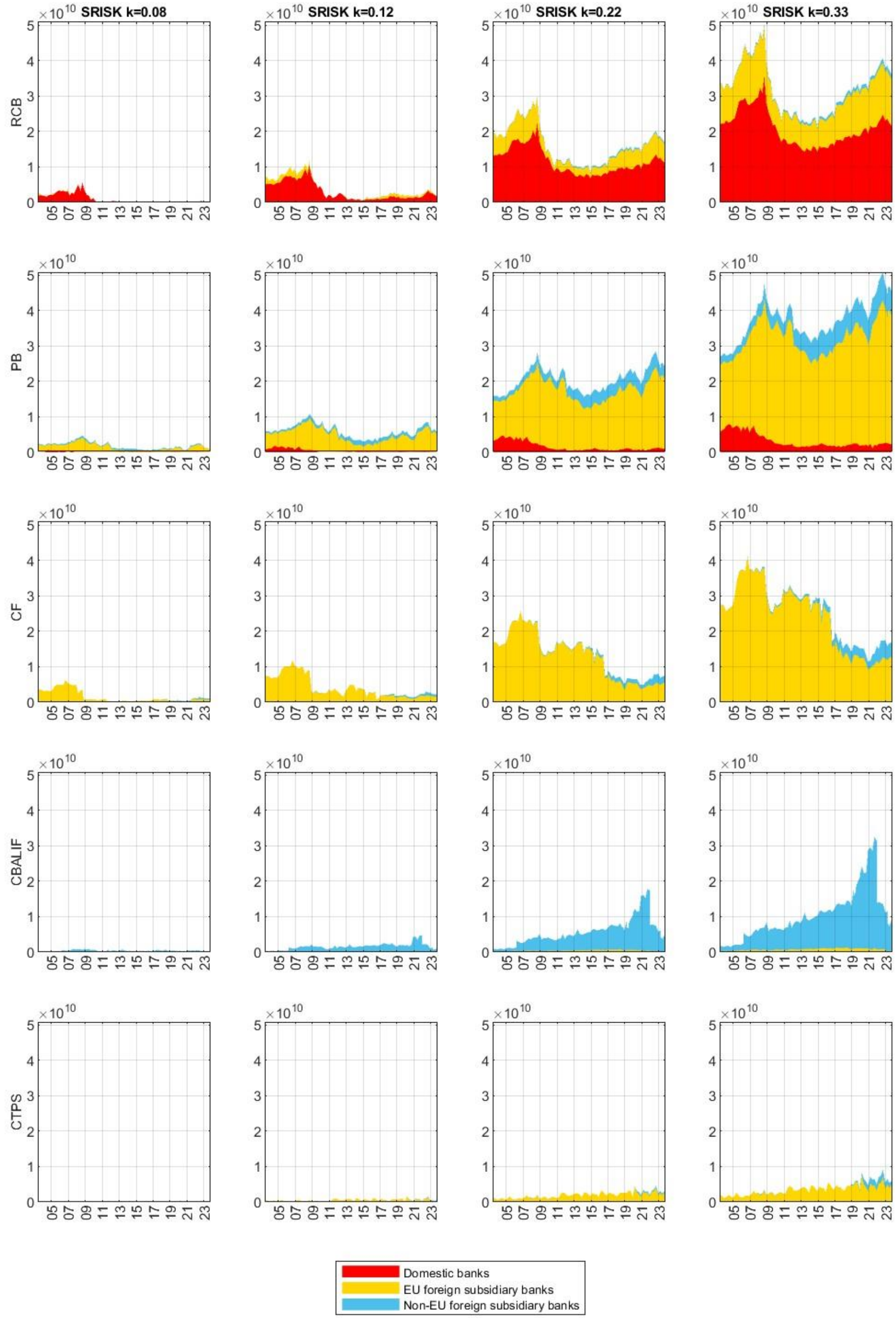


Figure 6A: Bank Solvency - Systemic Risk Indicators

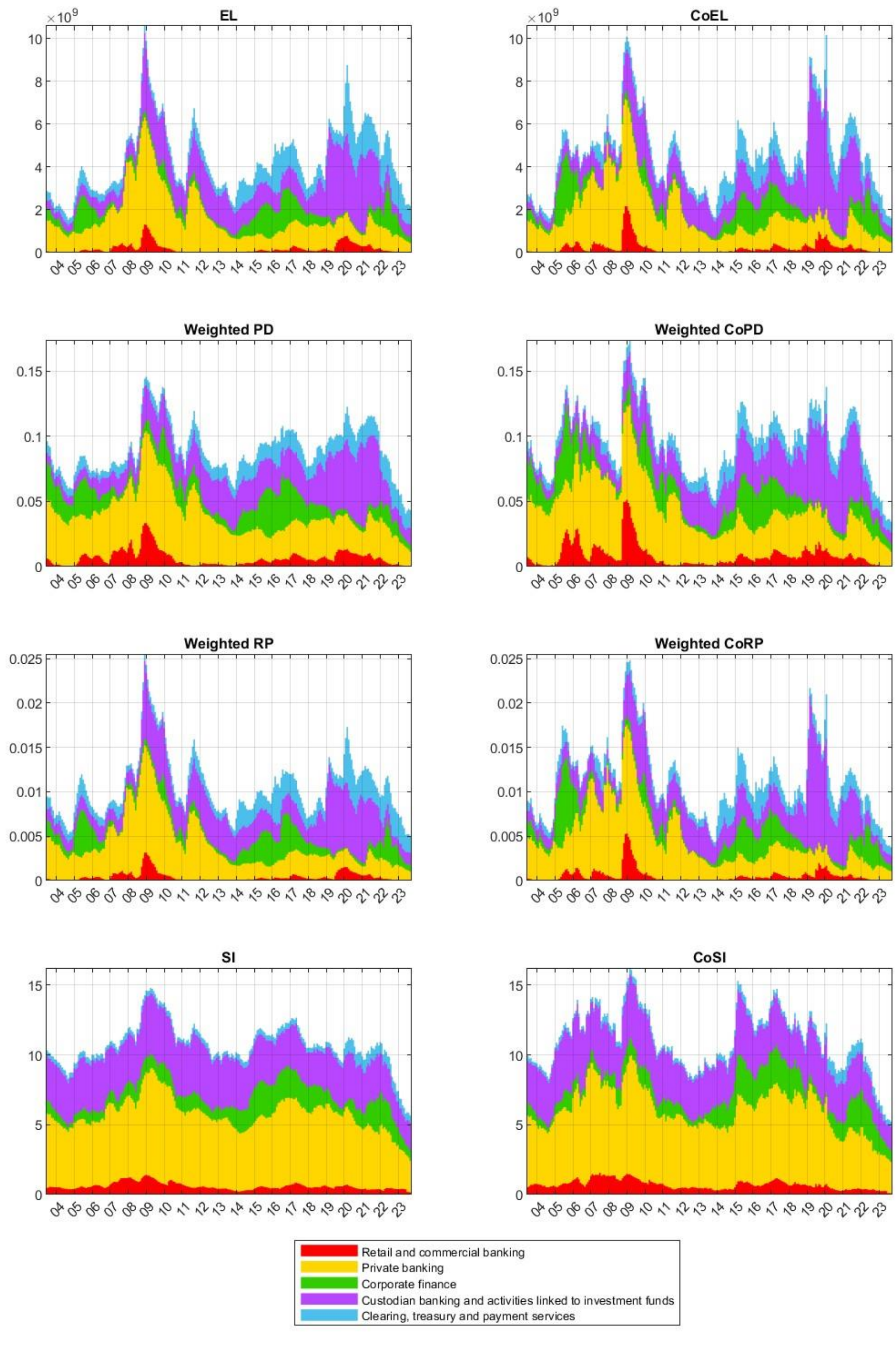


Figure 6B: Bank Solvency - Systemic Risk Indicators

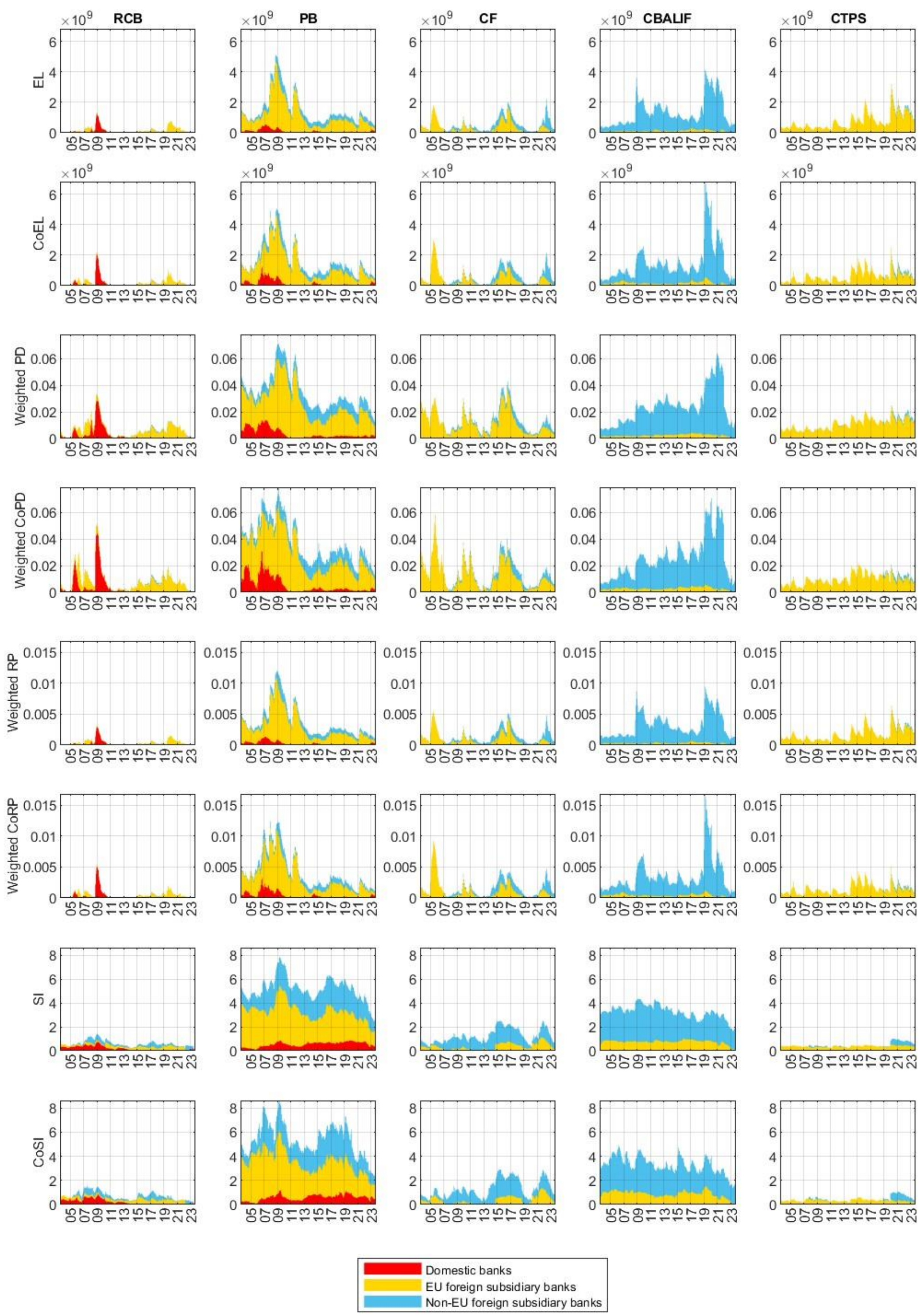


Figure 7: Bank Solvency - Probability of Cascade Effects

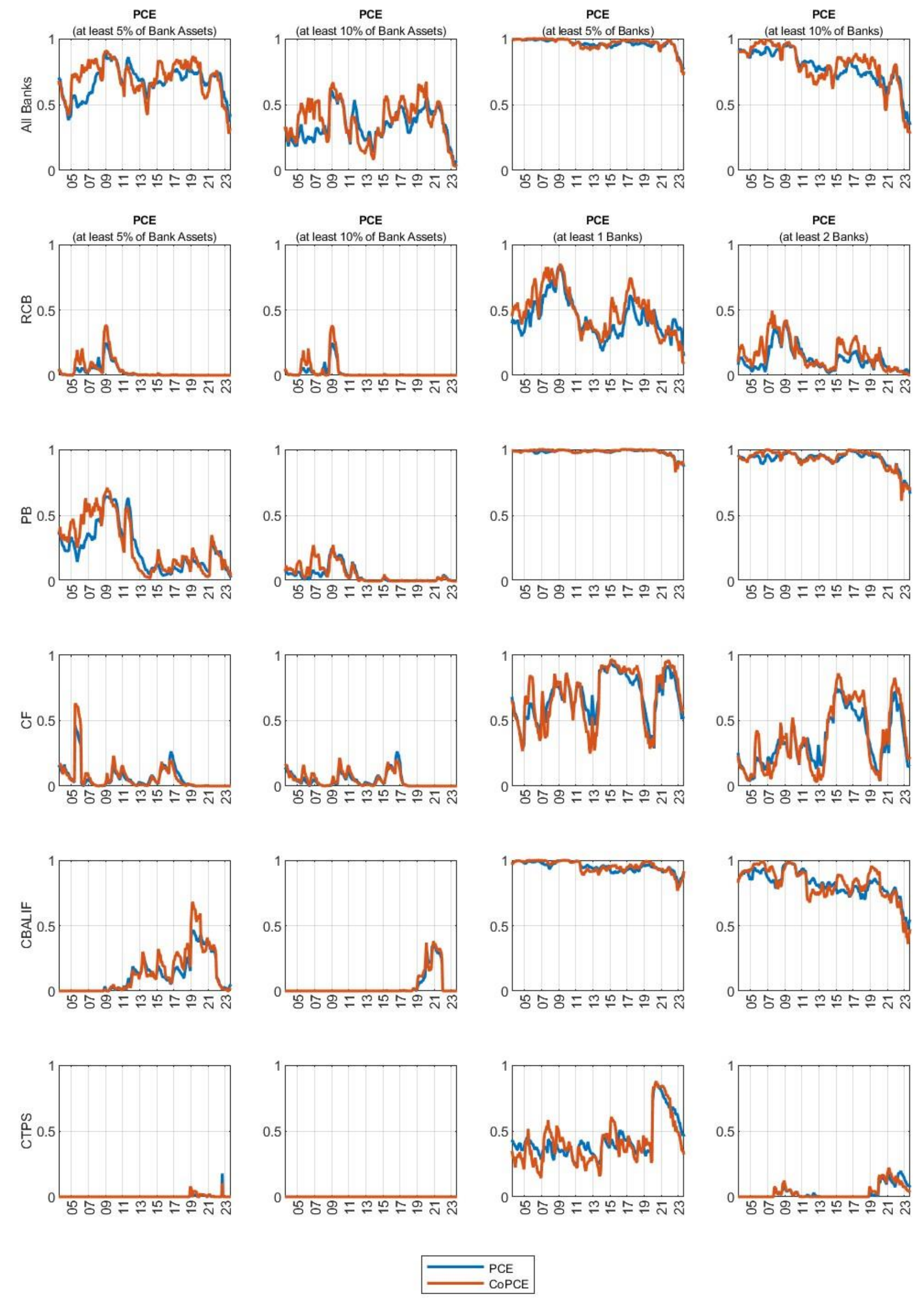


Figure 8A: ***Bank Solvency Maturity Structure*** **- Short-term Systemic Risk Indicators**

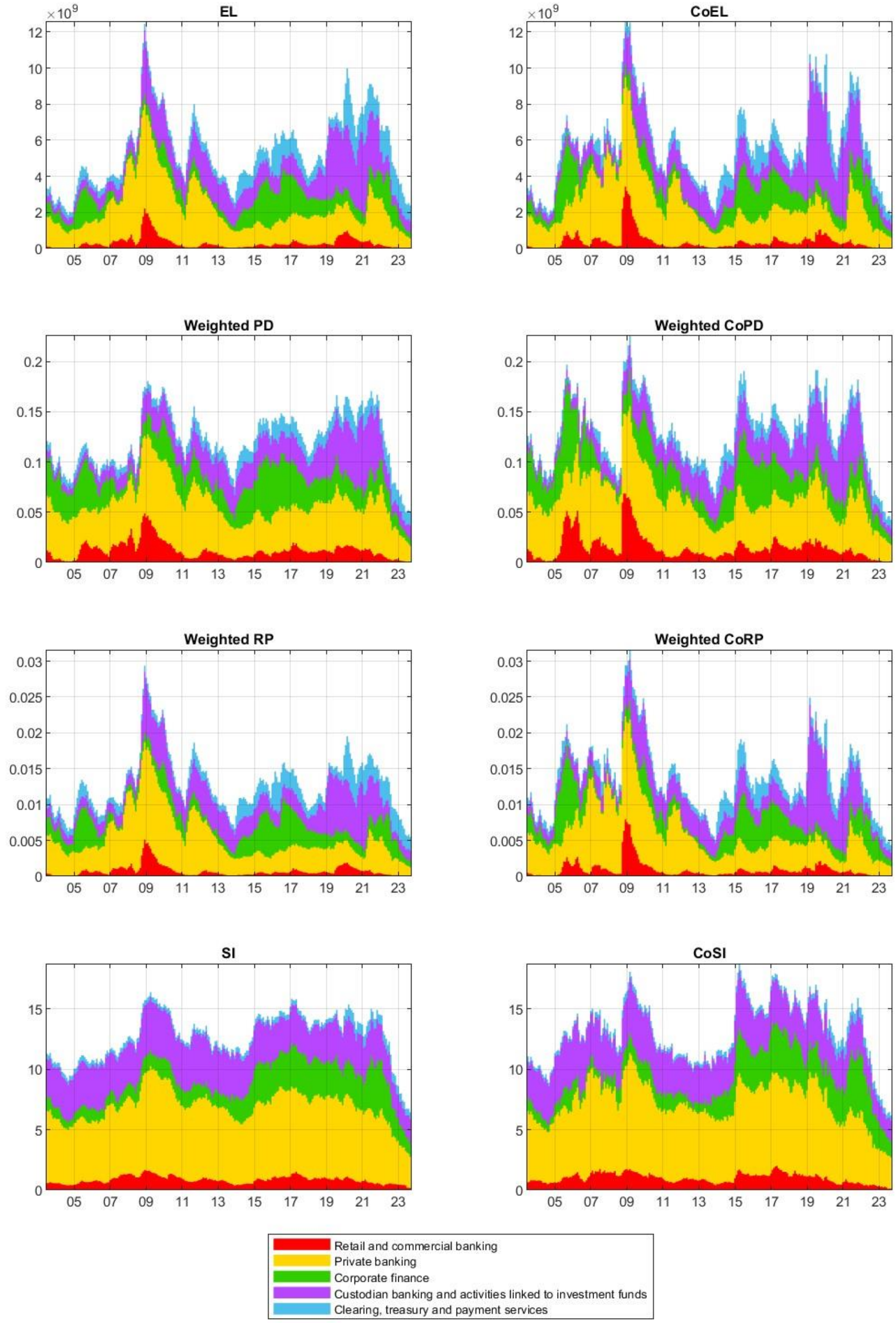


Figure 8B: ***Bank Solvency Maturity Structure*** **- Short-term Systemic Risk Indicators**

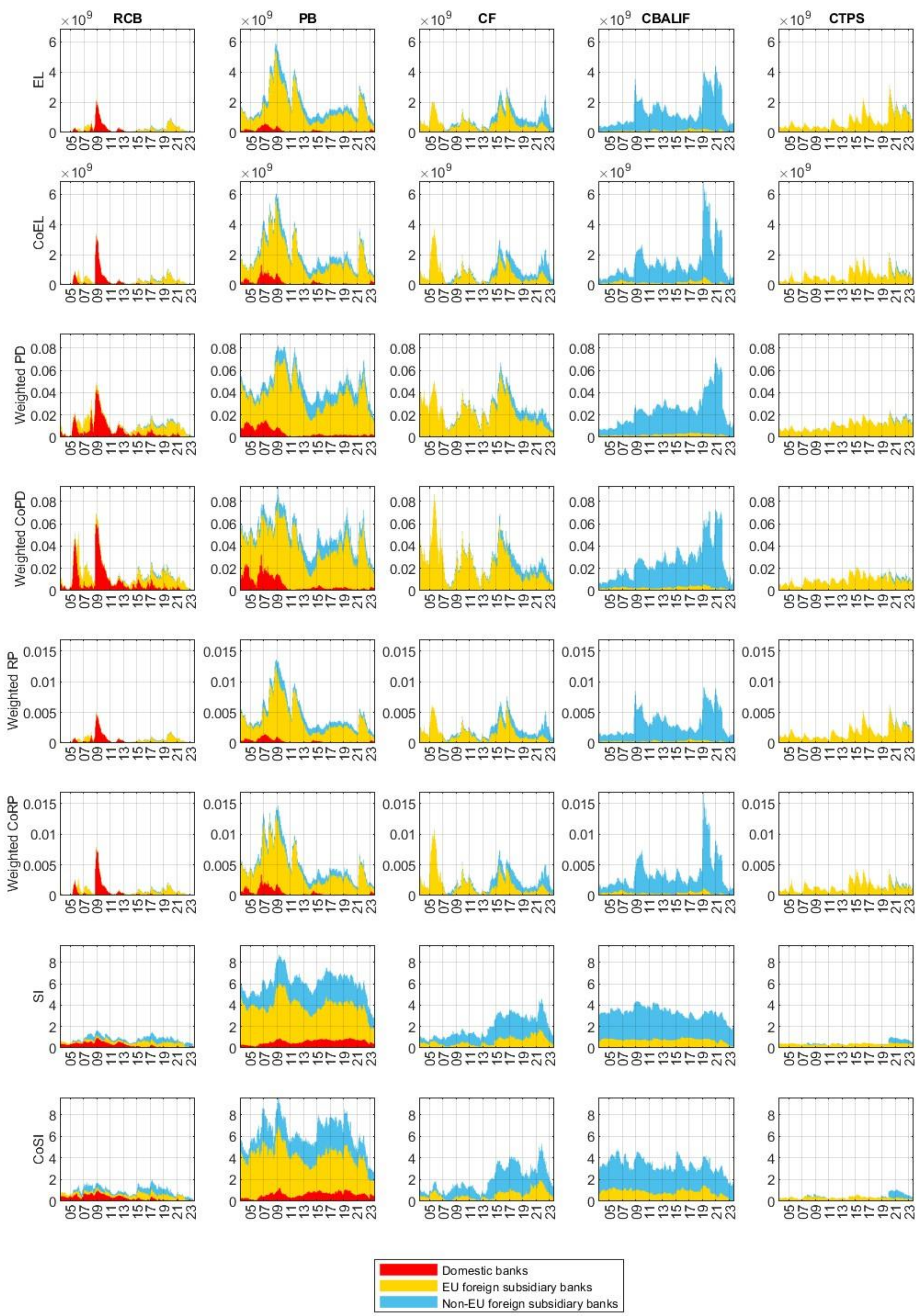


Figure 9: ***Bank Solvency Maturity Structure*** **- Short-term Probability of Cascade Effects**

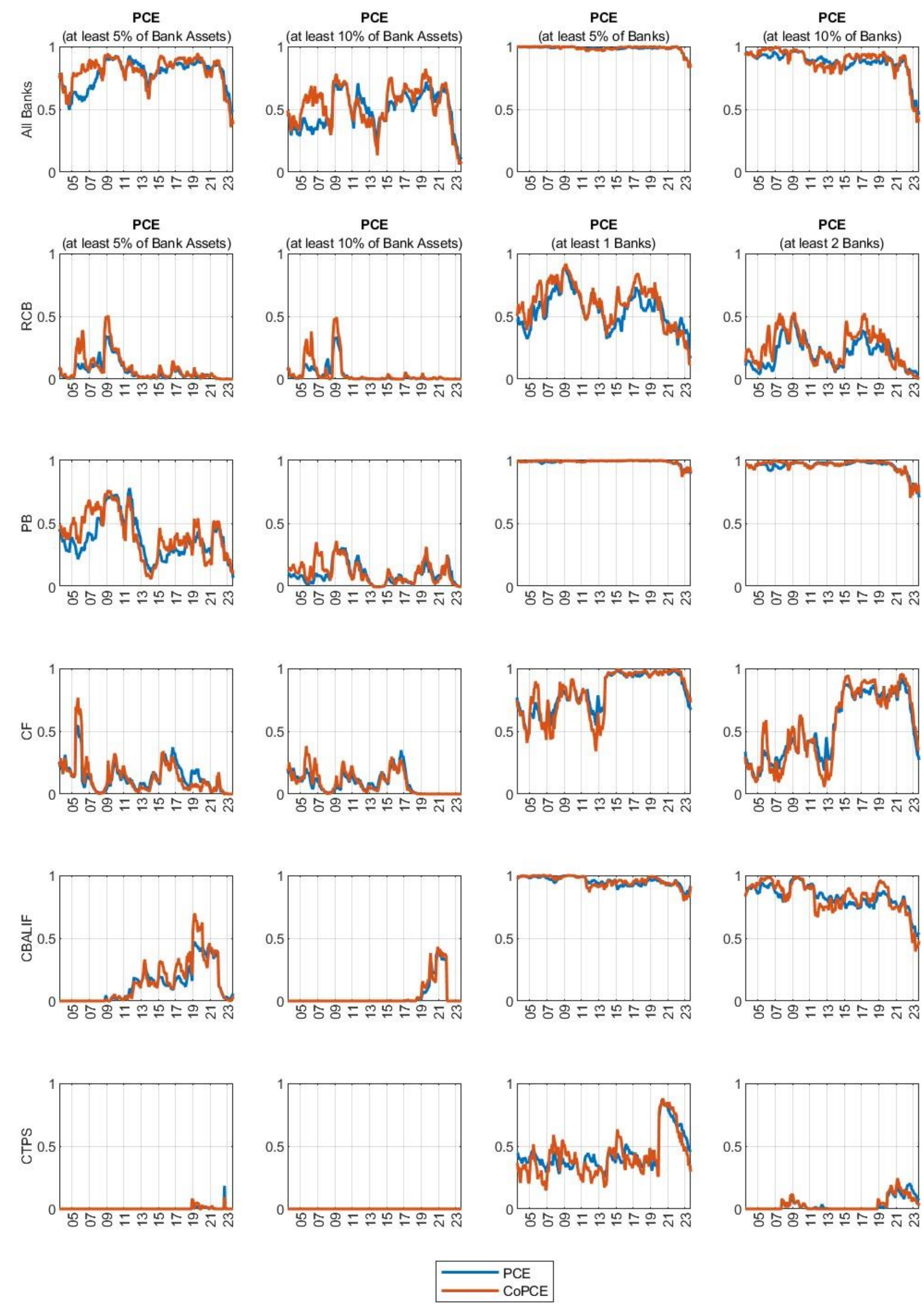


Figure 10A: ***Bank Solvency Maturity Structure*** **- Long-term Systemic Risk Indicators**

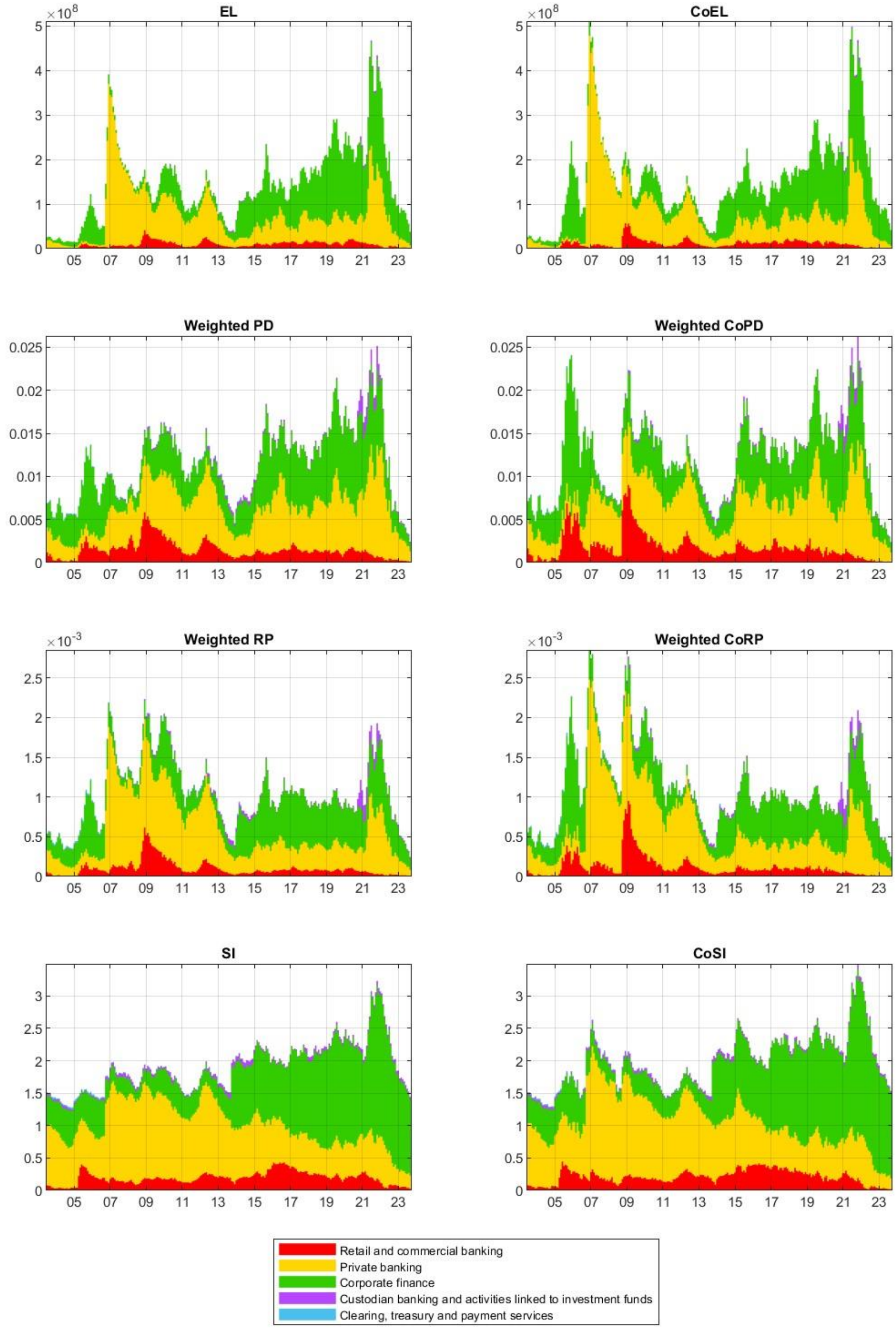


Figure 10B: ***Bank Solvency Maturity Structure*** **- Long-term Systemic Risk Indicators**

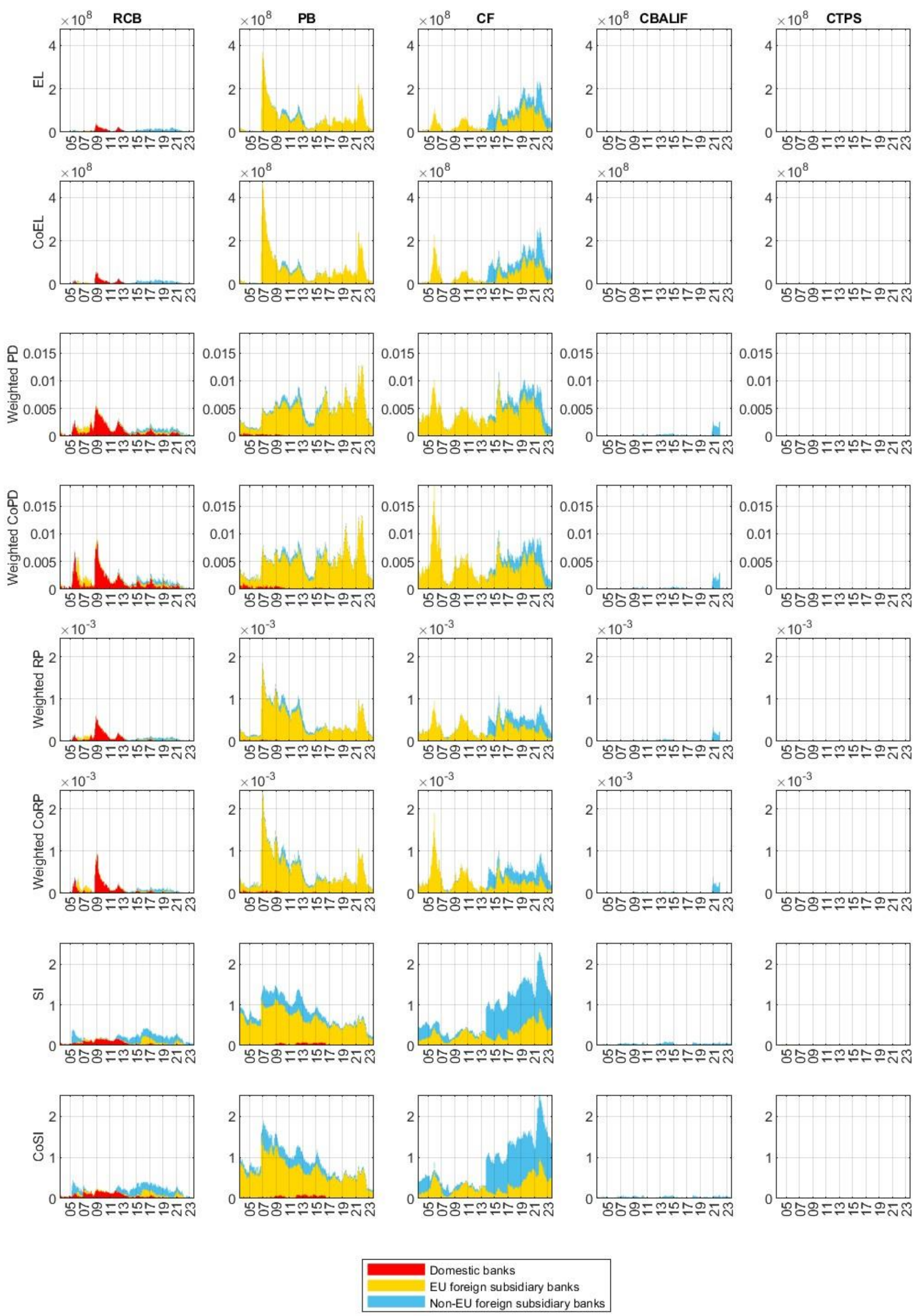


Figure 11: Bank Solvency Maturity Structure - Long-term Probability of Cascade Effects

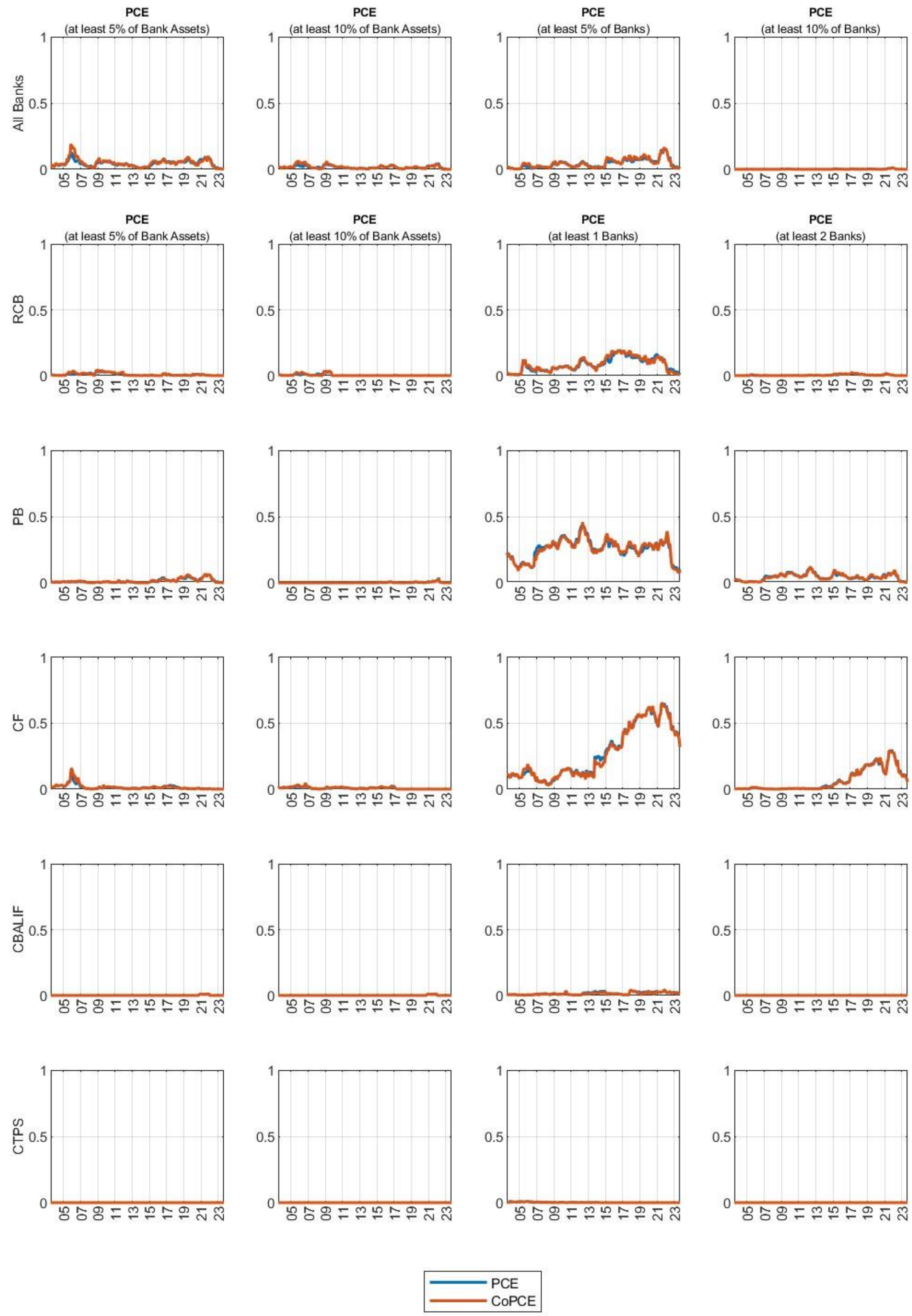


Figure 12: Explanatory Power of Systemic Risk Indicators for Future Nominal GDP Growth

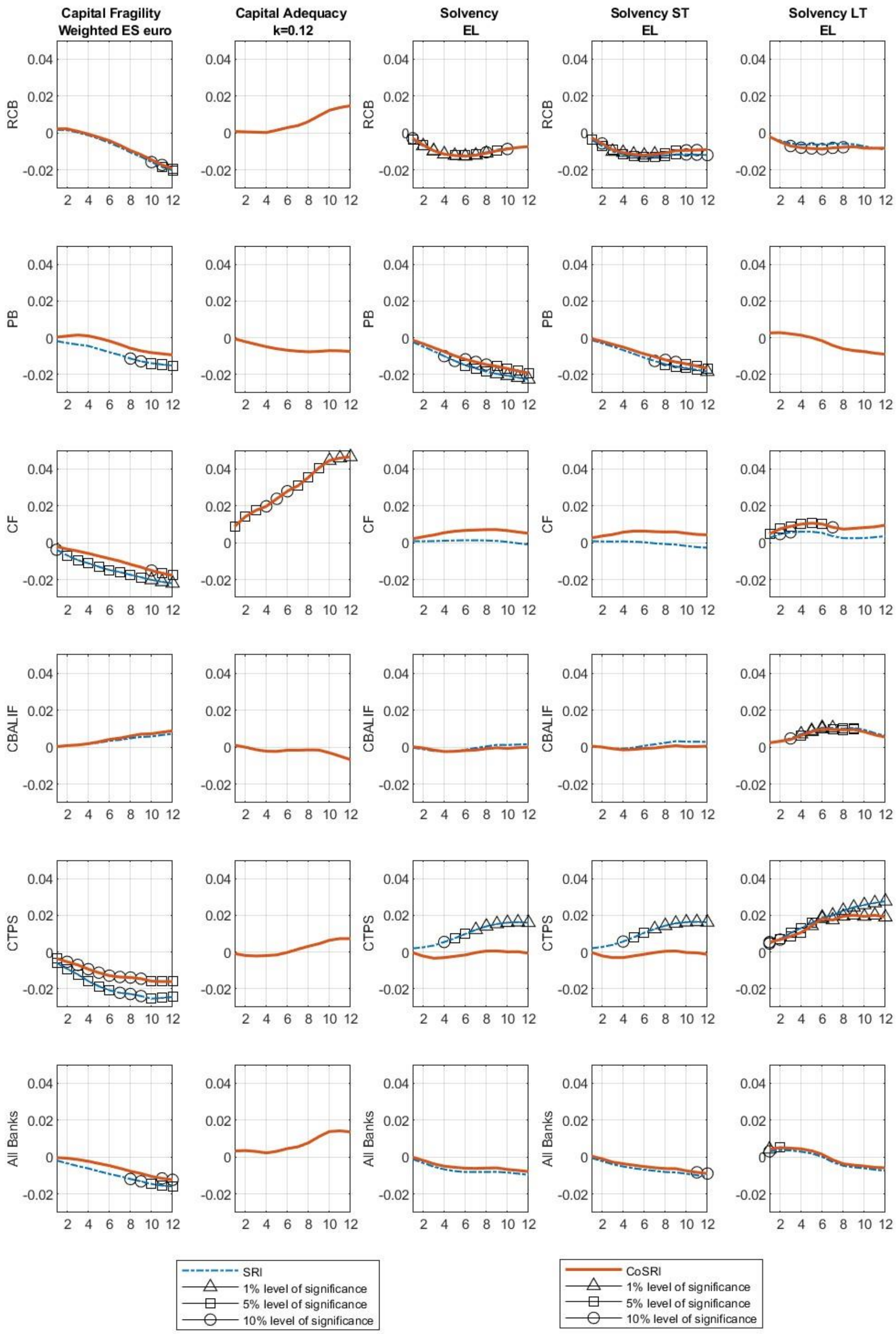
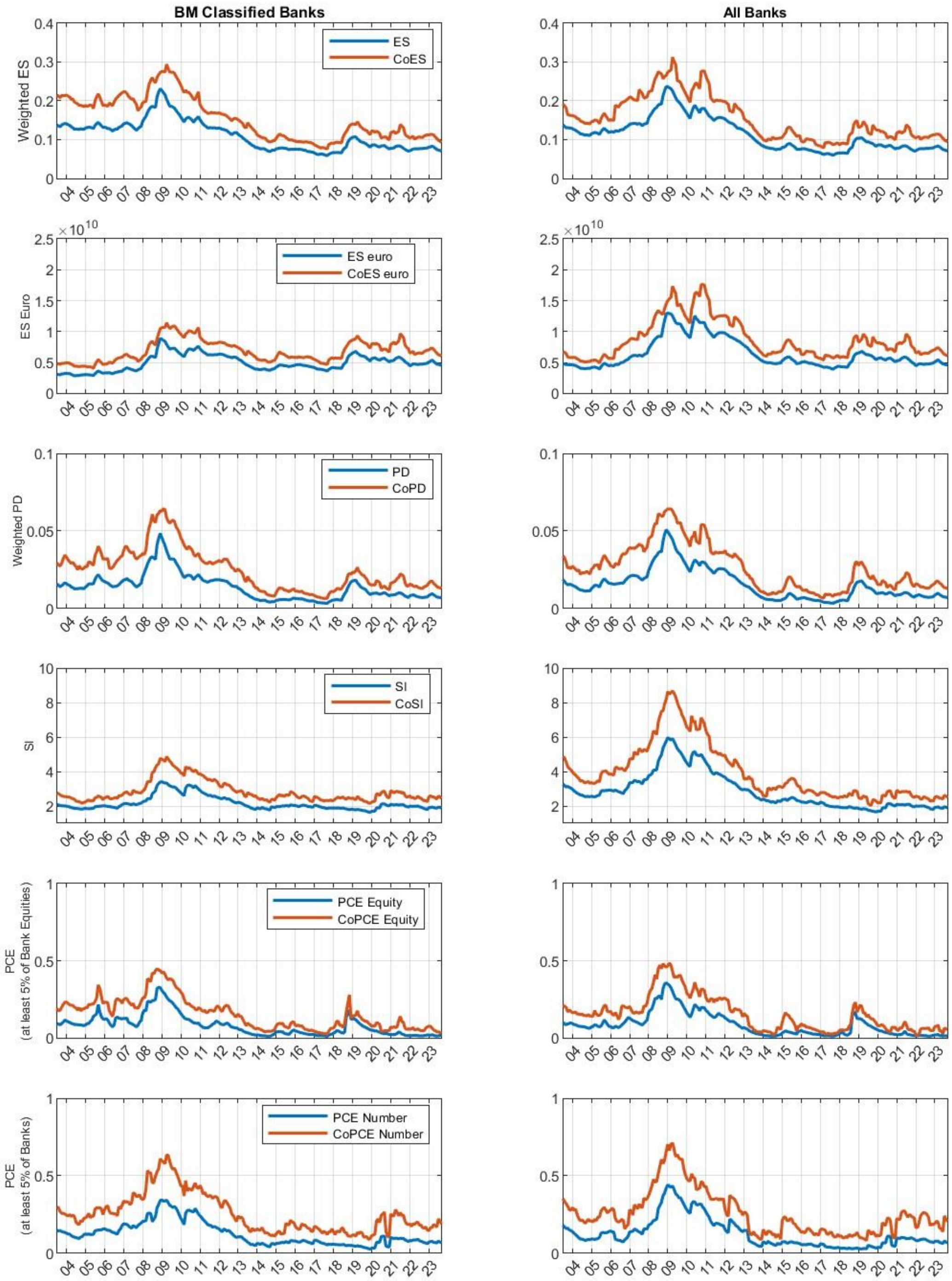


Table 1: Systemic Risk Indicator Association with Macroeconomic Variables

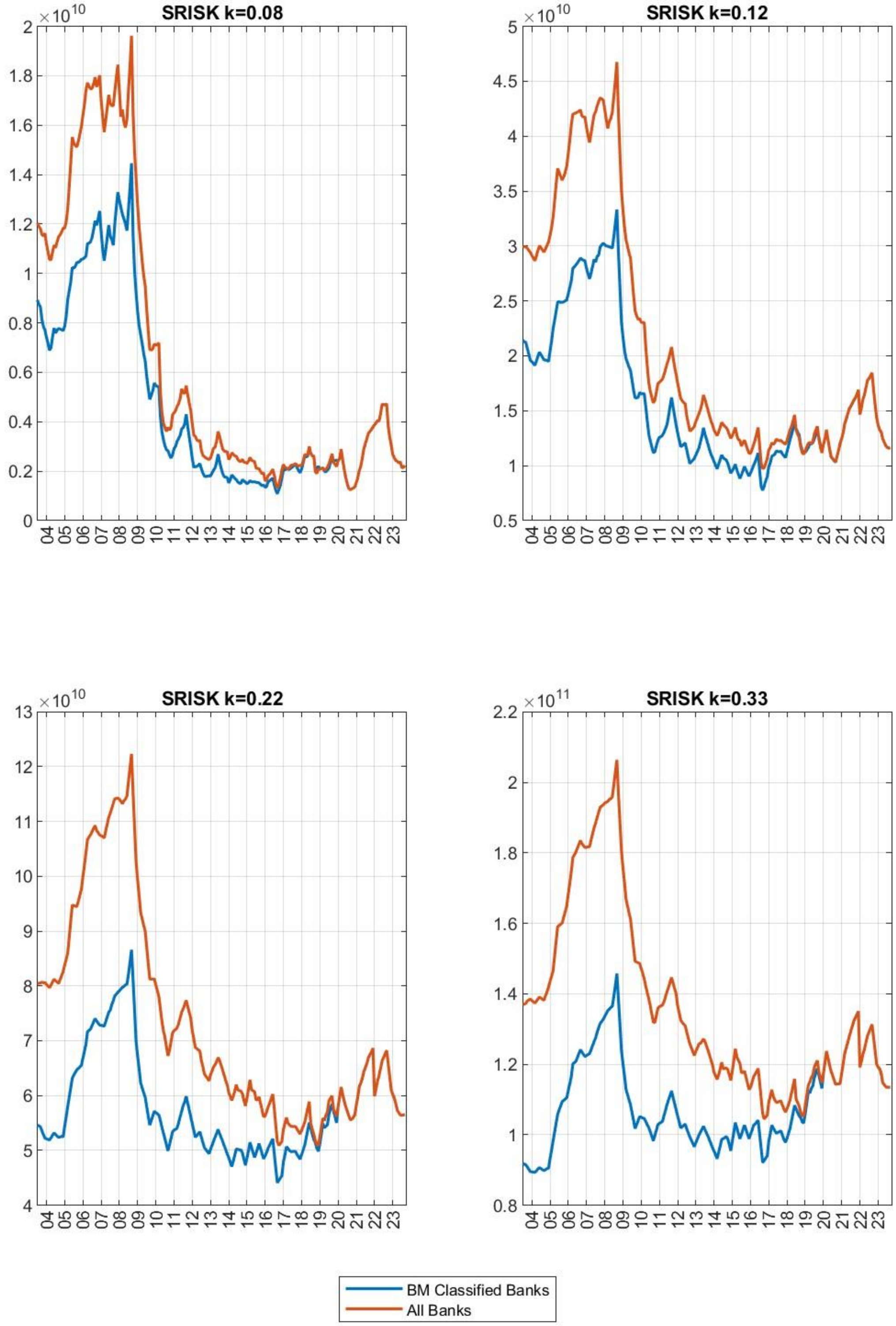
	RCB	PB	CF	CBALIF	CTPS	All Banks	RCB	PB	CF	CBALIF	CTPS	All Banks
	Bank Capital Fragility - Weighted PD						Bank Solvency - Weighted PD					
Constant	-0.26	-0.88	0.01	-0.07	0.19	-0.39	-0.27	-1.01	-1.06	0.21	0.38	-1.04
Lagged	95.90***	96.33***	85.69***	96.84***	96.68***	95.12***	91.14***	97.93***	96.22***	95.80***	88.87***	94.12***
Interest Rates ST	3.95	2.80*	5.67**	-0.74	0.47	4.06**	3.31	2.75	-0.88	-1.25	-7.68***	0.85
Interest Rates Spread	0.10	0.26	-2.28	2.43	4.17	-0.27	-5.48**	0.86	-0.63	-2.91*	-3.10	-2.07
Euribo TB 3M Spread	1.55	3.46***	15.66*	0.11	0.18	7.72**	11.73	2.61	-1.13	3.21	-4.03	6.78
Business Climate Indicator	0.20	0.97	-2.33	1.84	5.03	1.74	-4.32	0.85	-2.71	-4.62*	4.72	-4.56*
Consumer Confidence Sentiment	0.47	0.63	1.48	3.42*	2.21	1.37	4.88**	2.25	2.54	3.45**	-1.33	7.26***
VSTOXX Volatility Index	-2.28	0.85	1.96	-2.22	-0.13	-0.51	-1.50	-1.94	2.39	-1.60	2.58	-0.69
Market Return	-0.56	-0.81	0.52	-4.37	-3.72	-0.08	1.56	-1.72	0.63	-1.11	-1.52	-1.32
R-squared	97.86	98.29	96.61	95.59	94.13	98.63	95.00	97.86	94.44	97.01	92.58	95.30
	Bank Capital Fragility - Weighted CoPD						Bank Solvency - Weighted CoPD					
Constant	-0.36	-0.75	-0.09	0.08	0.03	-0.48	-0.20	-0.83	-0.90	0.09	0.08	-0.89
Lagged	94.33***	95.27***	89.75***	96.67***	94.44***	96.36***	89.65***	92.83***	95.30***	93.71***	85.23***	91.66***
Interest Rates ST	5.64**	3.18*	4.80**	-0.81	-1.51	3.89**	1.35	5.47**	-1.17	-3.49	-8.33**	0.25
Interest Rates Spread	1.32	1.88	-2.28	1.70	3.74*	0.34	-4.11*	4.05*	-0.10	-2.40	-3.91	-0.15
Euribo TB 3M Spread	-0.29	1.98	8.18*	-0.23	-0.44	2.40*	20.31*	4.60	0.42	2.98	0.26	11.52
Business Climate Indicator	-0.04	1.42	-1.93	1.85	4.31	1.96*	-5.59	-0.51	-4.13	-4.97**	1.79	-6.57**
Consumer Confidence Sentiment	1.62	0.68	0.13	2.73*	1.35	1.16	3.35	3.86**	2.50	3.12	1.64	7.37**
VSTOXX Volatility Index	-0.95	1.64	1.89	-2.94	-2.52	-0.32	-6.71**	-3.53**	-0.57	-6.26*	-1.91	-8.49**
Market Return	-1.71	-1.70	-1.67	-6.25**	-4.26	-2.91**	4.65	-1.79	0.39	-4.42*	-2.58	-2.03
R-squared	97.33	97.60	95.57	94.84	91.55	98.49	91.58	96.58	92.21	95.33	84.59	92.02
	Short-term Bank Solvency - Weighted PD						Long-term Bank Solvency - Weighted PD					
Constant	-0.42	-1.13	-1.07	0.24	0.38	-0.98	-0.36	-0.29	-0.29	0.20	-0.23	-0.38
Lagged	89.22***	97.49***	94.61***	94.62***	88.41***	93.17***	86.49***	94.32***	90.71***	86.99***	74.02***	90.54***
Interest Rates ST	4.12*	2.79	-1.66	-2.04	-8.00***	-0.65	3.83*	-0.55	-4.55*	-4.57*	13.99***	-3.45
Interest Rates Spread	-3.75	1.70	1.23	-3.84*	-3.61	-1.24	-0.11	-0.03	-0.38	-7.07	15.82***	-1.17
Euribo TB 3M Spread	11.11*	3.09*	0.06	2.85	-4.14*	5.97*	11.77**	3.70**	-0.28	0.51	-4.94	4.44**
Business Climate Indicator	-5.39*	-0.41	-4.75**	-4.99*	4.50	-5.78**	-5.81**	-2.52	-5.95***	-5.00	-1.44	-5.60**
Consumer Confidence Sentiment	5.88***	6.29***	3.60	3.59**	-1.72	8.72***	5.41***	8.98***	6.98***	-0.62	-3.46	9.88***
VSTOXX Volatility Index	-1.83	-2.38	-0.68	-0.76	2.90	-1.28	-1.19	0.71	-3.14	4.02	-4.65	-0.52
Market Return	-1.09	-3.21	0.64	-0.71	-1.20	-2.08	-3.06	-0.60	-1.57	4.90	-0.38	-1.48
R-squared	94.04	95.68	93.62	96.40	92.39	94.83	92.75	92.81	92.93	82.45	82.57	92.09
	Short-term Bank Solvency - Weighted CoPD						Long-term Bank Solvency - Weighted CoPD					
Constant	-0.28	-1.06	-0.88	0.10	0.08	-0.88	-0.30	-0.36	-0.12	0.14	0.10	-0.34
Lagged	87.77***	91.25***	94.24***	92.80***	84.82***	91.53***	83.57***	91.84***	92.61***	83.00***	33.82***	91.29***
Interest Rates ST	1.59	4.32	-1.32	-4.10*	-8.32**	-1.19	2.44	-1.72	-2.06	-5.48**	37.85***	-2.15
Interest Rates Spread	-2.41	4.74*	1.12	-2.88	-4.34	0.10	0.35	-0.24	0.27	-8.03*	31.99***	-0.98
Euribo TB 3M Spread	19.33*	6.85**	1.93	2.89	0.56	11.54	19.44**	7.11***	1.17	0.53	-3.09	9.73*
Business Climate Indicator	-7.16	-1.78	-5.72**	-5.09**	1.29	-7.51***	-8.55**	-2.55	-6.12***	-4.38	-6.54	-6.92***
Consumer Confidence Sentiment	3.92	8.06***	2.64	3.57	1.32	7.60***	4.56	9.05***	4.63	0.04	0.03	8.14***
VSTOXX Volatility Index	-7.98**	-6.05**	-2.75	-5.84*	-2.46	-9.51***	-5.57*	-2.76	-2.92	6.78	-3.46	-4.25
Market Return	2.74	-4.04	1.72	-4.13	-2.74	-1.74	2.17	-0.40	0.97	6.10	6.76	1.82
R-squared	89.97	92.32	91.46	94.60	83.57	91.39	86.37	90.08	89.60	76.93	56.66	89.16
	Bank Capital Adequacy - SRISK k = 0.12											
Constant	-0.73	-0.04	-0.71	0.40	0.07	-0.62						
Lagged	98.99***	101.09***	96.54***	91.61***	82.64***	99.54***						
Interest Rates ST	1.06	0.70	2.19	-3.12	-8.67**	0.77						
Interest Rates Spread	-0.05	-0.52	1.97**	-6.08**	-2.12	0.22						
Euribo TB 3M Spread	-4.15**	-2.17	-5.75**	1.73	-10.88***	-5.25***						
Business Climate Indicator	2.95***	2.26	0.95	-3.00	10.98**	2.06**						
Consumer Confidence Sentiment	0.16	3.04**	-1.29	4.44**	-4.29	0.71						
VSTOXX Volatility Index	0.33	0.10	-1.63*	3.03	3.91	-0.15						
Market Return	-1.61	0.57	-0.31	1.73	-5.35	-0.77						
R-squared	99.31	98.55	99.14	93.47	83.20	99.27						

Notes to Table: This table reports the regression results in percentage of several systemic risk indicators. Regressions are run on the lag of systemic risk indicator and a set of macroeconomic determinants with Newey-West robust standard errors using a Bartlett kernel. Asterisks indicate significance at the (*) 10%. (**) 5% and (***) 1% levels.

Appendix Figure 1: Bank Capital Fragility - Systemic Risk Indicators

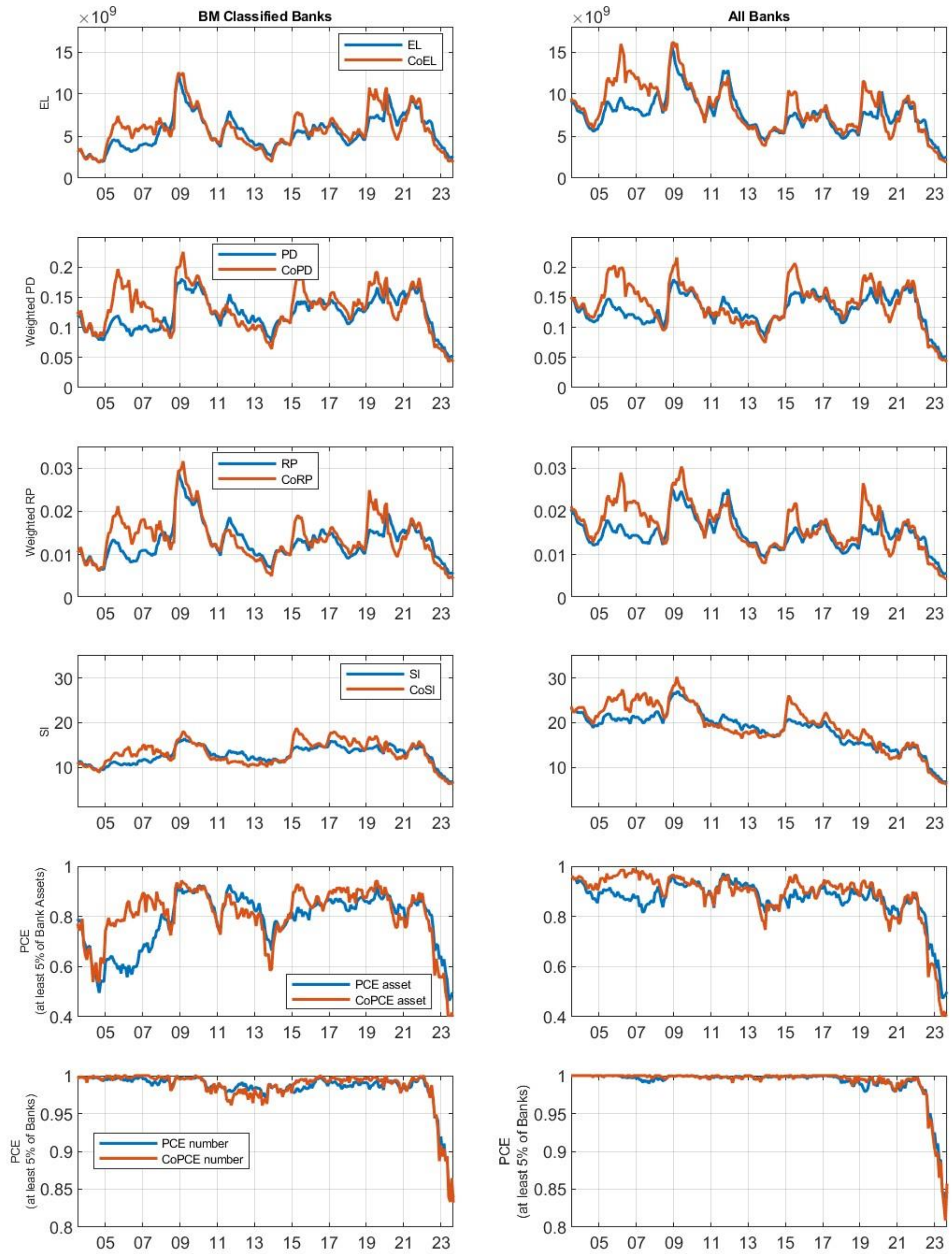


Appendix Figure 2: Bank Capital Adequacy - Conditional Expected Capital Shortage (SRISK)

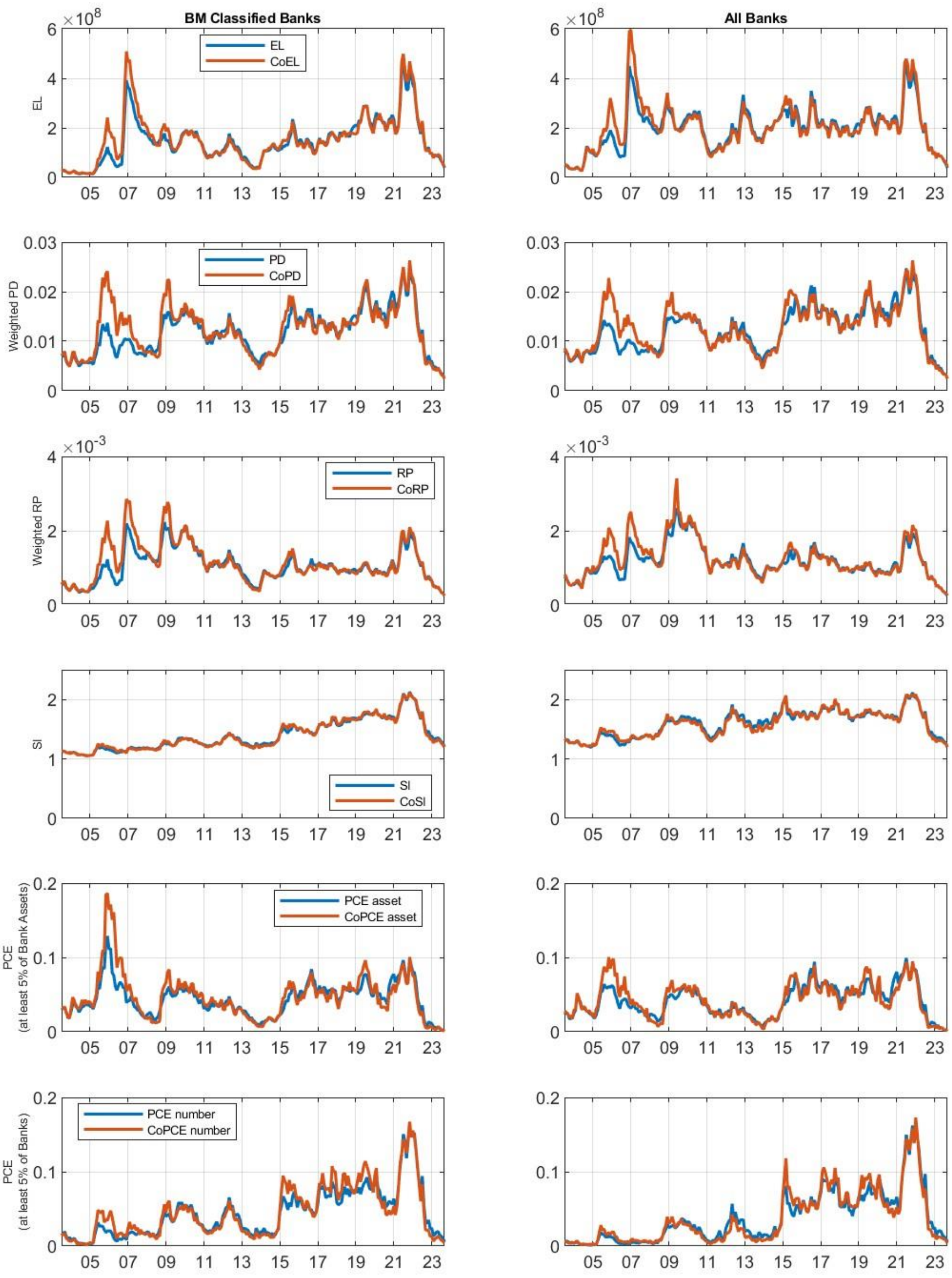


Appendix Figure 3: Bank Solvency - Systemic Risk Indicators

Appendix Figure 4: Bank Solvency Maturity Structure - Short-term Systemic Risk Indicators



Appendix Figure 5: Bank Solvency Maturity Structure – Long-term Systemic Risk Indicators



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