Heterogeneous Effects of Macroprudential Policies: Cross-Country Evidence from Composite Measures

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Abstract

Using a dimension-reduction approach, we construct composite measures of macroprudential policies (MaPPs) and apply them to a panel of 119 countries over 2000–2015 to evaluate the effectiveness of MaPPs in stabilizing private credit while explicitly accounting for unobserved cross-country heterogeneity. Overall, our findings indicate that the success of macroprudential interventions depends critically on country-specific structural and financial conditions rather than on the mere adoption of policy tools. Specifically, we show that MaPPs do not exert uniform effects: depending on the macro-financial environment, they may either dampen or amplify credit volatility. Borrower-targeted measures are generally effective in low-income and moderate-leverage economies, while financial-intermediary-targeted measures display context-dependent, and occasionally procyclical, effects.

Keywords: Macroprudential policies; Financial cycles; Unobserved heterogeneity; Generalized additive models for location, scale and shape.

JEL codes: E43, E58, G18, G28, C14, C38.

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1 Introduction

Since the global financial crisis of 2008, central banks and supervisory authorities have expanded their policy toolkit to contain systemic risk and smooth the financial cycle, making macroprudential regulation a central pillar of the post-crisis policy framework and placing the management of credit cycles at the core of financial stability objectives. Macroprudential policies (MaPPs) indeed aim to mitigate financial risks by curbing excessive credit growth, reducing high household and corporate debt levels, and preventing the formation of asset bubbles.

However, not all countries adopt the same set of MaPPs. The choice of these instruments depends on the degree of economic and financial development, the exchange-rate regime, the specific vulnerabilities of each economy, and the objectives the measures are designed to address. Some MaPPs directly target borrowers (e.g., loan-to-value, LTV, or debt-to-income, DTI, limits), while others focus on financial intermediaries through capital, liquidity, or concentration requirements. Their design must evolve dynamically with the macroeconomic environment. The common goal is to counter the accumulation of risks during expansionary phases and to mitigate credit tightening and excessive risk aversion during downturns.

Within this common goal, our work evaluates how MaPPs contribute to financial stability, specifically focusing on their effectiveness in reducing credit volatility.[1] We contribute to the ongoing debate in the literature in two ways. First, we introduce composite measures for MaPPs. Existing empirical studies typically proxy MaPP adoption through binary indicators of policy activation.[2] We improve on this approach by constructing composite indicators of MaPPs using a dimension-reduction technique suitable for multivariate, mixed-type panel data.[3] Derived as optimally weighted averages of individual MaPP instruments across countries and over time, these indicators summarize the joint dynamics of borrower-targeted and intermediary-targeted measures across 119 countries over 2000–2015, providing a consistent and empirically grounded measure of policy stance.

[1] Reducing credit volatility is only one of several criteria used to assess the effectiveness of MaPPs. Directional effectiveness also plays an important role: in some cases, tightening certain macroprudential measures may be associated with credit expansion, while loosening them may further fuel credit growth. In this paper, however, we focus on credit volatility reduction as a primary objective. This choice is in line with the view shared by many international financial institutions that the ultimate purpose of macroprudential policy is to safeguard the stability of the financial system as a whole (FSB-IMF-BIS, 2011; Constâncio et al., 2019).

[2] See, for instance, Hodula et al. (2025) or Moretti and Riva (2025) in the context of borrower-based MaPPs.

[3] Although several alternative dimension-reduction and factorization methods exist, most are restricted to cross-sectional or continuous data. For further methodological discussion and recent applications, see Farcomeni et al. (2021) and Acquah et al. (2023).

The second contribution of the paper lies in assessing how these composite measures influence credit volatility within a theoretical framework of heterogeneous intermediaries that endogenizes financial stability. Our results reveal that MaPPs have context-dependent effects: the same instrument can either stabilize or destabilize credit dynamics, depending on country-specific macro-financial conditions.

A key innovation of our empirical framework lies in its explicit treatment of bank heterogeneity across multiple dimensions—a feature increasingly central in recent theoretical macro-finance works, including Corbae and D'Erasmo (2021), Coimbra and Rey (2024), and Jamilov and Monacelli (2025). Specifically, in modeling the banking system, we follow Coimbra and Rey (2024), who develop a framework with heterogeneous intermediaries facing Value-at-Risk (VaR) constraints and a moral-hazard friction stemming from limited liability and government guarantees. Heterogeneity in VaR reflects differences in risk tolerance among intermediaries or in regulatory and supervisory stringency across countries. The resulting distribution of leverage across banks is a key determinant of financial stability. When high-risk intermediaries dominate, they inflate risky-asset prices and concentrate aggregate risk on their balance sheets. The leverage distribution thus becomes highly positively skewed, amplifying fragility during booms as a larger share of assets is held by institutions with a higher probability of default. Moreover, financing costs affect credit volatility asymmetrically: the elasticity of credit creation with respect to funding costs increases with the asymmetry of the leverage distribution. By extending this heterogeneous-intermediary framework to incorporate MaPPs, we obtain a tractable model that delivers closed-form expressions for financial stability as a function of macroprudential measures and can be directly mapped to the data.

The core of our second contribution is that cross-country heterogeneity is crucial both for identifying which MaPPs should be implemented to foster financial stability and for understanding how their effects may differ across national contexts. In our first set of results, credit volatility is proxied by the first difference of the credit-to-GDP ratio. Once a conditional mean model is specified, instead, volatility is reinterpreted as the conditional variance of the level of private credit, estimated within a Generalized Additive Model for Location, Scale, and Shape (GAMLSS) framework (Rigby and Stasinopoulos, 2005; Stasinopoulos and Rigby, 2008). Then, guided by the theoretical restrictions implied by the Coimbra and Rey (2024) model which we extend to account for MaPPs, we simultaneously estimate both the expected value of private credit and its conditional variance, which serves as the relevant measure of cyclical credit volatility after accounting for covariates and latent heterogeneity.

Unlike standard Fixed-Effects models, this approach allows each parameter of the conditional distribution (mean, variance, skewness, and kurtosis) to depend on observed covariates, including our composite MaPP indicators. This flexibility is essential to assess whether MaPPs influence not only average credit growth but also the higher-order moments of its distribution—such as volatility, asymmetry, and tail risk.

Once unobserved heterogeneity is accounted for, our estimates uncover distinct country clusters, each displaying differentiated effects of MaPPs on financial stability. Borrower-targeted measures exert a stabilizing influence, consistently reducing private credit volatility, in low-income countries. The picture is more nuanced for high-income countries. Although we estimate several model variants, each incorporating different sets of macroprudential indicators and interaction terms, the clustering structure remains remarkably stable within the OECD sample. Roughly half of these economies (Austria, Czech Republic, Finland, Germany, Mexico, Norway, Poland, Slovakia, Sweden, Switzerland, and the United Kingdom) remain anchored to the same regime across specifications, suggesting that the latent groups identified by the mixture-GAMLSS framework capture persistent macro-financial characteristics. Within these economies, borrower-targeted measures tend to stabilize credit dynamics in lower-income OECD members, while in more financially developed and credit-intensive economies they are often associated with destabilizing effects, consistent with amplification mechanisms typical of mature financial systems.

Among financial institution-targeted policies, those based on concentration limits—i.e., restrictions on the fraction of assets held by a limited number of borrowers—generally exhibit stabilizing effects, particularly in high-income and well-capitalized economies. This evidence is also consistent with the theoretical mechanism described by the model: MaPPs operate through both the intensive margin (leverage adjustments among active intermediaries) and the extensive margin (entry and exit decisions across intermediaries), the latter being primarily influenced by the financial-institution-targeted MaPP. In this sense, tighter regulation discourages new entrants into the leveraged regime, thereby promoting financial stability. By contrast, measures relying on levies or taxes on financial intermediaries are more frequently associated with destabilizing dynamics, suggesting that their effectiveness may weaken or even reverse in advanced credit markets. These patterns confirm that the mixture-GAMLSS approach successfully isolates persistent macro-financial regimes and reveals how the stabilizing capacity of MaPPs depends jointly on financial depth and leverage asymmetry. Taken together, our findings underscore that the formulation and implementation of MaPPs ought to be aligned with the current macroeconomic conditions and the underlying architecture of the financial sector.

Finally, we explore whether cross-country structural differences account for the observed heterogeneity in MaPP effectiveness by estimating a Multinomial Logit Model linking cluster membership to macroeconomic fundamentals. We find that faster credit growth and higher corporate leverage (debt-to-equity ratios) reduce the likelihood of belonging to more advanced clusters—precisely those where borrower-targeted MaPPs tend to be stabilizing—whereas higher banking-sector leverage increases the probability of being in clusters where financial-institution-targeted MaPPs are typically more effective.

Literature A concise review of the empirical literature can follow the four stylized facts summarized by Gómez et al. (2020). First, tighter MaPPs are associated with lower bank credit growth. Using data for 56 countries (1990–2012), Richter et al. (2019) document a positive association between limits on average LTV ratios and lower growth of household and mortgage credit. Second, there is evidence that prior adoption of MaPPs is associated with milder macroeconomic fallout during crises; for example, Boar et al. (2017) show, for a panel of 64 countries, that MaPP use correlates with higher growth and lower GDP-per-capita volatility. Third, MaPPs tend to be more effective when they complement monetary policy (Adrian et al. 2018). Finally, the effectiveness of MaPPs in reducing credit volatility tends to decline with higher levels of financial development and integration, as documented, among the others, by Cerutti et al. (2017) and Boar et al. (2017).

Outline The remainder of the paper is organized as follows. Section 2 describes the sample and presents the data-reduction methodology used to construct the composite MaPP indicators. Section 3 introduces the additional variables employed in the empirical analysis, outlines the econometric strategy, and discusses the main estimation results. Section 4 concludes. Robustness checks, country classifications, the detailed description of the dimension-reduction procedure, and the derivations of the theoretical model are provided in the Appendix.

2 MaPP indicators

Data We merge information from different data sources. Data on MaPPs are from Cerutti et al. (2017), private credit and bank financing data are from Coimbra and Rey (2018), data on GDP and other macroeconomic variables are sourced from the Penn World Tables PWT

(2023) and the World Bank. Due to data availability and merging requirements, our analysis is limited to the period 2000-2015.[4]

Table 1 reports the descriptive statistics. For each country i, with $i = 1, \ldots, N$ at date t, with $t = 1, \ldots, T$, *Credit* is the private credit to GDP ratio while *DCredit* is its annual change; *Leverage* measures the asset weighted skewness of the distribution of leverage of banks and *FundCost* is the asset weighted mean cost of funds for the banks;[5] λ, ϕ_1 and ϕ_2 are summarizing indices for MaPPs, obtained through the procedure described below. Finally, *MPI* is an indicator provided by Cerutti et al. (2017), ranging from 0 to 10, that counts the number of policies adopted by each country each year.

Notice that, in addition to our new MaPPs indicators, the other regressors used in the econometric analysis are grounded in Coimbra and Rey (2024), which shows that bank leverage can act as an amplifier of financial cycles. In particular, when banks raise their leverage during expansionary phases to boost profits, they increase their exposure to systemic risk and heighten their vulnerability to macroeconomic downturns.

Table 1: Descriptive Statistics

Variable	N	Mean	St. Dev.
Leverage	1,187	1.715	3.528
FundCost	1,187	3.575	4.416
Credit	1,187	68.541	51.275
DCredit	1,187	1.386	8.902
λ (borrower-targeted MaPP)	1,187	-0.800	0.516
ϕ_1 (financial institution-targeted MaPP)	1,187	0.187	0.479
ϕ_2 (financial institution-targeted MaPP)	1,187	0.105	0.361
GDP	1,187	23,894	20,063
Policy rate	1,187	6.724	11.341
MPI	1,187	2.127	1.753

Figure 1 highlights significant variation in the number of MaPPs adopted across OECD

[4] One potential limitation of our analysis is the use of annual rather than quarterly data. Although quarterly data could offer finer insight into the dynamics of credit growth and volatility, consistent cross-country series, particularly for banking-sector variables,are not publicly available at this frequency. Additionally, quarterly data may give rise to spurious short-term correlations that do not reflect persistent structural patterns. We are grateful to an anonymous referee for highlighting this point. In this paper, we follow the empirical design of Coimbra and Rey (2018), which also uses annual data. We do believe that the public nature of their dataset further supports the transparency and robustness of our approach.

[5] The weight for bank b, in country i, in year t is

$$\frac{\text{Total asset}_{b,t}}{\sum_{b\in i}\text{Total asset}_{b,t}}.$$

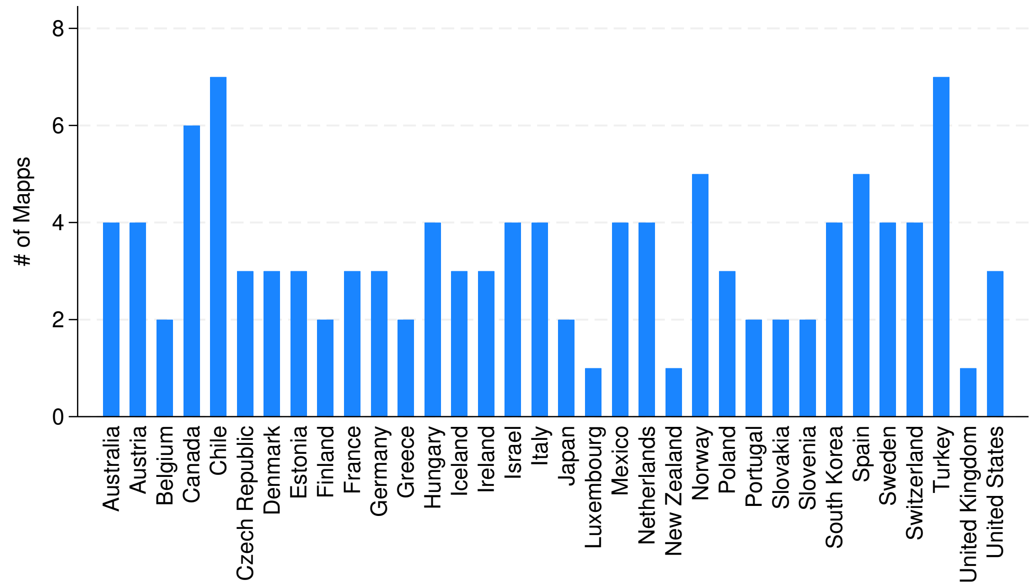

Figure 1: MaPPs Adoptions (by country) in OECD countries

countries. Nonetheless, the time-series pattern displayed in Figure 2 reveals a generally uniform upward trend in policy adoption, suggesting a global shift toward greater use of macroprudential tools.

Composite MaPP indicators Using data from the GMPI survey, Cerutti et al. (2017) identifies the following macroprudential instruments: General Counter-cyclical Capital Buffer/Requirement (cCyB); Bank Leverage Ratio (LEV); Time-Varying/Dynamic Loan-Loss Provisioning (DP); Loan-to-Value Ratio (LTV); Debt-to-Income Ratio (DTI); Limits on Domestic Currency Loans (CG); Limits on Foreign Currency Loans (FC); Reserve Requirement Ratio (RR); Levy/Tax on Financial Institutions (TAX); Capital Surcharges on SIFIs (SIFI); Limits on Interbank Exposures (INTER); Concentration Limits (CONC). Each of the twelve macroprudential policy instruments is expressed as a binary measure equal to one if, for a country in a given year, the macroprudential policy instrument was adopted and zero otherwise. Based on the taxonomy proposed above, these MaPPs can be classified as shown in Table 2.

In an exercise aimed at summarizing the indicators, it might seem natural to use classical dimension reduction methods (such as Principal Component Analysis). However, these would not be appropriate for two main reasons. First, the indicators are binary (as opposed to continuous); second, the panel data are dependent due to repeated measures for the same country at different years. Binary indicators do not suggest that they have a direction, but

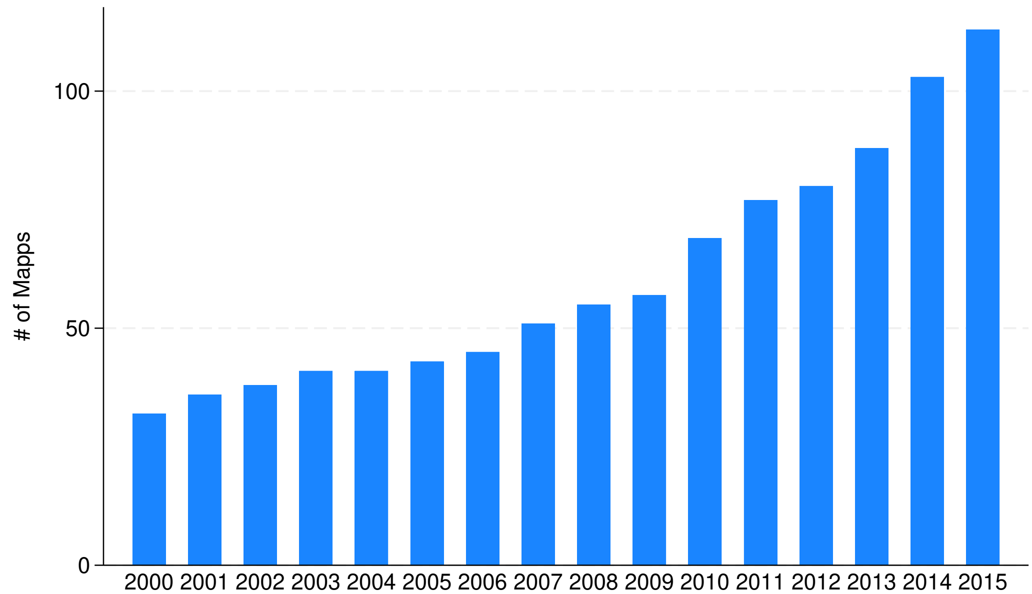

Figure 2: MaPPs Adoptions (by year) in OECD countries

Table 2: Indicators

Capital
1. General Counter-cyclical Capital Buffer/Requirement (cCyB)
2. Time-Varying/Dynamic Loan-Loss Provisioning (DP)
3. Capital Surcharges on SIFIs (SIFI)
4. Leverage Ratio (LEV)
Assets
5. Debt-to-Income Ratio (DTI)
6. Concentration Limits (CONC)
7. Levy/Tax on Financial Institutions (TAX)
8. Limits on Interbank Exposures (INTER)
9. Loan-to-Value ratio (LTV)
Liquidity
10. Limits on Domestic Currency Loans (CG)
11. Limits on Foreign Currency Loans (FC)
12. Reserve Requirement Ratio (RR)

Table 3: Optimal weights

Indicator	λ	ϕ_1	ϕ_2
Limits on domestic currency loans (CG)	0.001	0.001	0.001
Concentration limits (CONC)	0.017	0.462	0.017
General countercyclical capital buffer/requirement (cCyB)	0.006	0.000	0.000
Limits on foreign currency loans (FC)	0.073	0.002	0.012
Time-varying/dynamic loan-loss provisioning (DP)	0.012	0.036	0.194
Debt-to-income ratio (DTI)	0.212	0.010	0.102
Limits on interbank exposures (INTER)	0.014	0.270	0.212
Leverage ratio (LEV)	0.029	0.036	0.004
Loan-to-Value ratio (LTV)	0.410	0.008	0.058
FX and/or Countercyclical Reserve Requirements (RR)	0.001	0.000	0.001
Capital surcharges on SIFIs (SIFI)	0.014	0.000	0.010
Levy/tax on financial institutions (TAX)	0.203	0.168	0.384

capture only the presence of a given instrument, rather than its effect on credit dynamics. To address these issues, we use the methodology developed in Farcomeni et al. (2021), which is based on multivariate latent Markov models. Imposing a Latent structure on the data-reduction methods allows us to identify underlying common and dynamic patterns in the activation of macroprudential instruments without assuming an ex ante hypothesis on their direction. In this framework, conditional on an unobserved discrete latent variable, the outcomes are independent both from each other at a given time and from their own past values. It can be easily argued that the conditional independence assumptions allow the latent variable to capture all the information in the multidimensional outcome, thereby leading to a well specified dimension reduction technique. The latent variable summarizes a latent propensity through class-specific intercepts. Formally, the summary is a linear combination of the originally measured variables, as usual. Optimal weights are obtained by maximizing the distance among class-specific intercepts. The idea is that, in this way, the variability of the (weighted) summary is maximized. Unlike classical dimension reduction methods, this approach allows us to treat binary indicators appropriately from an inferential perspective and to acknowledge their dependence. Weights can be directly used for interpretation and an valuation of the importance of the variables in each dimension, as usual.[6] Table 3 reports the optimal squared weights. Caps on Loan-to-Value (LTV) ratios have the largest loading

[6]As with other composite indicators commonly used in empirical research—such as those measuring institutional quality, financial development, or regulatory restrictiveness—our synthetic MaPP indices involve aggregating multiple policy instruments using a weighting scheme. While this approach may mask the individual effect of specific measures, it enables a tractable, transparent, and replicable framework for empirical analysis of complex policy environments.

on λ (0.410), suggesting that this dimension mainly captures borrower-oriented restrictions. The second latent dimension ϕ_1 is dominated by Concentration Limits (CONC, 0.462), while the third component ϕ_2 is primarily driven by the taxation of financial institutions (TAX, 0.384), limits on interbank exposures (INTER, 0.212), and dynamic provisioning (DP, 0.194). Accordingly, while λ can be interpreted as a latent factor summarizing the activation of borrower-side measures, ϕ_1 and ϕ_2 appear to reflect constraints operating on the lending and balance-sheet structure of financial institutions.

To better visualize the associations between each instrument and the latent dimensions, Figure E1 presents arrow plots (biplots) based on the estimated weights. Each arrow represents one macroprudential instrument, with its direction and length corresponding to the correlation between that instrument and the latent dimensions shown on the axes (e.g., λ-ϕ_1, λ-ϕ_2, or ϕ_1-ϕ_2 planes). Longer arrows indicate stronger associations, while the sign (positive or negative) of the coordinates is purely conventional and depends on the rotation of the latent space.

In the first panel (λ-ϕ_1), the arrow for Concentration Limits (CONC) points leftward (negative on λ) and upward (positive on ϕ_1). This pattern does not contradict Table 3: the small weight of CONC on λ (0.017) means that its contribution to this dimension is negligible, while its strong loading on ϕ_1 (0.462) explains the steep vertical orientation. The negative coordinate on λ simply reflects the rotation of the latent axis, not an inverse relationship. Similarly, loan-to-value ratios (LTV) are mainly aligned with λ and almost orthogonal to ϕ_1, consistent with their dominant weight on the first component. In the λ-ϕ_2 plane, the arrows for taxes on financial institutions (TAX), limits to the fraction of liabilities held by the banking sector or by individual banks (INTER), and dynamic provisioning (DP), which requires banks to hold more loan-loss provisions during upturns, exhibit strong alignment with ϕ_2, again consistent with their large weights in Table 3. Finally, the ϕ_1-ϕ_2 projection highlights the separation between borrower-oriented measures (LTV, DTI) and balance-sheet measures (TAX, INTER, DP), illustrating the model's ability to disentangle distinct macroprudential policy domains.

Overall, the table and the biplot convey with a coherent picture: the first latent factor (λ) captures instruments targeting borrowers, while the second and third dimensions (ϕ_1, ϕ_2) summarize the joint activation of lender-oriented measures.

3 Quantitative analysis

We are now ready to add our synthetic MaPP indicators to the regressions of Coimbra and Rey (2018), which bring the baseline model of Coimbra and Rey (2024) to the data. Results are reported for both the Full Sample and the OECD sub-sample.

We begin by replicating the baseline specification in Coimbra and Rey (2018). The estimated coefficients, however, are generally non-significant. We then extend the analysis by jointly estimating the conditional mean and variance of private credit using a Generalized Additive Model for Location, Scale and Shape (GAMLSS). This framework allows for unobserved heterogeneity across countries and explicitly incorporates funding costs, banking-sector characteristics, and our composite MaPP indicators. The empirical specification builds on the extended version of Coimbra and Rey (2024) that introduces MaPPs into the theoretical setup (see Appendix A for details).

An important result of the theoretical model (Proposition 1) helps rationalize one of the main patterns we document with our estimates: borrower-targeted MaPPs tend to be effective primarily in low-income countries. The model shows that borrower-based instruments influence financial stability through two channels: the *scale of assets* and the *leverage response*. In credit-constrained economies (typically low-income and low-leverage systems) a tightening of borrower-based MaPPs reduces credit expansion and thus enhances stability. By contrast, when the VaR constraint binds (characteristic of advanced, highly leveraged intermediaries) further tightening can become counterproductive, as it increases equilibrium leverage and amplifies financial fragility.

A further theoretical result (Proposition 2) establishes that the stabilizing role of MaPPs operates through both the intensive margin, which captures leverage adjustments among active intermediaries, and the extensive margin, which captures participation decisions across intermediaries. The latter is primarily influenced by financial-intermediary-targeted measures: tighter regulation discourages intermediaries from entering the leveraged regime. Ultimately, the theoretical model indicates that both the magnitude—and even the direction—of MaPPs' effects depend critically on the prevailing financial regime.

In the remainder of the section, we focus primarily on ϕ_1, as ϕ_1 and ϕ_2 are conceptually similar. Estimates from models including ϕ_2 are reported in Appendix C for completeness. Importantly, the empirical specification also identifies latent country clusters characterized by distinct credit dynamics and volatility profiles. Lastly, we relate cluster membership to a set of macroeconomic and financial variables through a Multinomial Logit Model, which allows us to uncover the structural determinants underlying cross-country heterogeneity in the effectiveness of MaPPs.

Linear Model Using a large cross-country sample, Coimbra and Rey (2018) investigate the relationship between the (asset-weighted) mean cost of funding and the (asset-weighted) skewness of leverage across banks. Their empirical strategy is based on linear FE with instrumental variable regressions, where the dependent variable is the annual change in the ratio of private sector credit to GDP, a measure of observed (unconditional) credit volatility.

Table 4 reproduces their main results (columns 1 and 2) and reports our extended specification (columns 3 and 4), where the borrower- and institution-targeted MaPP indicators (λ, ϕ_1, and ϕ_2) are included among the regressors. The interaction between *FundCost* and *Leverage* remains negative across all specifications, but is only statistically significant in the full-sample regression (column 2), with a coefficient of -0.089 ($p < 0.05$). This finding is consistent with the theoretical expectation that tighter funding conditions combined with higher leverage may mitigate excessive credit expansion.

Table 4: Coimbra and Rey (2018) Model

Dependent Variable: *DCredit*	(1) Full Sample	(2) OECD	(3) Full Sample	(4) OECD	(5) Full Sample	(6) OECD
FundCost	-0.187**	-0.503*	-0.193*	-0.107	-0.193*	-0.176
	(-3.07)	(-2.45)	(-2.21)	(-0.26)	(-2.20)	(-0.48)
Leverage	0.098	0.377	0.112	0.497*	0.112	0.484
	(0.86)	(1.82)	(0.72)	(2.02)	(0.71)	(1.96)
FundCost × *Leverage*	-0.089*	-0.207	-0.080	-0.321	-0.080	-0.315
	(-1.98)	(-1.60)	(-1.08)	(-1.91)	(-1.09)	(-1.86)
λ			1.493	-1.197	1.476	-1.054
			(1.27)	(-0.46)	(1.25)	(-0.41)
ϕ_1			-0.116	0.308	-0.044	0.807
			(-0.13)	(0.19)	(-0.05)	(0.46)
ϕ_2			0.956	2.675		
			(0.78)	(1.34)		
Intercept	2.185***	3.839***	3.217***	1.454	3.296***	1.713
	(10.23)	(5.55)	(3.41)	(0.60)	(3.43)	(0.74)
Observations	2880	690	1811	489	1811	489
R^2	0.100	0.162	0.101	0.162	0.164	0.162
Adj R^2	0.020	0.066	0.021	0.021	0.064	0.062

t statistics in parentheses.
* p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table 5 further explores these relationships by adding an interaction between the borrower-targeted MaPP indicator (λ) and *Leverage*, as expected once the monetary authority's toolkit is extended to include borrower-based instruments such as loan-to-value (LTV) caps. The estimated coefficients for the interaction $\lambda \times Leverage$ are not statistically significant, suggesting that, in this linear framework, the borrower-targeted MaPPs do not exert a measurable effect on the volatility of credit growth.

For the OECD subsample, the inclusion of MaPP indicators slightly weakens the results originally reported by Coimbra and Rey (2018). Nevertheless, both the coefficients on *FundCost* and on its interaction with *Leverage* remain negative, in line with the theoretical prediction that higher funding costs and tighter leverage constraints act as stabilizing forces in credit markets.

Table 5: Coimbra and Rey (2018) Model with interactions

Dependent Variable: *DCredit*	(1) Full Sample	(2) OECD	(3) Full Sample	(4) OECD	(5) Full Sample	(6) OECD
FundCost	-0.187**	-0.503*	-0.193*	-0.112	-0.192*	-0.182
	(-3.07)	(-2.45)	(-2.19)	(-0.28)	(-2.18)	(-0.51)
Leverage	0.098	0.377	-0.105	0.555	-0.098	0.544
	(0.86)	(1.82)	(-0.29)	(0.97)	(-0.27)	(0.94)
FundCost $\times$ *Leverage*	-0.089*	-0.207	-0.077	-0.321	-0.078	-0.315
	(-1.98)	(-1.60)	(-1.01)	(-1.90)	(-1.02)	(-1.86)
Leverage $\times$ λ			-0.215	0.061	-0.208	0.062
			(-0.80)	(0.16)	(-0.77)	(0.16)
λ			1.772	-1.321	1.744	-1.181
			(1.33)	(-0.43)	(1.31)	(-0.38)
ϕ_1			-0.125	0.275	-0.047	0.773
			(-0.14)	(0.19)	(-0.05)	(0.46)
ϕ_2			1.031	2.673		
			(0.86)	(1.34)		
Intercept	2.185***	3.839***	3.426**	1.364	3.503**	1.621
	(10.23)	(5.55)	(3.17)	(0.50)	(3.19)	(0.62)
Observations	2880	690	1811	489	1811	489
R^2	0.100	0.162	0.101	0.162	0.164	0.163
Adj R^2	0.020	0.066	0.021	0.021	0.064	0.061

t statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Overall, these linear regressions fail to provide evidence supporting the stabilizing role of macroprudential instruments. The inclusion of λ, ϕ_1, and ϕ_2 does not improve model fit, as reflected in the persistently low values of R^2 (around 0.10-0.16) and adjusted R^2 (below 0.07) across all specifications.

These results suggest that the linear fixed-effects framework adopted by Coimbra and Rey (2018), while informative as a benchmark, lacks the flexibility required to capture the complex, heterogeneous responses of credit markets to MaPPs. In particular, the assumption of homogeneous slope coefficients across countries likely masks important regime-dependent effects that vary with financial development and leverage conditions. Consequently, such linear models can at best estimate an average relationship, providing only limited insight into the stabilizing or destabilizing role of individual MaPPs.

A more nuanced and informative picture emerges when heterogeneity and nonlinear interactions are explicitly modeled within the GAMLSS mixture framework presented in the next section. This approach allows both the mean and the variance of credit dynamics to depend on policy instruments in a data-driven, cluster-specific manner, revealing the latent structure underlying the observed cross-country heterogeneity in credit volatility.

Generalized Additive Model for Location, Scale and Shape (GAMLSS) We estimate the impact of MaPPs on both the level and volatility of private credit using a Generalized Additive Model for Location, Scale, and Shape (GAMLSS; Rigby and Stasinopoulos, 2005). This approach jointly models the conditional mean and variance of the credit-to-GDP ratio while allowing the distributional shape to vary across countries[7]. Specifically, the model assumes that observations are independent over time and across countries, conditional on an unobserved discrete latent variable that captures individual heterogeneity and jointly affects the mean and variance equations. The model is suitable for an unbalanced longitudinal design with few units and time points, which also allows for the estimation of the conditional volatility of credit, taking into account macroprudential variables and other country-specific measures. The underlying assumption of the finite mixture GAMLSS is that each country belongs to one of possibly many *hidden* clusters, sharing some common economic features (e.g. quality of financial institutions, quality of bank credit markets, etc.) represented by cluster-specific latent parameters. Formally, the conditional mean μ_{it} and variance σ^2_{it} are expressed as linear predictors linked to macroprudential indicators and other covariates through suitable link functions (see Appendix C for estimation details and model selection). In the

[7]In a panel, or in a multivariate time series design, the simultaneous estimation of mean and variance of a process, by allowing for individual and temporal correlations, is essentially based on: (i) a Multivariate GARCH Model (Bollerslev et al., 1988) allowing for a defined intra-individual correlation through some assumptions about overall errors or through a specific distribution of temporal and individual effects (Cermeño and Grier, 2006); (ii) that including sometime a covariate in variance specification of a GARCH process (Hwang, 2001; Han and Kristensen, 2014); (iii) using Dynamic Correlated Panel Regression (Chudik et al., 2013, 2016; Pesaran, 2006). Notice that, common correlated effects in a dynamic panel need a large number of observations over groups and time periods (Chudik et al., 2013).

baseline specification we estimate the following linear predictors:

$$g_1(\mu_{it}) = (\beta_0 + u_i) + \beta_1 FundCost_{it} + \beta_2 Leverage_{it} + \beta_3 FundCost_{it} \times Leverage_{it}, \quad \text{(1a)}$$

$$g_2(\sigma^2_{it}) = (\gamma_0 + \delta_{0i}) + (\gamma_1 + \delta_{1i})\lambda_{it} + (\gamma_2 + \delta_{2i})\phi_{1it} + (\gamma_3 + \delta_{3i})\phi_{2it}, \quad \text{(1b)}$$

$$g_3(\nu_{it}) = b, \quad \text{(1c)}$$

where u_i and $\boldsymbol{\delta}_i = (\delta_{0i}, \delta_{1i}, \delta_{2i}, \delta_{3i})$ are correlated random effects capturing country-specific deviations in the mean and variance. In the mean equation, only the intercept varies across individuals $(\beta_0 + u_i)$, whereas in the variance equation each coefficient has its own random component, e.g., $(\gamma_0 + \delta_{0i}), (\gamma_1 + \delta_{1i}), \ldots, (\gamma_3 + \delta_{3i})$. The random effects may be correlated, allowing for dependence between individual heterogeneity in the mean and variance[8]. To approximate the unknown distribution of random effects, we adopt a finite mixture representation with K latent components, each characterized by a probability weight π_k and a vector of location parameters $\mathbf{U}_k$. The likelihood is then expressed as a weighted sum of component-specific densities,

$$L(\cdot) = \prod_{i=1}^{N} \left\{ \sum_{k=1}^{K} \pi_k \prod_{t=1}^{T} f(y_{it} \mid \mathbf{x}_{it}, \mathbf{z}_{it}, \mathbf{U}_k) \right\}.$$

This representation enables the identification of latent groups of countries sharing similar responses to MaPPs. Let us specify what is the role played by π_k and $\mathbf{U}_k$ in the above $L(\cdot)$. The parameter π_k represents the probability that country i belongs to the latent location k (that is, to the vector of random effects $\mathbf{U}_k$). It is the location $\mathbf{U}_k$ (and the corresponding components $\gamma q_k = \gamma_q + \delta q_k$) that determines the sensitivity of the conditional variance to MaPPs, while the posterior probabilities simply aggregate or assign countries to similar locations with a certain estimated probability. In other words, location drives the impact of MaPPs, whereas posterior probability groups countries sharing the same (or a similar) location with some estimated likelihood.

Notice that this semiparametric specification unifies random-coefficient and mixture approaches: when $K = 1$, it reduces to a standard linear model estimated via ML or GLS; when $K > 1$, it identifies latent clusters of countries with homogeneous credit responses to MaPPs.

[8] Notice that in equation (C.2b), the estimated variance is not the usual OLS scalar σ^2 but it can be space-time dependent designing a heteroschedastic process, i.e., the conditional model variance σ^2_{it} can be a function of some covariates. The *observed* vector of σ^2_{it} is the estimated variance for the model in (C.2a), indeed the distribution of y_{it} is conditional on all covariates involved on the Data Generation Process (DGP) of the response.

Results Table 6 reports the main estimates of the GAMLSS mixture model for private credit-to-GDP ratios. The model includes regressions for the conditional mean, variance, and skewness, with random intercepts capturing cluster-specific effects and fixed coefficients for funding costs, leverage, and their interaction. Clusters are shown in Table 7 for the Full Sample and Table 8 for the OECD Sample. As in previous analyses, the latent cluster index (k) is ordered so that higher k corresponds to higher average GDP per capita, reflecting a transition from low-income, low-credit economies to high-income, credit-intensive financial systems.

For the conditional mean, intercepts increase monotonically across clusters, confirming that higher k values capture economies with deeper financial systems. *FundCost* are negatively associated with credit in both samples, while leverage has a positive effect in the Full Sample but is generally non-significant for OECD countries, except for the significant interaction with funding costs in Cluster 2. This suggests that the impact of funding costs on credit is partially moderated by leverage in specific advanced-economy clusters.

The conditional variance equation shows that borrower-targeted MaPPs (λ) significantly reduce volatility in low-credit, low-income countries (Cluster 1), but may become destabilizing in intermediate-income clusters (Cluster 3 in the Full Sample; Clusters 2 and 5 in the OECD Sample), consistent with the notion that credit-sensitive tightening can amplify volatility in already leveraged economies. Financial institution-targeted policies (ϕ_1) are statistically non-significant in the Full Sample, whereas in the OECD Sample they exert stabilizing effects in Clusters 3 and 4, suggesting that concentration-based measures help dampen credit volatility in advanced economies with asymmetric leverage structures.

The skewness intercept is highly significant in the Full Sample, reflecting positive asymmetry in credit distributions, but less precise for OECD countries, consistent with a more symmetric distribution among advanced economies. Overall, these results underscore the heterogeneous effectiveness of MaPPs: the borrower-targeted measure stabilizes credit primarily at early stages of financial development, while the institution-targeted instrument may gain relevance in more mature (Cluster 4) and leveraged (Cluster 3) credit markets. Taken together, these findings emphasize that within advanced economies, the effectiveness of MaPPs depends less on income level and more on the structure and maturity of credit markets.

Table 6: Model for Location, Scale and Shape I

	Full Sample Estimate (SE)	OECD Estimate (SE)
Dependent variable: *Credit*		
Model for conditional mean		
Random Coefficients		
$Intercept_{k=1}$	17.658*** (0.614)	47.893*** (1.429)
$Intercept_{k=2}$	33.142*** (0.767)	75.843*** (1.734)
$Intercept_{k=3}$	61.533*** (1.139)	106.719*** (1.962)
$Intercept_{k=4}$	105.867*** (1.467)	145.332*** (2.235)
$Intercept_{k=5}$	155.855*** (2.047)	187.322*** (2.092)
Fixed Coefficients		
FundCost	-1.104*** (0.125)	-3.682*** (0.336)
Leverage	0.993*** (0.249)	-0.008 (0.253)
FundCost × *Leverage*	0.051 (0.070)	0.245* (0.118)
Model for conditional variance		
Random Coefficients		
$Intercept_{k=1}$	1.672*** (0.089)	1.739*** (0.188)
$Intercept_{k=2}$	2.192*** (0.117)	3.154*** (0.225)
$Intercept_{k=3}$	3.201*** (0.127)	3.131*** (0.211)
$Intercept_{k=4}$	3.118*** (0.124)	3.118*** (0.227)
$Intercept_{k=5}$	3.081*** (0.145)	3.136*** (0.377)
Borrower-targeted MaPPs (λ)		
$\lambda_{k=1}$	-0.304** (0.105)	-0.685*** (0.204)
$\lambda_{k=2}$	-0.115 (0.080)	0.546*** (0.136)
$\lambda_{k=3}$	0.420*** (0.092)	0.054 (0.113)
$\lambda_{k=4}$	0.054 (0.091)	-0.160 (0.128)
$\lambda_{k=5}$	-0.205· (0.117)	0.691* (0.320)
Financial institution-targeted MaPPs (ϕ_1)		
$\phi_{1,k=1}$	-0.072 (0.162)	-0.306 (0.302)
$\phi_{1,k=2}$	0.144 (0.091)	-0.046 (0.137)
$\phi_{1,k=3}$	-0.116 (0.106)	-0.263* (0.121)
$\phi_{1,k=4}$	-0.014 (0.084)	-0.301** (0.117)
$\phi_{1,k=5}$	0.178 (0.117)	0.150 (0.289)
Model for conditional skewness		
Intercept	15.373*** (0.198)	12.075 (8.286)
N	5665	2425
BIC	9691.368	4375.558
AR1 Coefs ρ_1	-0.068	-0.075

· p-value<0.10, * p-value<0.05, ** p-value<0.01, *** p-value<0.001.

No evidence of serial correlation is detected. The estimated AR(1) coefficients ($\rho_1 = -0.049$ and $\rho_1 = -0.075$) for the All Sample and OECD specifications are small and statistically non-significant, indicating negligible temporal dependence in the residuals.

Table 7: Full sample, classification from Model I (Table 6)

	Clusters				
	k=1	k=2	k=3	k=4	k=5
	Benin	Albania	Belgium	Australia	Austria
	Burkina Faso	Angola	Brazil	Canada	Chile
	Burundi	Argentina	Bulgaria	France	China
	Ghana	Armenia	Costa Rica	Germany	Denmark
	Indonesia	Bangladesh	Croatia	Greece	Hong Kong
	Iraq	Colombia	Estonia	Hungary	Iceland
	Mali	Dominican Rep.	Finland	Ireland	Japan
	Mauritania	Ecuador	India	Italy	Luxembourg
	Myanmar	Guatemala	Jordan	Netherlands	Malaysia
	Nigeria	Jamaica	Kazakhstan	New Zealand	Norway
	Pakistan	Mexico	Kuwait	Portugal	Singapore
	Sierra Leone	Mongolia	Morocco	South Korea	South Africa
	Tajikistan	Peru	Romania	Spain	Switzerland
	Uganda	Philippines	Russian Fed.	Sweden	United Kingdom
	Zambia	Romania	Serbia	Turkey	United States
		Togo	Slovenia		
GDP p.c. (PPP)	1,195	6,628	16,431	37,509	39,170
GDP growth rate	0.029	0.031	0.021	0.021	0.010
Private Credit (% GDP)	16.16	31.09	56.41	106.42	156.37
Credit σ	7.407	11.313	19.79	20.794	26.643
Leverage	1.503	2.474	8.136	1.329	1.765
$\hat{\sigma}$	6.747	10.127	17.280	20.831	25.546

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit σ* is the observed standard deviation of Private Credit over GDP.

Table 8: OECD Sample, classification from Model I (Table 6)

	Clusters				
	k=1	k=2	k=3	k=4	k=5
	Czech Republic	Belgium	Austria	Australia	Denmark
	Mexico	Estonia	Chile	Canada	Japan
	Poland	Finland	France	Iceland	United States
	Slovakia	Hungary	Germany	New Zealand	
		Israel	Greece		
		Italy	Ireland		
		Slovenia	Luxembourg		
		Turkey	Netherlands		
			Norway		
			Portugal		
			Spain		
			Sweden		
			Switzerland		
			United Kingdom		
			South Korea		
GDP p.c. (PPP)	12,146	25,085	43,393	44,690	45,866
GDP growth rate	0.027	0.017	0.011	0.010	0.007
Private Credit % GDP	35.28	63.29	98.36	138.32	178.68
Credit σ	12.595	19.937	20.443	24.135	15.108
Leverage	2.141	2.219	2.938	3.224	1.947
$\hat{\sigma}$	10.369	15.453	19.119	22.406	13.266

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit σ* is the observed standard deviation of Private Credit on GDP.

Table 9 summarizes the estimated effects of our MaPP indicators. A *Stabilizing* (*Destabilizing*) effect corresponds to a negative (positive) and statistically significant coefficient of the MaPP indicator on conditional credit volatility, while *Non-significant* denotes the absence of statistical significance. Two main patterns stand out. Borrower-targeted measures are especially effective in fostering stability in low-income countries and among the lower-income segment of the OECD Sample (Cluster 1), whereas financial-intermediary-targeted measures exhibit a broadly stabilizing influence across the more advanced OECD countries.

Table 9: Summary of MaPP indicator effects on credit volatility, Model I

Cluster	Full Sample		OECD Sample	
	λ	ϕ_1	λ	ϕ_1
$k = 1$	Stabilizing	Non-significant	Stabilizing	Non-significant
$k = 2$	Non-significant	Non-significant	Destabilizing	Non-significant
$k = 3$	Destabilizing	Non-significant	Non-significant	Stabilizing
$k = 4$	Non-significant	Non-significant	Non-significant	Stabilizing
$k = 5$	Non-significant	Non-significant	Destabilizing	Non-significant

Figures E2 and E3 illustrate the goodness-of-fit of the GAMLSS mixture for both samples. They provide a coherent joint representation of both the level and volatility of private credit. The five clusters capture economically meaningful regimes, from low-credit, low-volatility economies to highly leveraged, high-volatility systems, highlighting the heterogeneous responses of credit markets to macroprudential conditions. Panel A compares the observed and fitted private credit-to-GDP ratios, showing that the models for both the Full Sample and OECD countries effectively reproduce the cross-country heterogeneity in credit levels. The clear separation of countries across clusters further indicates that the latent classification is well identified.

Panel B relates the observed standard deviation of private credit to the conditional standard deviation $\hat{\sigma}$ estimated by the model. The positive association confirms that the GAMLSS specification correctly classifies countries by volatility, although the values $\hat{\sigma}$ appear smoother and less dispersed, consistent with the shrinkage implied by the hierarchical structure. In contrast to the OECD Sample, the Full Sample exhibits greater variability in credit volatility, reflecting the broader economic heterogeneity of the dataset, which includes countries at markedly different stages of financial development.

In general, the results confirm that the effectiveness of MaPPs is highly dependent on the state. Borrower-targeted MaPPs act as stabilizers primarily in financially under-developed systems, while institution-targeted MaPPs contribute to stability in mature credit markets where leverage asymmetries dominate. This evidence supports a non-linear view of macroprudential transmission, in which the same instrument can either dampen or amplify volatility depending on the macroeconomic regime.

Including ϕ_2 As a robustness check, we include the second institution-targeted MaPP indicator (ϕ_2) among the regressors (Model II). The resulting estimates, reported in Table D1, and the corresponding cluster classifications (Tables D2 and D3) show a reconfiguration of macroprudential policy effects across both samples. Low-income and low-leverage clusters exhibit limited credit levels (Full sample Cluster 1, OECD Cluster 1), while high-income, highly leveraged clusters record the highest credit levels (Full sample Clusters 3-4, OECD Cluster 4).

Table 11 summarizes the prevailing effects of the three MaPP indicators on credit volatility. Borrower-targeted policies (λ) are generally non-significant, except for a destabilizing effect in intermediate-leverage clusters of the OECD (Cluster 2). Institution-targeted measures display more heterogeneous patterns: ϕ_1, associated with concentration limits, stabilizes credit in moderate-leverage clusters but destabilizes highly leveraged clusters, while ϕ_2, reflecting levies or taxes on financial institutions, stabilizes low-leverage clusters but amplifies volatility in advanced, highly leveraged economies, particularly OECD Cluster 4.[9]

Table 10: Summary of MaPP indicator effects on credit volatility, Model II

Cluster	Full Sample			OECD Sample		
	λ	ϕ_1	ϕ_2	λ	ϕ_1	ϕ_2
$k=1$	Non-significant	Non-significant	Stabilizing	Non-significant	Non-significant	Stabilizing
$k=2$	Non-significant	Stabilizing	Non-significant	Destabilizing	Non-significant	Non-significant
$k=3$	Non-significant	Non-significant	Destabilizing	Non-significant	Stabilizing	Non-significant
$k=4$	Non-significant	Destabilizing	Destabilizing	Non-significant	Destabilizing	Destabilizing

At the country level, Austria, Canada, Czech Republic, Germany, Norway, Poland, Sweden, Switzerland, and the United Kingdom experience predominantly stabilizing regimes, whereas the United States, Denmark, Italy, Japan, and the Netherlands exhibit destabilizing or swinging regimes. Some countries, such as Luxembourg, Spain, and New Zealand, display

[9]The exceptionally high value of $\phi_{2,k=4}$ in the OECD Sample can be rationalized by considering both the observable characteristics of countries in this cluster and the construction of ϕ_2 in the applied data reduction framework. Cluster 4 includes high-income countries with mature financial systems, such as Canada, Denmark, Japan, Switzerland, and the United States. These countries exhibit very high private credit-to-GDP ratios (156–171%) and elevated financial leverage (Leverage ≈ 2.5), indicative of credit markets that are particularly sensitive to regulatory interventions. The composition of ϕ_2 further amplifies its impact in these countries. As shown in Table 3, the most influential components are: taxation/levies on financial institutions (weight 0.384), interbank exposure limits (0.212), and dynamic loan-loss provisioning (0.194). These instruments are especially relevant in concentrated, leveraged banking systems, thus magnifying the cluster-specific effect of ϕ_2 on credit volatility. Economically, ϕ_2 captures the effect of financial institution-targeted MaPPs on the variance of credit. In highly developed financial markets, policies such as capital surcharges, interbank exposure limits, and loan-loss provisioning have a disproportionate influence on credit volatility, explaining the peak value observed for Cluster 4 ($\phi_{2,k=4} = 12.672$). This interpretation is consistent with the estimated conditional volatility $\hat{\sigma}$ for this cluster ($\hat{\sigma} \approx 685$), which indicates a substantial dispersion in credit growth that is amplified by financial institution-targeted measures.

adaptive regimes where λ contributes to stabilization in some clusters and institution-targeted instruments are non-significant or mildly destabilizing.

Overall, Model II highlights that macroprudential instruments operate through partially independent channels. Borrower-targeted measures are most effective in intermediate-leverage or less developed financial systems, whereas institution-targeted policies can stabilize or destabilize credit depending on cluster-specific characteristics such as leverage, financial depth, and the maturity of domestic credit markets. The joint inclusion of ϕ_1 and ϕ_2 shows that institution-targeted instruments capture distinct mechanisms, with ϕ_1 primarily reflecting concentration limits and ϕ_2 representing liquidity- or balance-sheet-based interventions.

Interactions Table D7 presents the estimates of Model III, in which not only the *FundCost* but also the MaPP indicators λ, ϕ_1, and ϕ_2 interact with *Leverage*. In this specification, the additional interaction terms are included only in the variance equation, while the mean equation omits them to ensure the stability of the EM algorithm. Consequently, the *Leverage* and *FundCost* $\times$ *Leverage* terms appearing in Models I and II are excluded here. Although this choice limits direct comparability with the baseline models, it allows for a more precise evaluation of MaPPs' effects on private credit volatility through the conditional variance implied by the GAMLSS structure.

This formulation is closely aligned with the broad literature estimating the determinants of observed credit volatility, including Cerutti et al. (2017), Coimbra and Rey (2018), and Coimbra and Rey (2024). However, our approach departs from these contributions by modeling the *conditional* variance, $\hat{\sigma}_{it}$, jointly with the conditional mean within the GAMLSS framework.

Table 11: Summary of MaPP indicator effects on credit volatility, Model III

Cluster	Full Sample			OECD Sample		
	λ	ϕ_1	ϕ_2	λ	ϕ_1	ϕ_2
$k = 1$	Non-significant	Non-significant	Stabilizing	Stabilizing	Stabilizing	Destabilizing
$k = 2$	Non-significant	Stabilizing	Non-significant	Destabilizing	Non-significant	Destabilizing
$k = 3$	Non-significant	Non-significant	Destabilizing	Stabilizing	Stabilizing	Destabilizing
$k = 4$	Stabilizing	Destabilizing	Destabilizing			

Cluster classifications (Tables D8 and D9) reveal four regimes in the Full Sample, from low-income, low-leverage economies (Cluster 1) to highly developed, financially deep systems (Cluster 4), with a similar three-cluster partition for the OECD subset.

The results indicate heterogeneous effects of MaPPs across clusters. Borrower-targeted instruments (λ) are significantly stabilizing only in highly leveraged, advanced clusters (Full Sample Cluster 4; OECD Clusters 1 and 3), and destabilizing or non-significant elsewhere[10].

Institution-targeted measures show contrasting patterns: ϕ_1 generally stabilizes credit, particularly in high-leverage clusters, but may destabilize in the most advanced economies, whereas ϕ_2 is predominantly destabilizing, except in low-income, low-leverage clusters.

These findings highlight that MaPP effectiveness depends critically on cluster-specific leverage and financial development: borrower-targeted instruments are most effective in highly leveraged contexts, while institution-targeted measures can amplify volatility as systems deepen. The joint modeling of conditional mean and variance ensures a consistent evaluation of these heterogeneous effects across both credit levels and volatility.

Table 12: Summary of MaPP indicators effects across models and samples

MaPP indicator	Model	Stabilized Clusters	Destabilized Clusters
λ	Model I	Full: 1 OECD: 1	Full: 3 OECD: 2, 5
	Model II	–	OECD: 2
	Model III	Full: 4 OECD: 1, 3	OECD: 2
ϕ_1	Model I	OECD: 3, 4	–
	Model II	Full: 2 OECD: 3	Full: 4
	Model III	Full: 2 OECD: 1, 3	Full: 4
ϕ_2	Model I	–	–
	Model II	Full: 1 OECD: 1	Full: 3, 4 OECD: 4
	Model III	Full: 1	Full: 3, 4 OECD: 1, 2, 3

Note: only statistically significant effects are reported.

Alternative MaPP indicators Comparing the baseline specification (Model I) with the version based on the unweighted Cerutti et al. (2017)'s indices (Model IV, Table D10) highlights the value of the composite MaPP indicators constructed in this paper. In the base-

[10]The exceptionally high value of $\phi_{2,k=4}$ for the Full Sample (Table D7) is consistent with the pattern previously identified in the model without interactions (Model II, Table D1), where Cluster 4 in the OECD Sample also exhibited an anomalously large estimate of $\phi_2 \approx 12$. In Model III, Cluster 4 for the Full Sample largely overlaps with Cluster 4 from Model II (OECD Sample); that is, it includes high-income, highly financialized countries such as Canada, Denmark, Japan, Switzerland, and the United States, characterized by very high private credit-to-GDP ratios (see Table D9) and substantial banking sector leverage (Leverage ≈ 2.5). These structural features make their credit markets particularly sensitive to regulatory interventions.

line model, borrower-targeted policies stabilize credit in low-income countries and weaken or turn destabilizing in financially advanced systems—a pattern consistent with prior evidence (Claessens et al., 2013; Cerutti et al., 2017; Akinci and Olmstead-Rumsey, 2015). When the indicators proposed by Cerutti et al. (2017) are employed in our model, these relationships become weaker and often reverse sign: borrower-based MaPPs appear destabilizing in low-income clusters and stabilizing only in high-income regimes (see Table D11). Similarly, the stabilizing role of institution-targeted measures remains but shifts toward middle-income countries. These discrepancies suggest that our MaPP indicators better capture the effective intensity and structure of macroprudential interventions, improving the economic interpretability of the results.

Cross-model comparison Confronting Models I–III, Table 12 highlights three broad regularities. First, λ is associated with lower credit volatility—that is, it exhibits stabilizing effects—primarily in low-income or low-leverage environments (Cluster 1 in the Full Sample, Model I; Cluster 1 in the OECD Sample, Models I and III; and Cluster 3 in the OECD Sample, Model III). Conversely, it is associated with higher credit volatility (destabilizing effects) in several middle-income OECD countries (Cluster 2, Models II and III) and in a few high-leverage systems (Clusters 3 and 5 in the OECD Sample, Model I).

Second, ϕ_1, mainly based on concentration limits, generally plays a stabilizing role (most clearly in Full-Sample Cluster 2 and in OECD Clusters 1 and 3) but turns destabilizing in countries with deep credit markets (Full-Sample Cluster 4 in Models II and III).

Finally, ϕ_2), reflecting levies and taxes on financial intermediaries, stabilizes low-income and, to some extent, middle-income economies (Full-Sample Cluster 1 in Models II and III; OECD Cluster 1 in Model II), but amplifies volatility in more financially developed and leveraged contexts (Clusters 3-4 in the Full Sample, both Models II and III; OECD Cluster 4 in Model II and Clusters 1-3 in Model III).

Overall, these patterns underscore the regime-dependent transmission of macroprudential policies: borrower-targeted instruments tend to be effective in moderate-leverage environments, while lender-targeted measures show context-specific, and at times procyclical, effects.

3.1 OECD Sample

We now focus on the OECD Sample, where financial systems are more mature and policy frameworks more comparable.

Cross-cluster mobility and prevailing MaPPs effects Table 13 summarizes cross-cluster mobility among OECD countries across Models I–III. Roughly half of the sample remains *anchored*, consistently assigned to the same latent cluster. A smaller group of *adaptive* countries (e.g., Austria, France, Germany, Portugal) move once between adjacent clusters, reflecting moderate sensitivity to model specification and the inclusion of additional MaPP indicators. Finally, a few *swinging* economies (e.g., Denmark, Japan, Switzerland, and the United States) exhibit recurrent or large reassignments across distant clusters, pointing to more heterogeneous macro-financial regimes and higher cyclical volatility.

Table 13: Cross-model cluster stability (OECD Sample)

Country	Model I Cluster	Model II Cluster	Model III Cluster	Classification
Austria	3	2	3	Adaptive
Australia	4	4	3	Adaptive
Belgium	2	2	1	Anchored
Canada	4	4	2	Anchored
Chile	3	2	3	Adaptive
Czech Republic	1	1	1	Anchored
Denmark	5	4	2	Swinging
Finland	2	2	1	Anchored
France	3	2	3	Adaptive
Germany	3	2	3	Adaptive
Greece	3	3	3	Anchored
Hungary	2	1	1	Anchored
Iceland	4	4	2	Anchored
Ireland	3	3	3	Anchored
Italy	3	3	3	Anchored
Japan	5	4	2	Swinging
Luxembourg	3	3	3	Anchored
Mexico	1	1	1	Anchored
Netherlands	3	3	3	Anchored
New Zealand	4	4	2	Anchored
Norway	3	3	3	Anchored
Poland	1	1	1	Anchored
Portugal	3	3	2	Adaptive
Slovakia	1	1	1	Anchored
Slovenia	2	2	1	Anchored
Spain	3	3	2	Adaptive
Sweden	3	3	3	Anchored
Switzerland	3	4	2	Swinging
Turkey	2	2	1	Anchored
United Kingdom	3	3	2	Adaptive
United States	5	4	2	Swinging

Table 14 reports the prevailing effect of each MaPP indicator across Model I, II and III, focusing only on OECD countries. A clear gradient emerges across OECD clusters in terms of income, leverage, and credit volatility. Borrower-targeted measures (λ) tend to stabilize credit dynamics in lower-leverage and moderately developed systems (e.g., Czech Republic, Poland, and Mexico), whereas they are often associated to increased credit volatility in highly leveraged or financially developed economies (e.g., the United States, Japan, Denmark). The concentration limit-based MaPP (ϕ_1) displays a broadly stabilizing pattern, particularly in continental European countries, while the profit-based MaPP (ϕ_2) is predominantly destabilizing, especially in high-income, credit-intensive systems. Overall, the cross-model comparison highlights a structural asymmetry: borrower-based MaPPs are typically associated with more stable credit dynamics in shallow or bank-centered markets, whereas profit-based MaPPs tend to be associated with higher credit volatility in more financially developed economies.

Table 14: Prevailing MaPP effects by country across models (OECD Sample)

Country	λ (prev.)	ϕ_1 (prev.)	ϕ_2 (prev.)
Australia	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
Austria	Mixed	Stabilizing	Destabilizing (weak)
Belgium	Mixed	Stabilizing (weak)	Destabilizing (weak)
Canada	Destabilizing (weak)	Mixed	Destabilizing
Chile	Mixed	Stabilizing	Destabilizing (weak)
Czech Republic	Stabilizing	Stabilizing (weak)	Mixed
Denmark	Destabilizing	Destabilizing (weak)	Destabilizing
Estonia	Mixed	Stabilizing (weak)	Destabilizing (weak)
Finland	Mixed	Stabilizing (weak)	Destabilizing (weak)
France	Mixed	Stabilizing	Destabilizing (weak)
Germany	Mixed	Stabilizing	Destabilizing (weak)
Greece	Mixed	Stabilizing	Destabilizing (weak)
Hungary	Mixed	Stabilizing (weak)	Mixed
Iceland	Destabilizing (weak)	Stabilizing	Destabilizing (weak)
Ireland	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
Israel	Mixed	Stabilizing (weak)	Destabilizing (weak)
Italy	Mixed	Stabilizing (weak)	Destabilizing (weak)
Japan	Destabilizing	Destabilizing (weak)	Destabilizing
Korea (South)	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
Luxembourg	Mixed	Stabilizing	Destabilizing (weak)
Mexico	Stabilizing	Stabilizing (weak)	Mixed
Netherlands	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
New Zealand	Destabilizing (weak)	Stabilizing	Destabilizing (weak)
Norway	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
Poland	Stabilizing	Stabilizing (weak)	Mixed
Portugal	Destabilizing (weak)	Stabilizing	Destabilizing (weak)
Slovakia	Stabilizing	Stabilizing (weak)	Mixed
Slovenia	Mixed	Stabilizing (weak)	Destabilizing (weak)
Spain	Destabilizing (weak)	Stabilizing	Destabilizing (weak)
Sweden	Stabilizing (weak)	Stabilizing	Destabilizing (weak)
Switzerland	Destabilizing (weak)	Mixed	Destabilizing
Turkey	Mixed	Stabilizing (weak)	Destabilizing (weak)
United Kingdom	Destabilizing (weak)	Stabilizing	Destabilizing (weak)
United States	Destabilizing	Destabilizing (weak)	Destabilizing

Notes: "(weak)" = sign appears once and others are non-significant; "Mixed" = at least one stabilizing and one destabilizing significant estimate across models. ϕ_2 is available only in Models II–III.

Cluster membership: Multinomial Logit Model The econometric analysis above highlights the importance of unobserved heterogeneity. Our multinomial logit estimates indicate that banking and macro-financial indicators have heterogeneous effects on cluster membership probabilities, with both magnitude and statistical significance varying across clusters. To enhance interpretability, we next discuss how these covariates influence the likelihood of belonging to each latent cluster, based on Table 8.[11]

Table 15: Multinomial Logit Model for Estimated Cluster Membership (OECD Sample)

Dep. Variable: Estimated Cluster Membership	Odds Ratio	z	p-value
Cluster 2			
Intercept	0.076	-2.275	0.0229
Private bank credit facilities (annual change)	0.811	-3.630	0.0003
Intermediaries' value added	0.994	-0.448	0.654
Banking sector leverage (level)	1.372	5.303	0.0000
Financial corporations debt to equity ratio	0.680	-3.686	0.0002
Trade openness	1.009	1.988	0.0468
Cluster 3			
Intercept	0.344	-0.965	0.3346
Private bank credit facilities (annual change)	0.828	-3.225	0.0013
Intermediaries' value added	0.991	-0.623	0.533
Banking sector leverage (level)	1.453	6.240	0.0000
Financial corporations debt to equity ratio	0.569	-5.239	0.0000
Trade openness	0.998	-0.545	0.586
Cluster 4			
Intercept	1.127	0.089	0.929
Private bank credit facilities (annual change)	0.800	-3.671	0.0002
Intermediaries' value added	1.002	0.124	0.901
Banking sector leverage (level)	1.530	6.889	0.0000
Financial corporations debt to equity ratio	0.457	-5.533	0.0000
Trade openness	0.972	-4.066	0.00005
Cluster 5			
Intercept	9.728	1.489	0.137
Private bank credit facilities (annual change)	0.814	-3.057	0.0022
Intermediaries' value added	1.000	-0.014	0.989
Banking sector leverage (level)	1.531	6.678	0.0000
Financial corporations debt to equity ratio	0.369	-5.529	0.0000
Trade openness	0.951	-5.456	0.0000

Cluster 1 is the reference group.

In Table 15, we report odds ratios ($\exp(\beta)$) derived from the Multinomial Logit Model with five latent clusters. This specification reveals substantial latent heterogeneity in the

[11] For this model, banking data from the OECD are only available starting in 2016.

relationship between macro-financial variables and the probability of belonging to different country groups.

Private bank credit facilities (annual change) consistently exhibit odds ratios below one across all clusters, indicating that faster credit expansion significantly reduces the probability of belonging to higher-numbered clusters. This suggests that credit acceleration is a distinguishing feature of countries positioned in the lower part of the distribution, possibly reflecting less mature or more volatile financial systems.

Banking sector leverage (level) displays a robust and highly significant positive association across all clusters. An odds ratio above one implies that countries with more leveraged banking systems are systematically associated with higher cluster membership probabilities, indicating that leverage acts as a structural determinant of financial differentiation.

Conversely, the *Financial corporations' debt-to-equity ratio* exerts a strong and negative influence, with odds ratios ranging from 0.37 to 0.68. This pattern implies that greater corporate indebtedness lowers the likelihood of being classified into more advanced or stable clusters, highlighting the stabilizing role of balanced corporate funding structures.

Trade openness exhibits heterogeneous effects: while it marginally increases the probability of belonging to Cluster 2, its impact turns negative and statistically significant in Clusters 4 and 5. This suggests that higher external exposure may increase vulnerability to external shocks in more financially developed economies.

Overall, these findings point to structural rather than purely policy-driven determinants of financial heterogeneity across countries. The five-cluster decomposition identifies distinct macro-financial regimes in which the marginal effects of credit expansion, leverage, and openness differ substantially, reflecting diverse stages of financial development and systemic resilience.

4 Conclusion

This paper investigates whether macroprudential policies (MaPPs) are effective in reducing credit volatility. We first construct composite indicators of MaPPs that systematically summarize the wide array of policy instruments, improving on the dummy-based measures commonly used in the literature. These indicators are then embedded in an econometric framework that jointly models credit levels and volatility while accounting for unobserved heterogeneity across countries. The empirical design is grounded in a theoretical model that explicitly incorporates heterogeneous financial intermediaries, representing a significant improvement over standard approaches that regress credit volatility on macroeconomic aggregates while capturing the banking sector only through coarse proxies or *ad hoc* indicators.

We employ a Generalized Additive Model for Location, Scale, and Shape (GAMLSS), which extends standard panel regressions by allowing the parameters of the conditional distribution—mean, variance, skewness, and kurtosis—to depend on covariates. This flexibility enables policy variables to influence not only average credit growth (first moment) and volatility (second moment) but also higher-moment risks associated with financial instability.

The results show that differences in macroprudential frameworks do not uniformly translate into lower credit volatility. Unobserved heterogeneity across countries plays a crucial role. In high-income economies, lender-targeted measures that restrict financial institutions' lending capacity can have unintended, volatility-amplifying effects. By contrast, borrower-based instruments—such as caps on loan-to-value ratios—are associated with greater financial stability in lower-income and credit-constrained economies. At intermediate levels of development, the evidence is mixed: borrower-based tools may turn mildly destabilizing, while concentration-limit policies retain stabilizing effects and taxes on intermediaries become countercyclical, reflecting growing sensitivity to financial cycles. In highly leveraged, advanced financial systems, all instruments tend to lose effectiveness or even amplify volatility, consistent with the procyclical amplification typical of mature, complex credit markets.

Finally, when the leverage distribution of the banking sector is highly skewed—meaning that a large share of assets is held by riskier intermediaries—only financial-institution-targeted measures, especially concentration limits, retain stabilizing power. Overall, these findings highlight the state-dependent nature of macroprudential transmission: the effectiveness, and even the direction, of MaPPs depend critically on a country's stage of financial development and structural characteristics of its banking system.

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A A Model with heterogeneous intermediaries and MaPPs

This appendix provides a simple extension of the Coimbra and Rey (2024) model to include MaPPs.

Fundamentals Time is discrete, indexed by $t = 0, 1, 2, \dots, \infty$. The economy is populated by an infinitely lived representative household, a financial intermediary with a two-period lifespan, and a stylized governmental entity responsible for determining the interest rate, tax rate, and regulatory obligations for financial intermediaries. Both in the production sector and the financial sector agents are price taker. The economy is subject to idiosyncratic uncertainty, in the form of productivity shocks, and aggregate uncertainty, arising from monetary shocks.

Firm The final output, which is the numeraire of the economy, is produced by a competitive firm using the following technology

$$y_t = Z_t \kappa_t^{\theta} \ell_t^{1-\theta}, \tag{A.1}$$

where κ_t denotes physical capital, ℓ_t labor, normalized to 1, $\theta \in (0, 1)$ and Z_t is the stochastic TFP. Financial markets are incomplete, in that firms face a collateral constraint given by

$$\kappa_t \leq \mathsf{m}_{\lambda} A_t, \tag{A.2}$$

where $\mathsf{m}_{\lambda} \geq 1$ denotes a borrower-targeted MaPP operating as a collateral multiplier (looser if higher), and A_t is a long-lived asset in fixed supply paying no dividends and with no alternative uses.[12] Notice that, unlike in the empirical analysis, a policy tightening in this theoretical setting corresponds to a *decrease* in m_{λ}.

[12] This assumption is equivalent to imposing a debt limit. A firm can leverage debt, B, backed by a fraction ϑ of the acquired capital, which acts as collateral (i.e., $B_t \leq \vartheta \kappa_t$). ϑ can be interpreted as the Loan-to-Value ratio (LTV). Firm's net worth is then given by $A_t \equiv \kappa_t - B_t$, and the debt constraint can be reformulated as (A.2), where $\mathsf{m}_{\lambda} \equiv (1-\vartheta)^{-1}$. Moreover, as $\lim_{\vartheta \to 1^-} \mathsf{m}_{\lambda} = \infty$ it signals the efficient functioning of capital markets. Notice that, in practice, borrower-targeted MaPPs are typically applied to households and also include measures like DSTI, DTI, and other creditworthiness criteria beyond collateral constraints. In the model, we simplify by focusing exclusively on the LTV constraint, noting that firms are assumed to be owned by households.

Standard optimality conditions require

$$R_t^i = \theta Z_t^i \kappa_t^{\theta-1} + (1-\delta), \tag{A.3}$$

$$w_t = (1-\theta) Z_t \kappa_t^{\theta}, \tag{A.4}$$

where δ is the depreciation rate and (A.3) indicates that there is an idiosyncratic risk to financial intermediation (i.e., the return on a unit of capital is intermediary specific).

Household The representative household supplies labor inelastically and chooses consumption and savings. The program is

$$\max_{\{c_t^h, s_t^h, d_t^h\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t^h\right) \qquad \text{s.t.} \tag{A.5}$$
$$c_t^h + s_t^h + d_t^h = R_t^d d_{t-1}^h + R_t^s s_{t-1}^h + w_t - \tau_t,$$

where β is the subjective discount factor and $u(\cdot)$ is the period utility function, with $u' > 0$ and $u'' < 0$ defined over consumption, c_t^h, w_t is the wage and τ_t are lump-sum taxes. There are two different investment options for any savings the household has: deposits (d_t^h) or one-to-one storage technology (s_t^h). Both forms of investment are risk-free, but for different reasons. Deposits are protected by a public guarantee, which is financed by tax proceeds, and have a gross return denoted by R_t^d. The storage technology, instead, is assumed having a returns $R_t^s = 1$. The Euler condition is

$$\frac{u'\left(c_t^h\right)}{u'\left(c_{t+1}^h\right)} = \beta R_t^d. \tag{A.6}$$

Intermediary The financial sector consists of financial intermediaries that operate over two periods. Intermediaries secure funding through inside equity and deposits from households. They use these funds to invest in the overall risky capital stock and/or the risk-free one-to-one storage technology. The intermediaries are risk-neutral agents and maximize their expected consumption in the second period subject to a Value-at-Risk (VaR) constraint.[13] Intermediaries are not all alike and their heterogeneity is captured by the parameter α^i, which represents the highest likelihood that they will experience a negative return on equity as determined by their specific VaR constraint. At each date t, the balance sheet of the intermediary is structured in such a way that the assets comprise the sum of the intermediary's

[13] VaR measures are frequently employed in risk management by various types of intermediaries.

shares of the overall capital stock (κ_t^i) and the amount of storage they hold (s_t^i). On the other side of the balance sheet, the liabilities are made up of the deposits received and the inside equity.

Assets	**Liabilities**
Capital Stock (κ_t^i)	Deposits (D_t^i)
Storage (s_t^i)	Internal Equity (ω_t^i)
Total: $\kappa_t^i + s_t^i$	Total: $D_t^i + \omega_t^i$

At $t+1$, aggregate and idiosyncratic shock are revealed and the net cash flow is

$$(1 - \mathsf{m}_\phi)\pi_{t+1}^i = R_{t+1}^i \kappa_t^i + s_t^i - R_t^d D_t^i,$$

where D_t^i is the demand for deposits and $\mathsf{m}_\phi \in (0,1)$ is the tax rate on intermediary's profit. To decouples the volatility of the return on assets from the volatility of the aggregate capital stock, we assume that the productivity of capital features an idiosyncratic and an aggregate productivity component. Let ζ denote an operational risk shock, we assume that

$$R_{t+1}^i = \begin{cases} 1-\delta & \text{with probability } \zeta, \\ \theta \widetilde{Z}_t \kappa_t^{\theta-1} + (1-\delta) & \text{with probability } 1-\zeta, \end{cases} \tag{A.7}$$

where $\widetilde{Z}$ is the productivity of capital conditional on no idiosyncratic shock, which follow the following AR(1) process:

$$\widetilde{Z}_{t+1} = (1-\rho^z)\mu^z + \rho^z \log \widetilde{Z}_t + \varepsilon_{t+1}^z, \tag{A.8}$$

$$\varepsilon_{t+1}^z \sim \mathcal{N}\left(0, \sigma_z^2\right). \tag{A.9}$$

We assume that expected return on capital is equal across intermediaries.

Assume wholesale funding is a fixed share of deposits, i.e.,

$$L_t^i = \chi D_t^i, \qquad \chi \geq 0. \tag{A.10}$$

Balance-sheet feasibility gives, for participants with $s_t^i = 0$,[14]

$$\kappa_t^i \;=\; \omega + D_t^i + L_t^i \;=\; \omega + (1+\chi) D_t^i. \tag{A.11}$$

We define the *effective funding rate* R^f as

$$R_{t+1}^f \;\equiv\; \frac{R_{t+1}^d + \chi\, R_{t+1}^l}{1+\chi}, \tag{A.12}$$

so that the total interest cost on market funding is

$$R_{t+1}^d D_t^i + R_{t+1}^l L_t^i \;=\; R_{t+1}^f\,(k_t^i - \omega). \tag{A.13}$$

Setting $\chi = 0$ or $R_{t+1}^l = R_{t+1}^d$ nests the baseline without wholesale premia.

Deposit insurance covers any shortfall on intermediaries' demandable liabilities, guaranteeing full repayment to depositors in the event of losses; the transfer is

$$t_{t+1}^i \;\equiv\; \max\{0,\, -\pi_{t+1}^i\}. \tag{A.14}$$

Hence the intermediary's net payoff to owners at $t{+}1$ is $\max\{0, \pi_{t+1}^i\}$, while depositors always receive $R_{t+1}^d D_t^i$.

The VaR constraint implies that the investment strategy of intermediary i is designed in a way that the likelihood of receiving a negative return on equity is less than α^i, an exogenous intermediary-specific parameter distributed according to a cdf $G(\alpha^i)$ with $\alpha^i \in [\underline{\alpha}, \overline{\alpha}]$. We assume that the risk neutral intermediaries receive a constant endowment of equity $\omega_t^i = \overline{\omega}$ in the first period and consume their net worth in the second period.

The value of an active intermediary is

$$V_t^i = \max_{\{c_t^i\}} \; \mathbb{E}\Big(c_{t+1}^i\Big) \quad \text{s.t.} \tag{A.15}$$

$$\Pr\Big(\pi_{t+1}^i < \overline{\omega}\Big) \leq \alpha^i, \tag{A.16}$$

$$\kappa_t^i + s_t^i \;=\; \overline{\omega} + D_t^i + L_t^i, \tag{A.17}$$

$$\pi_{t+1}^i \;=\; R_{t+1}^i k_t^i \;+\; R_{t+1}^s s_t^i \;-\; R_{t+1}^f\,(D_t^i + L_t^i), \tag{A.18}$$

[14]Non-participating intermediaries instead allocate their equity entirely to storage ($\kappa_t^i = 0$, $s_t^i = \omega$). This assumption simplifies the leverage definition and reflects that leveraged intermediaries optimally invest only in risky capital rather than in the safe storage technology.

where R^f_{t+1} is the (endogenous) weighted average funding cost

$$R^f_{t+1} \;\equiv\; \frac{R^d_{t+1} D^i_t \;+\; R^l_{t+1} L^i_t}{D^i_t + L^i_t},$$

and $R^s_{t+1} = 1$. If $L^i_t = \chi D^i_t$, then $R^f_{t+1} = R^d_{t+1} + \frac{\chi}{1+\chi}(R^l_{t+1} - R^d_{t+1})$.

The value of an inactive intermediary, when $\kappa^i_t = 0$ and $D^i_t = 0$, is given by $\overline{V}^i_t = \overline{\omega}$. Moreover, intermediaries benefit from limited liability, i.e.

$$\mathbb{E}\left[\max(0, \pi_{t+1})\right] \geq \mathbb{E}\left(\pi_{t+1}\right). \tag{A.19}$$

If the cash flow is negative ($\pi_{t+1} < 0$), then the Government provides the deposit insurance transfer

$$t_{t+1} = \max\{0, -\pi_{t+1}\}. \tag{A.20}$$

Each financial intermediary must take two decisions. Fist, it decides whether to engage in the market for risky assets or to allocate funds into storage technology, distinguishing them as either *participating* or *non-participating intermediaries.* Second, if participating, it must determine whether to leverage their investments using deposits (thereby becoming a *risky* intermediary) or to invest solely with their own equity (a *safe* intermediary).[15]

Government and deposit insurance The government—which also operates as resolution authority—sets the policy rate that determines R^d_t, and two MaPP instruments: a borrower-based constraint m_λ and a lender-based profit tax $\mathsf{m}_\phi \in [0, 1)$. It levies lump-sum taxes τ_t on the representative household and provides full deposit insurance.

The after-tax profit is given by:

$$\pi^i_{t+1} = (1 - \mathsf{m}_\phi)\big(R^i_{t+1}\kappa^i_t + s^i_t - R^d_{t+1} D^i_t - R^l_{t+1} L^i_t\big). \tag{A.21}$$

Let $T^\phi_t \equiv \int T^{\phi,i}_t \,\mathrm{d}i$ and $T^{\mathrm{ins}}_t \equiv \int t^i_t \,\mathrm{d}i$ denote, respectively, aggregate profit-tax revenues and aggregate insurance payouts at time t. The per-period government balanced budget is

$$\tau_t \;+\; T^\phi_t \;=\; T^{\mathrm{ins}}_t. \tag{A.22}$$

[15]Notice that the terms *risky* and *safe* refer to the potential to default on loans, not the volatility of returns on assets or equity. As a consequence, in this model, only *non-participating intermediaries*, which invest exclusively in storage, can be considered truly risk-free.

Monetary policy sets the policy rate R_t^d, which determines the cost of retail deposits. The wholesale rate R_t^l is, instead, market-determined. Given the fixed composition of funding $L_t^i = \chi D_t^i$, the effective average cost of funds faced by intermediaries is

$$R_t^f = R_t^d + \frac{\chi}{1+\chi}(R_t^l - R_t^d), \tag{A.23}$$

For brevity, in what follows we treat R_t^f as a sufficient statistic summarizing the stance of monetary policy and funding conditions.

Aggregation and market clearing Let κ_t^i, s_t^i, D_t^i be individual intermediary choices, and s_t^h, d_t^h the household's storage and deposits. Market clearing conditions are

$$\mathcal{K}_t = \int \kappa_t^i \,\mathrm{d}i, \qquad S_t = s_t^h + \int s_t^i \,\mathrm{d}i, \qquad D_t = d_t^h = \int D_t^i \,\mathrm{d}i, \tag{A.24}$$

and the borrower-based MaPP binds (for participants). Goods can be used for consumption, physical investment, and storage formation. Let $I_t^{\mathcal{K}} \equiv \mathcal{K}_{t+1} - (1-\delta)\mathcal{K}_t$ and $I_t^S \equiv S_t$ be, respectively, gross physical investment and storage formed at t (which returns one good per unit at $t+1$). Then the aggregate resource constraint is

$$y_t \;=\; c_t^h \;+\; I_t^{\mathcal{K}} \;+\; I_t^S, \tag{A.25}$$

and next period goods availability includes S_t via $R_{t+1}^s = 1$.

Competitive equilibrium with MaPPs Given policy rate sequences $\{R_t^d\}_{t\geq 0}$ and MaPP instruments $\{\mathsf{m}_\lambda, \mathsf{m}_\phi\}$, an equilibrium is a collection of allocations $\{c_t^h, s_t^h, d_t^h\}_{t\geq 0}$, intermediary decisions $\{\kappa_t^i, s_t^i, D_t^i\}_{i,t}$, a wage rate $\{w_t\}_{t\geq 0}$ and a effective rate $\{R_t^f\}_{t\geq 0}$, and aggregates $\{\mathcal{K}_t, S_t, D_t\}_{t\geq 0}$ such that: (i) $\{c_t^h, s_t^h, d_t^h\}$ solve the household problem (A.5); (ii) $w_t = (1-\theta)Z_t\kappa_t^\theta$, and $R_t^i = \theta Z_t^i \kappa_t^{\theta-1} + (1-\delta)$ holds; (iii) for each i, $\{\kappa_t^i, s_t^i, D_t^i\}$ maximize expected consumption subject to balance-sheet feasibility, the VaR constraint $\Pr(\pi_{t+1}^i < 0) \leq \alpha^i$, and limited liability, taking R_t^f, κ_t, and prices as given; (iv) the government budget constraint (A.22) holds each period; (v) market-clearing conditions (A.24) hold; and (vi) the feasibility constraint (A.25) holds for all t.

Leverage and financial stability Let $\widetilde{Z}_t^q$ denote the quantile of the technology shock at which the Value-at-Risk (VaR) constraint binds, that is,

$$\widetilde{Z}_t^q = \mathcal{F}^{-1}\left(\frac{\alpha^i}{1-\zeta}\right), \tag{A.26}$$

so that

$$\Pr(\pi_{t+1}^i < 0 \mid \text{“no-idiosyncratic-loss”}) = \frac{\alpha^i}{1-\zeta}, \tag{A.27}$$

where $\mathcal{F}^{-1}(\cdot)$ is the inverse cumulative distribution function (cdf) of the idiosyncratic productivity shock, α^i is the intermediary's VaR tolerance (the maximum admissible default probability), and ζ is the probability of an idiosyncratic operational loss. Intuitively, $\widetilde{Z}_t^q$ represents the threshold productivity level below which the intermediary's equity return becomes zero in the “no-idiosyncratic-loss” branch.[16]

The zero-profit quantile condition is

$$0 \;=\; \left[\theta\, \widetilde{Z}_t^q\, (k_t^i)^{\theta-1} + (1-\delta)\right] k_t^i - R_t^f\,(k_t^i - \omega). \tag{A.28}$$

Defining leverage $\mathcal{L} \equiv k_t^i/\omega$ and using the collateral corner $k_t^i = \mathsf{m}_\lambda A_t$ for participants, we obtain

$$\mathcal{L} \;=\; \frac{R_t^f}{R_t^f - \theta\, Z_{t+1}^e\,(\mathsf{m}_\lambda A_t)^{\theta-1}\,\mathcal{F}^{-1}\!\left(\frac{\alpha^i-\zeta}{1-\zeta}\right) + \delta}\,. \tag{A.29}$$

For $\chi = 0$ (or $R_t^l = R_t^d$), $R_t^f = R_t^d$ and (A.29) collapses to the baseline expression.

The following result follows from Coimbra and Rey (2024, Proposition 1), extending the anaysis to the case in which intermediaries face both a borrower-based collateral constraint and a Value-at-Risk (VaR) constraint.

Proposition 1 *Under participation ($s_t^i = 0$) and a binding VaR with default possible only in*

[16] In the model, each intermediary faces two types of uncertainty: (i) aggregate shocks, which affect the entire economy (e.g., changes in overall productivity or interest rates); and (ii) idiosyncratic shocks, which affect only individual intermediaries (e.g., portfolio losses or management failures). The expression *“no-idiosyncratic-loss” branch* refers to the state of the world in which the second type of shock does not occur, i.e., the intermediary operates under normal conditions and is affected only by aggregate (economy-wide) risk. Formally, each intermediary faces an operational loss with probability ζ, so the “no-idiosyncratic-loss” branch corresponds to the complementary probability $(1-\zeta)$, under which the return on assets depends solely on the aggregate productivity shock.

the "no-idiosyncratic-loss" branch,

$$\mathcal{L} \equiv \frac{\kappa_t}{\omega} = \frac{R_t^f}{R_t^f - \theta\, Z_{t+1}^e\, (\mathsf{m}_\lambda A_t)^{\theta-1}\, F^{-1}\!\left(\frac{\alpha^i}{1-\zeta}\right) \;-\; (1-\delta)}.$$

Hence $\partial\mathcal{L}/\partial R_t^f < 0$, $\partial\mathcal{L}/\partial\alpha^i > 0$, $\partial\mathcal{L}/\partial Z_{t+1}^e > 0$, *and*

$$\frac{\partial\mathcal{L}}{\partial \mathsf{m}_\lambda} \;<\; 0 \quad \textit{(VaR binding)}.$$

If instead the collateral constraint binds while the VaR is slack, then $\kappa_t = \mathsf{m}_\lambda A_t$ *implies* $\partial\mathcal{L}/\partial\mathsf{m}_\lambda > 0$.

Proof 1 *Under participation we set* $s_t^i = 0$. *Let wholesale funding be a fixed share of deposits,* $L_t^i = \chi D_t^i$, *with* $\chi \geq 0$. *Balance-sheet feasibility implies*

$$k_t^i \;=\; \omega + D_t^i + L_t^i \;=\; \omega + (1+\chi)D_t^i \quad\Rightarrow\quad D_t^i = \frac{k_t^i - \omega}{1+\chi}, \quad L_t^i = \frac{\chi}{1+\chi}\,(k_t^i - \omega).$$

Define the (asset-weighted) effective funding rate

$$R_t^f \;\equiv\; \frac{R_t^d + \chi R_t^l}{1+\chi},$$

so that the total funding cost is $R_t^f\,(\kappa_t^i - \omega)$.

The borrower-based MaPP imposes the collateral constraint

$$\kappa_t \;\leq\; \mathsf{m}_\lambda A_t.$$

Under participation at the collateral corner we have $\kappa_t = \mathsf{m}_\lambda A_t$.

Assume default can occur only in the "no-idiosyncratic-loss" branch (probability $1-\zeta$*). A VaR threshold* α^i *on the unconditional default probability implies that in the no-loss branch the VaR binds at conditional probability*

$$q \;=\; \frac{\alpha^i}{1-\zeta}, \qquad \widetilde{Z}_t^q \;=\; F^{-1}\!\left(\frac{\alpha^i}{1-\zeta}\right).$$

Using $R_{t+1}^i = \theta\,\widetilde{Z}_t^q\,\kappa_t^{\theta-1} + (1-\delta)$ *in the no-loss branch, the zero-equity condition at the binding quantile is*

$$0 \;=\; \left[\theta\,\widetilde{Z}_t^q\,\kappa_t^{\theta-1} + (1-\delta)\right]\kappa_t \;-\; R_t^f\,(\kappa_t - \omega).$$

Rearranging and dividing by ω gives the leverage ratio

$$\mathcal{L} \;\equiv\; \frac{\kappa_t}{\omega} \;=\; \frac{R_t^f}{R_t^f - \theta\, \widetilde{Z}_t^q\, \kappa_t^{\theta-1} - (1-\delta)}.$$

Substituting the collateral corner $\kappa_t = \mathsf{m}_\lambda A_t$ and writing $\widetilde{Z}_t^q = Z_{t+1}^e\, F^{-1}(\frac{\alpha^i}{1-\zeta})$ yields the expression in the proposition:

$$\mathcal{L} = \frac{R_t^f}{R_t^f - \theta\, Z_{t+1}^e\, (\mathsf{m}_\lambda A_t)^{\theta-1}\, F^{-1}(\frac{\alpha^i}{1-\zeta}) - (1-\delta)}.$$

Let

$$\Phi \;\equiv\; \theta\, Z_{t+1}^e\, (\mathsf{m}_\lambda A_t)^{\theta-1}\, F^{-1}\Big(\frac{\alpha^i}{1-\zeta}\Big) \;+\; (1-\delta).$$

Hence:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial R_t^f} &= \frac{(R_t^f - \Phi) - R_t^f}{(R_t^f - \Phi)^2} = -\frac{\Phi}{(R_t^f - \Phi)^2} \;<\; 0,\\
\frac{\partial \mathcal{L}}{\partial \alpha^i} &= \frac{R}{(R_t^f - \Phi)^2}\, \theta\, Z_{t+1}^e\, (\mathsf{m}_\lambda A_t)^{\theta-1}\, (F^{-1})'\Big(\frac{\alpha^i}{1-\zeta}\Big) \frac{1}{1-\zeta} \;>\; 0,\\
\frac{\partial \mathcal{L}}{\partial Z_{t+1}^e} &= \frac{R}{(R_t^f - \Phi)^2}\, \theta\, (\mathsf{m}_\lambda A_t)^{\theta-1}\, F^{-1}\Big(\frac{\alpha^i}{1-\zeta}\Big) \;>\; 0,\\
\frac{\partial \mathcal{L}}{\partial \mathsf{m}_\lambda} &= \frac{R}{(R_t^f - \Phi)^2}\, \theta\, Z_{t+1}^e\, (\theta-1)\, (\mathsf{m}_\lambda A_t)^{\theta-2}\, A_t\, F^{-1}\Big(\frac{\alpha^i}{1-\zeta}\Big) \;<\; 0,
\end{aligned}$$

since $\theta \in (0,1)$ implies $(\theta - 1) < 0$, F^{-1} is increasing, and all other terms are positive. This delivers the signs stated for the VaR-limited case.

If instead the VaR does not bind while the collateral cap does, then $\kappa_t = \mathsf{m}_\lambda A_t$ determines scale and

$$\mathcal{L} \;=\; \frac{\kappa_t}{\omega} \;=\; \frac{\mathsf{m}_\lambda A_t}{\omega} \quad\Rightarrow\quad \frac{\partial \mathcal{L}}{\partial \mathsf{m}_\lambda} \;>\; 0.$$

Thus the sign of $\partial\mathcal{L}/\partial\mathsf{m}_\lambda$ is regime-dependent: negative under VaR-limited, positive under collateral-limited.

Borrower-based MaPPs (m_λ) influence stability through two channels: the collateral constraint (A.2) and the VaR constraint (A.16). Thus, the effect of borrower-based MaPPs is regime-dependent: when the collateral constraint binds (VaR slack), tightening lowers leverage and is stabilizing; when the VaR constraint binds, the same tightening raises equilibrium leverage and is destabilizing.

Intermediaries' leverage decreases with the funding cost R^d, which is ultimately determined by the policy rate set by the monetary authority. Intermediaries will also increase leverage until their probability of distress reaches the VaR constraint. Additionally, for high α, leverage can be substantially increased before hitting the Var constraint. Consequently, the leverage of the most risk-taking intermediaries will be more sensitive to interest rate changes. This variability in the intensive margin's response to shifts in the cost of funds means that as interest rates decrease, the distribution of leverage becomes more skewed across intermediaries. This leads to a composition effect, where a larger share of assets is held by more risk-taking intermediaries. For this reason, the (asset weighted) skewness of the distribution of intermediaries' leverage will be explicitly taken into account in our quantitative analysis.

From Coimbra and Rey (2024, Proposition 3.3) follows that there exists a cutoff value α^L for which an intermediary is indifferent between leveraging up or not.

Proposition 2 *There exists a cutoff α^L such that if $\alpha^i \leq \alpha^L$, the intermediary i will borrow to leverage up to its constraint. The cutoff α^L, which is an implicit function of r^D, Z^e_{t+1} and κ_t is decreasing in m_λ and m_ϕ.*

Notice that, while m_ϕ does not affect $\mathcal{L}^i$ conditional on participation (intensive-margin neutrality), it shifts the participation cutoff α^L, i.e., $\frac{d\,\alpha^L}{d\mathsf{m}_\phi} < 0$, which implies

$$\frac{d}{d\mathsf{m}_\phi}\Big[\text{asset-weighted leverage across active leveraged intermediaries.e}\Big] < 0.$$

The profit tax m_ϕ generates revenues T_t^ϕ in good states that co-finance insurance payouts T_t^{ins} in bad states, reducing the required lump-sum adjustment τ_t under (A.22). The borrower-targeted MaPP m_λ operates on the intensive margin by capping collateralizable exposures (smaller κ_t for given A_t), while m_ϕ operates on the extensive margin by lowering the incentive to enter the leveraged regime, thereby shifting the α^L cutoff (Proposition 2).

In this model, a deterioration in financial stability corresponds to a higher probability that, in the next period, all leveraged intermediaries will be unable to fully repay their stakeholders (both depositors and shareholders). By extending the framework of Coimbra and Rey (2024) to include macroprudential instruments—here represented by the borrower-based measure m_λ and the profit-based measure m_ϕ—we showed that the relationship between MaPPs and financial stability is inherently non-linear. Tighter borrower-based measures (lower m_λ) typically reduce leverage and enhance stability when the collateral constraint binds, as in credit-constrained or low-income economies. However, once the VaR constraint becomes binding—a situation more typical of advanced, highly leveraged financial systems—further tightening of borrower-based MaPPs can increase equilibrium leverage and amplify systemic fragility. Thus, the stabilizing role of MaPPs operates through both the intensive margin (leverage adjustment within active intermediaries) and the extensive margin (participation decisions across intermediaries). The extensive margin is primarily influenced by financial-intermediary-targeted policies such as the profit-based measure m_ϕ, which affects the entry of intermediaries into the leveraged regime. Overall, the strength and even the sign of MaPPs' effects depend critically on the prevailing financial regime.

B Dimension reduction approach: a formal description

Let $x_{it} \in \mathcal{R}^p$ denote a vector of p binary measurements, recorded for the i-th country at time t; $t = 1, \ldots, T_i$, $i = 1, \ldots, n$. We assume there exists an unobserved latent variable u_{it} with discrete support such that, for a specific set of weights $w_1, \ldots, w_p$,

$$\sum_h w_h x_{ith} \, | u_{it} = j \sim MVN(\xi_j, \sigma^2);$$

additionally, $\sum_h w_h x_{ith}$ is independent of $\sum_h w_h x_{ish}$ for all $s \neq t$. In words, a linear combination of the binary indicators, conditionally on an unobserved latent variable, is Gaussian and independent of previous and future measurements. Note that, unconditionally, observations arising from the same nations are obviously dependent. A more detailed discussion on this and the Gaussian assumption can be found in Farcomeni et al. (2021). The model is completed by Markovian assumptions on u_{it}, that is, that u_{it} is independent of the past conditionally on $u_{i,t-1}$. Let $p_{tj}(w) = \Pr(u_{it} = j)$, to underline the dependence on weights w. Similarly, we denote $\xi_j(w)$ as conditional means of the Gaussian covariates. Optimal weights are determined by maximizing the objective function

$$\sum_{tj} \hat{p}_{tj}(w)(\hat{\xi}_j(w) - \bar{\xi}_t(w))^2, \tag{B.1}$$

where $\bar{\xi}_t = \sum_j \hat{p}_{tj}(w)\hat{\xi}_j / \sum_j \hat{p}_{tj}(w)$. It can be seen that (B.1) is a measure of (latent) class separation, and parallels the idea of maximizing the variance of the projected variables in principal components analysis. Optimization is performed under the constraint that $\sum w_h^2 = 1$.

C Specification of the GAMLSS Finite Mixture Model

Let y_{it} denote the private credit-to-GDP ratio for country $i = 1, \ldots, N$ and period $t = 1, \ldots, T_i$. Conditional on covariates $\mathbf{x}_{it}$ (mean equation) and $\mathbf{z}_{it}$ (variance equation), we assume

$$y_{it} \mid \mathbf{U}_i \sim \mathcal{F}(\mu_{it}, \sigma_{it}, \nu_{it}), \tag{C.1}$$

where $\mathcal{F}$ belongs to the exponential family of distributions, thus allowing for skewness and heavy tails that are typical of credit cycles influenced by macroprudential policies (MaPPs).[17] The parameters μ_{it}, σ^2_{it}, and ν_{it} represent the conditional mean, variance, and skewness, linked to the covariates through monotonic functions $g_p(\cdot)$ $(p = 1, 2, 3)$ as follows:

$$g_1(\mu_{it}) = (\beta_0 + u_i) + \sum_{m=1}^{M} \beta_m x_{itm}, \tag{C.2a}$$

$$g_2(\sigma^2_{it}) = (\gamma_0 + \delta_{0i}) + \sum_{q=1}^{Q} (\gamma_q + \delta_{qi}) z_{itq}, \tag{C.2b}$$

$$g_3(\nu_{it}) = b, \tag{C.2c}$$

where u_i and $\boldsymbol{\delta}_i = (\delta_{0i}, \ldots, \delta_{Qi})$ are correlated random effects capturing country-specific deviations in the mean and variance equations. The vector of random effects $\mathbf{U}_i = (u_i, \boldsymbol{\delta}_i)$ has mean zero, $\mathbb{E}(\mathbf{U}_i) = 0$, and follows an unspecified distribution to avoid restrictive parametric assumptions. In this model, the mean equation (g_1) describes the expected level of private credit as a function of structural factors such as the funding cost, leverage, and their interaction, while the variance equation (g_2) allows the conditional volatility of credit to depend on macroprudential instruments: borrower-targeted MaPPs (λ) and two institution-targeted MaPPs (ϕ_1, ϕ_2), whose effects may differ across countries. The model thus explicitly accommodates heterogeneity in both the level and volatility of credit dynamics.

Since the true distribution of $\mathbf{U}_i$ is unknown, we approximate it using a discrete distribu-

[17] Periods of financial stability may approximate Gaussian behavior, with symmetric deviations around the mean, whereas episodes of abrupt tightening or loosening of credit conditions often generate skewness or heavy-tailed distributions, which are well captured by Gamma or t-location-scale models. As formalized by Nelder and Wedderburn (1972), the exponential density can be expressed as $f(y_{it}|\theta, \phi) = \exp\{\frac{y^\top\theta - b(\theta)}{a(\phi)} + c(y, \phi)\}$, where θ is the natural parameter, $b(\cdot)$ the cumulant generating function, and $a(\phi)$ and $c(y, \phi)$ depend on the dispersion parameter ϕ. In this framework, both variance and higher-order moments can depend on covariates through the conditional mean μ.

tion with K support points, following Lindsay (1983):

$$p(\mathbf{U}_i) \approx \sum_{k=1}^{K} \pi_k \delta(\mathbf{U}_i - \mathbf{U}_k), \qquad \pi_k \geq 0, \quad \sum_{k=1}^{K} \pi_k = 1, \tag{C.3}$$

so that the likelihood of the observed data becomes

$$L(\Theta) = \prod_{i=1}^{N} \left\{ \sum_{k=1}^{K} \pi_k \prod_{t=1}^{T_i} f(y_{it} \mid \mathbf{x}_{it}, \mathbf{z}_{it}, \mathbf{U}_k; \Theta) \right\}, \tag{C.4}$$

where Θ denotes the full parameter vector.

The model is estimated using the Expectation-Maximization (EM) algorithm, which iteratively alternates between two steps:

- *E-step:* compute the posterior probabilities $\hat{\tau}_{ik}$ that country i belongs to component k, given current parameter estimates:

$$\hat{\tau}_{ik} = \frac{\pi_k \prod_{t=1}^{T_i} f(y_{it} \mid \mathbf{x}_{it}, \mathbf{z}_{it}, \mathbf{U}_k; \Theta)}{\sum_{j=1}^{K} \pi_j \prod_{t=1}^{T_i} f(y_{it} \mid \mathbf{x}_{it}, \mathbf{z}_{it}, \mathbf{U}_j; \Theta)}. \tag{C.5}$$

- *M-step:* maximize the expected complete-data log-likelihood with respect to Θ using the posterior probabilities $\hat{\tau}_{ik}$ as weights, updating mixture weights π_k, component-specific parameters $(\beta_k, \gamma_k, \mathbf{U}_k)$, and distributional parameters of $\mathcal{F}$.

In summary, within the EM algorithm, the posterior probabilities $\hat{\tau}_{ik}$—representing the likelihood that country i belongs to the kth latent component—are used to maximize the weighted log-likelihood, thereby updating the component-specific parameters $(\beta_k, \gamma_k, \mathbf{U}_k)$ and the mixture weights π_k. These posterior probabilities should be interpreted as the assignment probabilities of each country to latent "locations" $\mathbf{U}_k$, which capture distinct combinations of intercepts and slopes. This semiparametric specification unifies random-coefficient and mixture approaches: when $K = 1$, it reduces to a standard linear model estimated via ML or GLS; when $K > 1$, it identifies latent clusters of countries with homogeneous credit responses to MaPPs.

D Tables

Model with three summarizing MaPP indicators Table D1 presents the GAMLSS estimates using λ, ϕ_1 and ϕ_2, while related classifications are reported in Tables D2 and D3. As in the main text, in both classifications, the index of the latent location parameter (k) is not arbitrary. For ease of exposition, clusters with higher k are systematically associated with higher average GDP per capita. This ordering reflects the progression from low-income, low-credit economies to high-income, credit-intensive financial systems.

In both models, for the conditional mean and conditional variance, there are four intercepts corresponding to different levels of the latent variable K in the sample of OECD countries, and five intercepts for different levels of the latent variable K in the Full Sample. The fit of the model is good as we can see in Figure E4 and Figure E5). Overall, our estimates provide compelling empirical evidence that MaPPs do not exert uniform effects, but instead vary significantly across different groups of countries, highlighting the nuanced, context-sensitive nature of their effectiveness.

Full sample. The first group ($k = 1$) shows that only financial institution-targeted MaPPs summarized by ϕ_2 are effective in stabilizing volatility (-0.675). The second group ($k = 2$) reveals that borrower-targeted MaPPs reduce volatility (-0.182), while financial institution-targeted policies of type ϕ_1 are associated with stabilizing effects (-0.268). The third group ($k = 3$) indicates no significant effect of borrower-targeted MaPPs, while ϕ_2 is associated with an increase in volatility (0.309). Finally, the fourth group ($k = 4$) displays positive and significant responses of volatility to both ϕ_1 and ϕ_2 (0.288 and 0.528, respectively), suggesting that in highly leveraged systems financial institution-based measures aimed at limiting intermediary profitability—especially ϕ_2, which is strongly influenced by taxation—may exacerbate instability.

OECD Sample. The results differ in important ways. The first group ($k = 1$), characterized by low credit levels and moderate GDP, shows that only ϕ_2 exerts a stabilizing effect (-1.088), while borrower-targeted MaPPs remain non-significant. The second group ($k = 2$), with GDP growth around 1.4% and a high asymmetry in the leverage of the banking sector, shows that borrower-targeted MaPPs amplify volatility (0.305), while neither ϕ_1 nor ϕ_2 appear effective. The third group ($k = 3$), composed of high-income economies with the highest leverage asymmetry, again shows no significant effect of borrower-targeted policies, but here ϕ_1 exerts a stabilizing role (-0.405), contrasting with the full-sample findings. Finally, the fourth group ($k = 4$), which gathers the most credit intensive economies, is characterized by strong positive responses of volatility to both financial institution-targeted policies, with coefficients of 1.789 for ϕ_1 and 12.672 for ϕ_2, pointing to the limits of such instruments in highly leveraged OECD economies.

In the Full Sample, the clusters are more clearly polarized: the extremes (low-income versus advanced economies) are distinguished primarily by differences in GDP per capita and leverage. Within the OECD Sample, by contrast, the main differences emerge in terms of lower volatility, reflecting the relatively more homogeneous level of development across these countries.

Table D1: Model for Location, Scale and Shape II

	Full Sample Estimate (SE)	OECD Sample Estimate (SE)
Dependent variable: *Credit*		
Model for conditional mean		
Random Coefficients		
$Intercept_{k=1}$	20.241*** (0.577)	46.418*** (1.767)
$Intercept_{k=2}$	21.679*** (0.892)	37.092*** (1.780)
$Intercept_{k=3}$	74.854*** (1.389)	88.305*** (2.142)
$Intercept_{k=4}$	135.778*** (2.011)	135.188*** (1.998)
Fixed Coefficients		
FundCost	-0.281** (0.107)	-3.193*** (0.348)
Leverage	0.952*** (0.248)	-0.470 (0.319)
FundCost × Leverage	-0.008 (0.067)	0.547*** (0.100)
Model for conditional variance		
Random Coefficients		
$Intercept_{k=1}$	2.091*** (0.067)	2.356*** (0.147)
$Intercept_{k=2}$	0.513*** (0.102)	0.806*** (0.177)
$Intercept_{k=3}$	1.125*** (0.102)	0.941*** (0.177)
$Intercept_{k=4}$	0.998*** (0.132)	0.830*** (0.258)
Borrower-targeted MaPPs (λ)		
$\lambda_{k=1}$	-0.026 (0.081)	0.007 (0.170)
$\lambda_{k=2}$	-0.143· (0.081)	0.305** (0.106)
$\lambda_{k=3}$	0.133 (0.079)	0.075 (0.112)
$\lambda_{k=4}$	-0.113 (0.118)	-0.493 (0.270)
Financial institution-targeted MaPPs (ϕ_1)		
$\phi_{1,k=1}$	0.170 (0.124)	0.169 (0.245)
$\phi_{1,k=2}$	-0.260*** (0.089)	0.189 (0.117)
$\phi_{1,k=3}$	0.132 (0.072)	-0.405*** (0.110)
$\phi_{1,k=4}$	0.288* (0.126)	1.789*** (0.346)
Financial institution-targeted MaPPs (ϕ_2)		
$\phi_{2,k=1}$	-0.669*** (0.139)	-1.088* (0.461)
$\phi_{2,k=2}$	0.072 (0.108)	-0.279 (0.217)
$\phi_{2,k=3}$	0.309** (0.107)	-0.127 (0.169)
$\phi_{2,k=4}$	0.529* (0.224)	12.672*** (2.483)
Model for conditional skewness		
Intercept	14.605*** (0.426)	15.818*** (0.194)
N	4532	1940
BIC	9833.978	4423.606

· p-value<0.10, * p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table D2: Full sample, classification from Model II (Table D1)

	Cluster			
	k=1	k=2	k=3	k=4
	Angola	Albania	Australia	Canada
	Argentina	Armenia	Austria	Denmark
	Benin	Bangladesh	Belgium	Hong Kong
	Burkina Faso	Brazil	Chile	Iceland
	Burundi	Bulgaria	China	Japan
	Dominican Rep.	Colombia	Czech Rep.	New Zealand
	Ecuador	Costa Rica	Estonia	United Kingdom
	Ghana	Croatia	Finland	United States
	Guatemala	Hungary	France	South Africa
	Indonesia	India	Germany	
	Iraq	Mongolia	Greece	
	Jamaica	Morocco	Ireland	
	Kenya	Honduras	Israel	
	Mauritania	Kazakhstan	Italy	
	Myanmar	Mexico	Jordan	
	Nigeria	Paraguay	Kuwait	
	Pakistan	Peru	Luxembourg	
	Romania	Philippines	Netherlands	
	Sierra Leone	Russian Fed.	Poland	
	Tajikistan	Saudi Arabia	Singapore	
	Togo	Serbia	Slovakia	
	Uganda	Sri Lanka	Slovenia	
	Zambia	Turkey	South Korea	
		Uruguay	Spain	
			Sweden	
			Switzerland	
			Thailand	
GDP per capita (PPP)	2,779	9,407	34,554	39,165
GDP growth rate	2.510	3.225	1.776	1.011
Private Credit % GDP	19.875	41.9	97.181	156.375
Credit σ	8.300	15.939	24.233	26.643
Leverage	0.825	1.624	2.643	2.064
$\hat{\sigma}$	63.99	225.431	42 579.353	685.236

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit* σ is the observed standard deviation of Private Credit on GDP.

Table D3: OECD Sample, classification from Model II (Table D1)

	Cluster			
	k=1	k=2	k=3	k=4
	Czech Republic Hungary Mexico Poland Slovakia	Austria Belgium Chile Estonia Finland France Germany Greece Israel Italy Luxembourg Slovenia Turkey	Netherlands Norway Portugal South Korea Spain Sweden United Kingdom Ireland Iceland Australia New Zealand	Canada Denmark Japan Switzerland United States
GDP level	11,828	33,888	41,790	52,608
GDP growth rate	2.601	1.379	1.089	0.836
Credit	37.615	76.896	128.328	171.516
Credit σ	12.95	21.516	24.365	18.262
Leverage	2.372	2.569	2.961	2.473
$\hat{\sigma}$	10.880	19.234	23.449	17.895

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit* σ is the observed standard deviation of Private Credit on GDP.

A comparison between Tables D1 and D4 reveals that the exclusion of the United States substantially affects both cluster composition and the estimated coefficients, particularly in the variance equation. The U.S. behaves as a high-leverage outlier with deep credit markets and very low funding costs, and its removal reduces heterogeneity within the OECD Sample, yielding more homogeneous parameter estimates.

In the conditional mean, the sensitivity of credit to funding costs becomes slightly stronger in both samples once the U.S. is excluded (the coefficient on *FundCost* changes from -0.28 to -0.99 in the Full Sample, and from -3.19 to -3.46 in the OECD Sample), confirming the dominant influence of the U.S. financial cycle on the aggregate relationship between credit and funding conditions. The interaction term between *FundCost* and *Leverage* remains positive and significant, suggesting that lower funding costs amplify the procyclicality of leverage in both specifications.

The most striking differences appear in the variance equation. In the Full Sample, borrower-targeted MaPPs (λ) shift from weakly negative or insignificant effects when the U.S. is included to significantly positive coefficients in Cluster 2 once it is removed. This indicates that, without the U.S., the stabilizing association of borrower-based measures is less evident—consistent with the notion that such tools operate mainly in financially less developed systems, whereas the U.S. belongs to the opposite extreme.

financial-intermediary-targeted MaPPs (ϕ_1) also display a marked sign reversal. With the

U.S. included, ϕ_1 is destabilizing in high-income clusters (positive and significant coefficients), but after exclusion, the estimated effects become neutral or mildly stabilizing, especially for Cluster 3 in the Full Sample and Cluster 4 in the OECD Sample. This suggests that the procyclical pattern observed earlier is largely driven by U.S.-specific financial dynamics.

Finally, the profit-based measure (ϕ_2) becomes more uniformly stabilizing after removing the U.S. (notably negative in Clusters 1–2), while the extreme and implausibly large positive estimate for the OECD Cluster 4 (12.7 in the baseline) disappears. This confirms that the U.S. introduces substantial leverage asymmetry and cross-country distortion in the tails of the distribution.

Overall, the exclusion of the United States improves model fit (BIC decreases from 9833.9 to 9887.0 in the Full Sample, and from 4423.6 to 4300.3 in the OECD Sample) and yields more internally consistent coefficient patterns. The evidence reinforces the interpretation of the U.S. as a structural outlier whose financial depth, leverage skewness, and policy regime make its MaPP transmission mechanisms fundamentally distinct from those of other advanced economies.

Model with interactions Table D7 reports the GAMLSS estimates for λ, ϕ_1, and ϕ_2, with λ interacting with *Leverage*. The corresponding cluster classifications are shown in Tables D8 and D9.

Table D4: Model for Location, Scale and Shape II (without the U.S.)

	Full Sample Estimate (SE)	OECD Sample Estimate (SE)
Dependent variable: *Private Credit*		
Model for conditional mean		
Random Coefficients		
$Intercept_{k=1}$	27.012*** (0.734)	46.595*** (1.991)
$Intercept_{k=2}$	38.782*** (1.181)	35.766*** (1.798)
$Intercept_{k=3}$	106.545*** (1.721)	72.269*** (2.159)
$Intercept_{k=4}$	–	115.129*** (2.572)
Fixed Coefficients		
Funding Cost	-0.993*** (0.144)	-3.461*** (0.384)
Leverage	1.454*** (0.338)	-0.202 (0.494)
Funding Cost × *Leverage*	-0.018 (0.090)	0.548*** (0.131)
Model for conditional variance		
Random Coefficients		
$Intercept_{k=1}$	2.368*** (0.058)	2.387*** (0.147)
$Intercept_{k=2}$	0.922*** (0.094)	0.824*** (0.180)
$Intercept_{k=3}$	0.972*** (0.099)	0.594** (0.186)
$Intercept_{k=4}$	–	0.634** (0.201)
Borrower-targeted MaPPs (λ)		
$\lambda_{k=1}$	-0.107 (0.067)	0.006 (0.175)
$\lambda_{k=2}$	0.303*** (0.077)	0.379*** (0.112)
$\lambda_{k=3}$	-0.074 (0.085)	0.055 (0.126)
$\lambda_{k=4}$	–	-0.092 (0.144)
Financial institution-targeted MaPPs (ϕ_1)		
$\phi_{1,k=1}$	0.313*** (0.086)	0.144 (0.245)
$\phi_{1,k=2}$	0.224** (0.083)	-0.120 (0.169)
$\phi_{1,k=3}$	-0.155* (0.078)	-0.066 (0.115)
$\phi_{1,k=4}$	–	0.422* (0.169)
Financial institution-targeted MaPPs (ϕ_2)		
$\phi_{2,k=1}$	-0.423*** (0.111)	-0.974* (0.461)
$\phi_{2,k=2}$	-0.292** (0.093)	-0.107 (0.245)
$\phi_{2,k=3}$	-0.456** (0.144)	0.495* (0.222)
$\phi_{2,k=4}$	–	0.411 (0.272)
Model for conditional skewness		
Intercept	13.986*** (0.798)	49.075*** (0.000)
N	3351	1880
BIC	9887.047	4300.304

· p-value<0.10, * p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table D5: Full sample, classification from Model II (without the U.S.) (Table D4)

	Cluster		
	k=1	k=2	k=3
	Albania	Austria	Australia
	Angola	Belgium	Canada
	Argentina	Brazil	China
	Armenia	Bulgaria	Denmark
	Bangladesh	Chile	Hong Kong
	Benin	Costa Rica	Iceland
	Burkina Faso	Croatia	Ireland
	Burundi	Czech Republic	Japan
	Colombia	Estonia	Malaysia
	Dominican Republic	Finland	Netherlands
	Ecuador	France	New Zealand
	Ghana	Germany	Norway
	Guatemala	Greece	Portugal
	Honduras	Hungary	Singapore
	Indonesia	India	South Africa
	Iraq	Israel	South Korea
	Jamaica	Italy	Spain
	Kenya	Jordan	Sweden
	Mali	Kazakhstan	Switzerland
	Mauritania	Kuwait	Thailand
	Mexico	Luxembourg	United Kingdom
	Mongolia	Morocco	
	Myanmar	Paraguay	
	Nigeria	Poland	
	Pakistan	Romania	
	Peru	Russian Federation	
	Philippines	Saudi Arabia	
	Romania	Serbia	
	Sierra Leone	Slovakia	
	Sri Lanka	Slovenia	
	Tajikistan	Turkey	
	Togo	Uganda	
	Zambia	Uruguay	
GDP per capita (PPP)	4,678	22,764	36,297
GDP growth rate	3.012	1.850	1.870
Private Credit % GDP	25.736	64.822	134.642
Credit σ	12.369	23.697	28.374
Funding cost	3.316	3.269	3.320
Leverage	2.195	7.139	1.542
$\hat{\sigma}$	1.804	4.351	3.931

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit* σ is the observed standard deviation of Private Credit to GDP.

Table D6: OECD Sample, classification from Model II NOUSA (Table D4)

	Cluster			
	k=1	k=2	k=3	k=4
	Czech Republic Hungary Mexico Poland Slovakia	Austria Belgium Estonia Finland France Germany Greece Israel Italy Luxembourg Slovenia Turkey	Australia Chile Ireland Netherlands New Zealand Norway South Korea Sweden	Canada Denmark Iceland Japan Portugal Spain Switzerland United Kingdom
GDP per capita (PPP)	11,973	35,806	42,201	42,568
GDP growth rate	2.524	1.282	1.668	0.676
Private Credit % GDP	37.615	75.704	115.742	154.174
Credit σ	12.953	21.898	20.182	26.460
Funding cost	2.518	3.342	3.832	2.772
Leverage	3.176	2.695	1.485	1.431
$\hat{\sigma}$	1.830	3.600	3.178	4.810

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, that is, the conditional standard deviation given the estimated conditional non-linear mean in general setting equation (C.2b). *Credit* σ is the observed standard deviation of Private Credit to GDP.

Table D7: Model for Location, Scale and Shape III (with interactions)

	Full Sample Estimate (SE)	OECD Sample Estimate (SE)
Dependent variable: *Private Credit*		
Model for conditional mean		
Random Coefficients		
$Intercept_{k=1}$	21.856*** (0.513)	64.653*** (1.430)
$Intercept_{k=2}$	27.017*** (0.864)	46.962*** (1.628)
$Intercept_{k=3}$	88.733*** (1.239)	98.395*** (2.016)
$Intercept_{k=4}$	156.311*** (1.095)	–
Fixed Coefficients		
FundCost	-0.377*** (0.073)	-3.231*** (0.271)
Model for conditional variance		
Random Coefficients		
$Intercept_{k=1}$	2.815*** (0.098)	3.885*** (0.123)
$Intercept_{k=2}$	0.655*** (0.118)	0.103 (0.171)
$Intercept_{k=3}$	1.142*** (0.131)	-0.209 (0.206)
$Intercept_{k=4}$	-0.298 (0.445)	–
$FundCost_{k=1}$	-0.073*** (0.019)	-0.022 (0.036)
$FundCost_{k=2}$	-0.007 (0.009)	-0.114* (0.050)
$FundCost_{k=3}$	-0.017 (0.027)	0.004 (0.068)
$FundCost_{k=4}$	0.389*** (0.112)	–
$Leverage_{k=1}$	-0.051 (0.068)	-0.158** (0.059)
$Leverage_{k=2}$	-0.047 (0.031)	-0.036 (0.038)
$Leverage_{k=3}$	-0.024 (0.029)	-0.087 (0.059)
$Leverage_{k=4}$	0.246 (0.255)	–
$FundCost \times Leverage_{\ k=1}$	0.006* (0.014)	0.010 (0.015)
$FundCost \times Leverage_{\ k=2}$	0.001 (0.006)	0.006 (0.013)
$FundCost \times Leverage_{\ k=3}$	0.005 (0.005)	-0.001 (0.008)
$FundCost \times Leverage_{\ k=4}$	-0.044 (0.059)	–
$FundCost \times \lambda_{\ k=1}$	-0.039 (0.042)	0.846*** (0.137)
$FundCost \times \lambda_{\ k=2}$	-0.041 (0.028)	-0.354*** (0.073)
$FundCost \times \lambda_{\ k=3}$	0.011 (0.027)	-0.394*** (0.077)
$FundCost \times \lambda_{\ k=4}$	0.178 (0.175)	1.847*** (0.202)

* p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table D7: Model for Location, Scale and Shape III (with interactions) — continued

	Full Sample Estimate (SE)	OECD Sample Estimate (SE)
Borrower-targeted MaPPs (λ)		
$\lambda_{k=1}$	-0.063 (0.164)	-0.986*** (0.151)
$\lambda_{k=2}$	0.069 (0.058)	0.362* (0.154)
$\lambda_{k=3}$	0.186 (0.104)	-0.479*** (0.094)
$\lambda_{k=4}$	-1.079* (0.522)	–
Financial institution-targeted MaPPs (ϕ_1)		
$\phi_{1\,k=1}$	-0.063 (0.164)	-0.986*** (0.151)
$\phi_{1\,k=2}$	-0.336*** (0.079)	0.695*** (0.204)
$\phi_{1\,k=3}$	0.115 (0.114)	-0.513*** (0.079)
$\phi_{1\,k=4}$	1.792*** (0.194)	–
Financial institution-targeted MaPPs (ϕ_2)		
$\phi_{2\,k=1}$	-0.719*** (0.153)	0.974*** (0.274)
$\phi_{2\,k=2}$	0.116 (0.114)	0.506* (0.234)
$\phi_{2\,k=3}$	0.389* (0.187)	0.695*** (0.204)
$\phi_{2\,k=4}$	14.068*** (3.990)	–
Model for conditional skewness		
Intercept	3.879*** (0.094)	0.846*** (0.137)
N	4532	1455
AIC	9748.428	4413.064
BIC	9959.798	4546.956

* p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table D9: OECD Sample, classification from Model III (Table D7)

	Cluster		
	k=1	k=2	k=3
	Belgium	Canada	Australia
	Czech Republic	Denmark	Austria
	Estonia	Iceland	Chile
	Finland	Japan	France
	Hungary	New Zealand	Germany
	Israel	Portugal	Greece
	Mexico	Spain	Ireland
	Poland	Switzerland	Italy
	Slovakia	United Kingdom	Luxembourg
	Slovenia	United States	Netherlands
	Turkey		Norway
			South Korea
			Sweden
GDP p.c. (PPP)	11,549	45,906	35,875
GDP growth rate (%)	2.962	1.112	1.695
Private credit (% GDP)	46.273	165.762	110.635
Leverage skewness	6.760	1.046	1.536
$\hat{\sigma}$	4.729	28.039	10.343

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, computed as the square root of the average conditional variance (σ^2) estimated within each cluster. Values are cluster means. The specification includes random intercepts for both the location (μ_{it}) and scale (σ_{it}) parameters to capture unobserved country heterogeneity.

Table D8: Full sample, classification from Model III (Table D7)

	Cluster			
	k=1	k=2	k=3	k=4
	Angola	Albania	Australia	Canada
	Argentina	Armenia	Austria	Denmark
	Benin	Bangladesh	Belgium	Hong Kong
	Burkina Faso	Brazil	Chile	Iceland
	Burundi	Bulgaria	China	Japan
	Dominican Republic	Colombia	Czech Republic	New Zealand
	Ecuador	Costa Rica	Estonia	Spain
	Ghana	Croatia	Finland	Switzerland
	Guatemala	Hungary	France	United Kingdom
	Indonesia	India	Germany	United States
	Iraq	Mongolia	Greece	
	Jamaica	Morocco	Ireland	
	Kenya	Honduras	Israel	
	Mauritania	Kazakhstan	Italy	
	Myanmar	Mexico	Jordan	
	Nigeria	Paraguay	Kuwait	
	Pakistan	Peru	Luxembourg	
	Philippines	Poland	Malaysia	
	Romania	Russian Federation	Netherlands	
	Sierra Leone	Saudi Arabia	Norway	
	Tajikistan	Serbia	Portugal	
	Togo	Sri Lanka	Singapore	
	Uganda	Turkey	Slovakia	
	Zambia	Uruguay	Slovenia	
			South Africa	
			South Korea	
			Sweden	
			Thailand	
GDP p.c. (PPP)	2,775	11,549	35,875	45,906
GDP growth rate (%)	2.539	2.962	1.695	1.112
Private credit (% GDP)	20.463	46.273	110.635	165.762
Credit standard deviation	8.580	18.598	26.752	24.355
Leverage	2.352	6.760	1.536	1.046
$\hat{\sigma}$	3.261	4.729	10.343	28.039

Note: $\hat{\sigma}$ denotes the estimated conditional volatility from the GAMLSS model, i.e., the conditional variance given the estimated conditional non-linear mean in the general setting of equation (C.2b). Values are cluster means.

Table D10: Model for Location, Scale and Shape IV with MaPPs *ex* Cerutti et al. (2017)

	Full Sample	OECD
	Estimate (SE)	Estimate (SE)
Dependent variable: *Credit*		
Model for conditional mean		
	Random Coefficients	
$Intercept_{k=1}$	18.939 (0.612)***	39.899 (1.597)***
$Intercept_{k=2}$	21.475 (0.877)***	26.977 (1.815)***
$Intercept_{k=3}$	74.208 (1.430)***	50.139 (1.800)***
$Intercept_{k=4}$	133.127 (2.042)***	94.539 (2.046)***
$Intercept_{k=5}$	-	143.887 (2.257)***
	Fixed Coefficients	
FundCost	-0.218 (0.117).	-1.732 (0.293)***
Leverage	1.112 (0.257)***	0.124 (0.249)
FundCost × Leverage	-0.025 (0.071)	0.136 (0.112)
Model for conditional variance		
	Random Coefficients	
$Intercept_{k=1}$	2.132 (0.065)***	1.998 (0.139)***
$Intercept_{k=2}$	0.478 (0.091)***	1.068 (0.188)***
$Intercept_{k=3}$	0.984 (0.090)***	0.814 (0.172)***
$Intercept_{k=4}$	1.011 (0.115)***	1.303 (0.163)***
$Intercept_{k=5}$	-	0.881 (0.284).
	Borrower-targeted MaPPs *ex* Cerutti et al. (2017)	
$\widetilde{\lambda}_{k=1}$	0.170 (0.088).	0.388 (0.180)*
$\widetilde{\lambda}_{k=2}$	-0.179 (0.060)**	0.247 (0.128).
$\widetilde{\lambda}_{k=3}$	0.017 (0.061)	0.192 (0.110).
$\widetilde{\lambda}_{k=4}$	0.108 (0.073)	-0.417 (0.079)***
$\widetilde{\lambda}_{k=5}$	-	0.087 (0.275)
	Financial-targeted MaPPs *ex* Cerutti et al. (2017)	
$\widetilde{\phi}_{k=1}$	-0.092 (0.031)**	0.145 (0.093)
$\widetilde{\phi}_{k=2}$	0.070 (0.028)*	-0.483 (0.101)***
$\widetilde{\phi}_{k=3}$	0.016 (0.032)	-0.124 (0.057)*
$\widetilde{\phi}_{k=4}$	0.053 (0.047)	0.016 (0.045)
$\widetilde{\phi}_{k=5}$	-	-0.201 (0.111).
Conditional Skewness		
(Intercept)	12.156 (5.005)*	12.464 (5.576)*
No. of obs.	4532	2425
BIC	9724.12	4235.37

Note: Signif. codes: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1.

The $\widetilde{\lambda}$ and $\widetilde{\phi}_1$ measures are not estimated parameters; rather, they correspond to the simple . sum of measures classified as borrower-based or financial-based, following the classification in Cerutti et al. (2017)

Model with Cerutti et al. (2017)'s measures The specification reported in Table D10 produces broadly consistent insights with those in Table 6 on the dynamics of private credit between country clusters, even when using alternative MaPP indicators from Cerutti et al. (2017). Borrower-targeted policies ($\widetilde{\lambda}$) tend to stabilize credit in low-income groups, while financial-intermediary-targeted measures ($\widetilde{\phi}$) generally stabilize advanced groups, confirming the main patterns identified with baseline indicators.

Minor discrepancies are observed. For example, some intermediate clusters exhibit destabilizing effects of borrower-targeted MaPPs captured by the indicators proposed by Cerutti et al. (2017), whereas they were non-significant in our baseline model. This difference can be statistically explained by the construction method: our approach applies a Markovian weighting of subcomponents, identifying discrete latent variables that summarize MaPPs, effectively capturing both the intensity and scope of interventions and smoothing cluster-specific effects. In Cerutti et al. (2017), instead, the borrower- and institution-targeted indicators are simple counts of the macroprudential measures active in a given country and year.

Both models reproduce the increasing pattern of credit levels between clusters and the positive skewness of the distribution, while the model in Table D10 further allows modeling variance as a function of policy-cluster interactions, providing a richer characterization of heteroskedasticity. Overall, the results highlight that MaPP effectiveness is conditional on structural cluster characteristics.

Table D11: Summary of MaPP indicator effects on credit volatility, Model IV (*ex* Cerutti et al., 2017)

Cluster	Full Sample		OECD Sample	
	$\widetilde{\lambda}$	$\widetilde{\phi}$	$\widetilde{\lambda}$	$\widetilde{\phi}$
$k = 1$	Non-significant	Stabilizing	Destabilizing	Non-significant
$k = 2$	Stabilizing	Destabilizing	Non-significant	Stabilizing
$k = 3$	Non-significant	Non-significant	Non-significant	Stabilizing
$k = 4$	Non-significant	Non-significant	Stabilizing	Non-significant
$k = 5$			Non-significant	Non-significant

E Figures

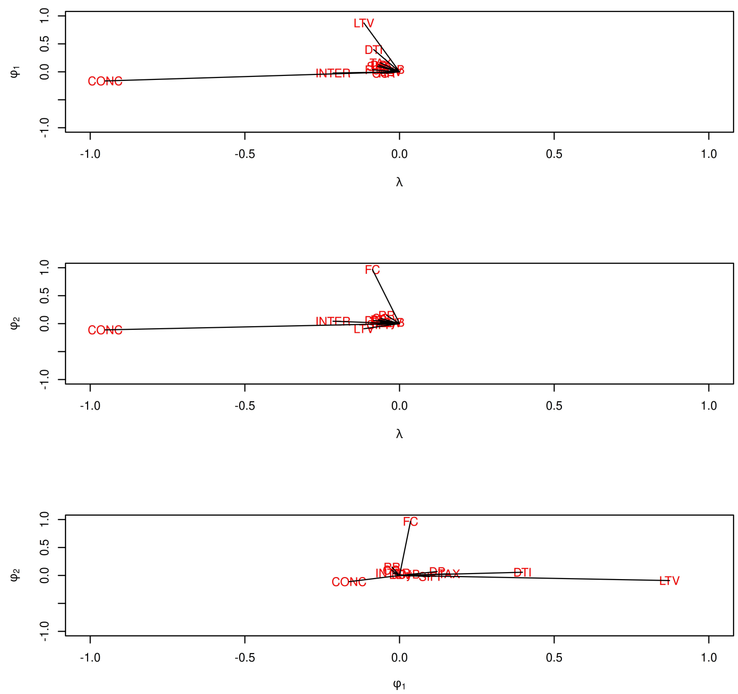

Figure E1: Composite MaPP indicators: arrow plot for optimal weights

MaPPs Indicators Optimal weights for each of the synthetic dimensions, are obtained following the formal framework outlined in this Appendix B. Specifically, for the vector of binary indicators for country i at time t, the corresponding sum of optimal the weights $w = (w_1, \ldots, w_p)$, conditional on the unobserved latent variable u_{it}, are derived by maximizing the latent class separation criterion:

$$\widehat{w} = \arg \max_{w: \sum_h w_h^2 = 1} \sum_{t,j} \widehat{p}_{tj}(w) \left(\widehat{\xi}_j(w) - \bar{\xi}_t(w) \right)^2, \tag{C.6}$$

where $\widehat{p}_{tj}(w)$ denotes the estimated posterior probability of belonging to latent class j at time t, and $\bar{\xi}_t(w) = \sum_j \widehat{p}_{tj}(w)\widehat{\xi}_j(w) / \sum_j \widehat{p}_{tj}(w)$ represents the class-averaged conditional mean. Expression (C.6) parallels the principal component analysis (PCA) approach, with the key difference that separation occurs across latent classes rather than along observed sample directions.

This optimization yields a unique vector of weights $\widehat{w}$ for each dimension, subject to the normalization constraint $\sum_h w_h^2 = 1$, ensuring that each component is interpretable as a synthetic MaPP index. Negative values may arise naturally, as the weighted combination captures deviations from the latent class mean rather than absolute frequencies. The weights are obtained by maximizing the distance between class-specific intercepts of the latent Markov model, such that the variability of each latent summary is maximized. This yields a composite representation that appropriately treats binary data and serial dependence. The squared weights can then be interpreted as the relative contribution of each instrument to the variance of each latent dimension.[18]

[18] As with other composite indicators widely used in empirical research—such as indices of institutional quality, financial development, or regulatory restrictiveness—our synthetic MaPP indices aggregate multiple instruments using a data-driven weighting scheme. While this approach may obscure individual effects, it provides a tractable, transparent, and replicable framework for empirical analysis of complex policy configurations.

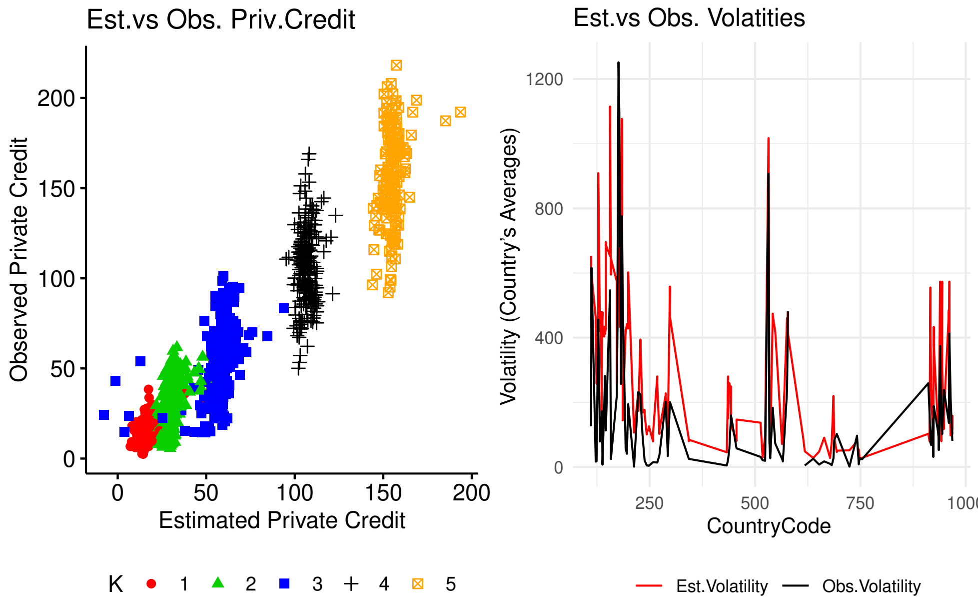

Figure E2: Observed vs Est. Priv. Cred levels by Groups & Observed vs Est. Volatility, Full Sample. Observed Volatility is the variance of the Private Gredit (%on GDP). Estimated Volatility is the predicted variance of the model in C.2b.

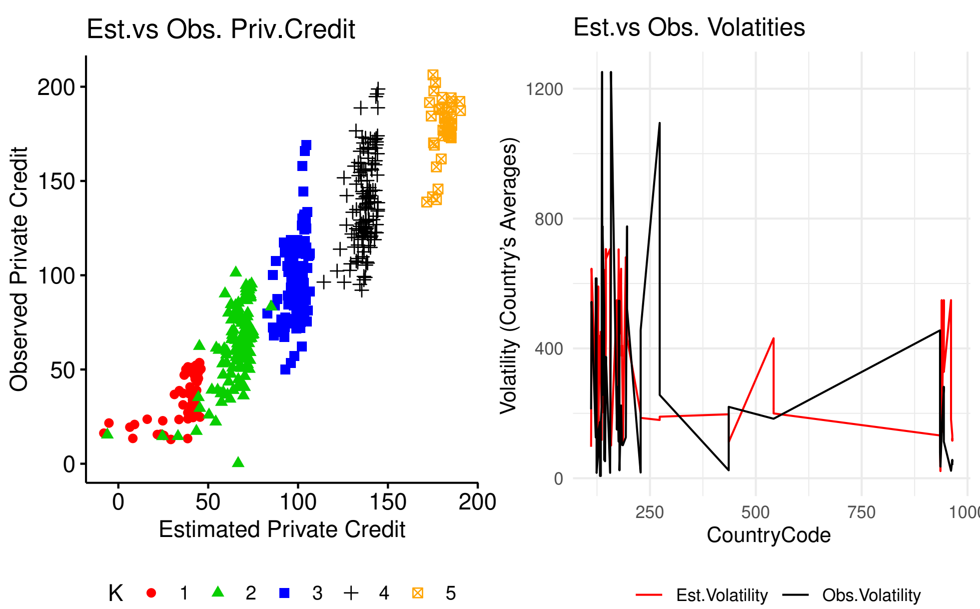

Figure E3: Observed vs. estimated private credit levels by groups and observed vs. estimated volatility, OECD countries. Observed volatility is the variance of private credit (as % of GDP). Estimated volatility is the predicted variance from equation (C.2b).

Model I

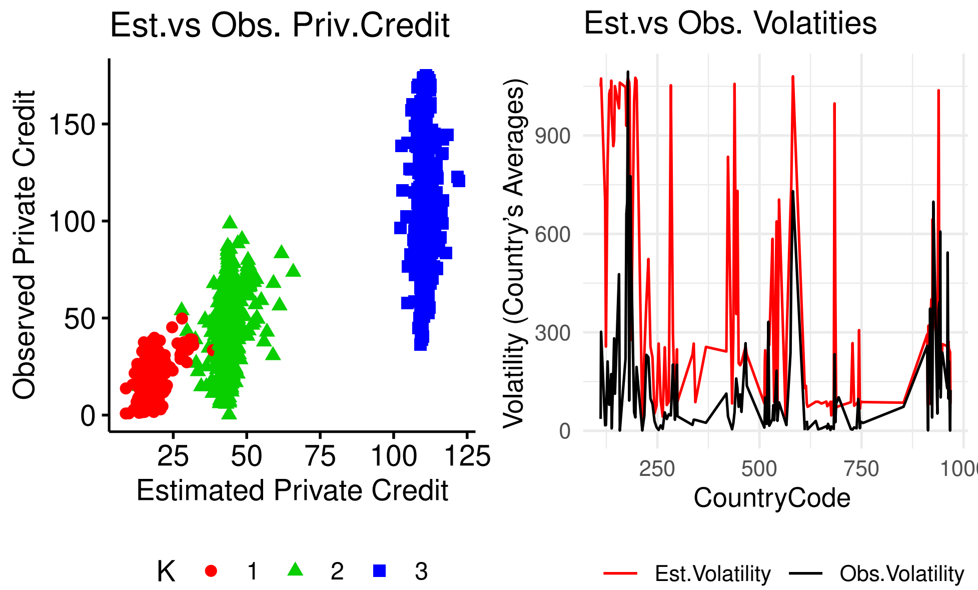

Figure E4: Observed vs Est. Priv. Cred levels by Groups & Observed vs Est. Volatility, Full Sample. Observed Volatility is the variance of the Private Gredit (%on GDP). Estimated Volatility is the predicted variance of the model in C.2b.

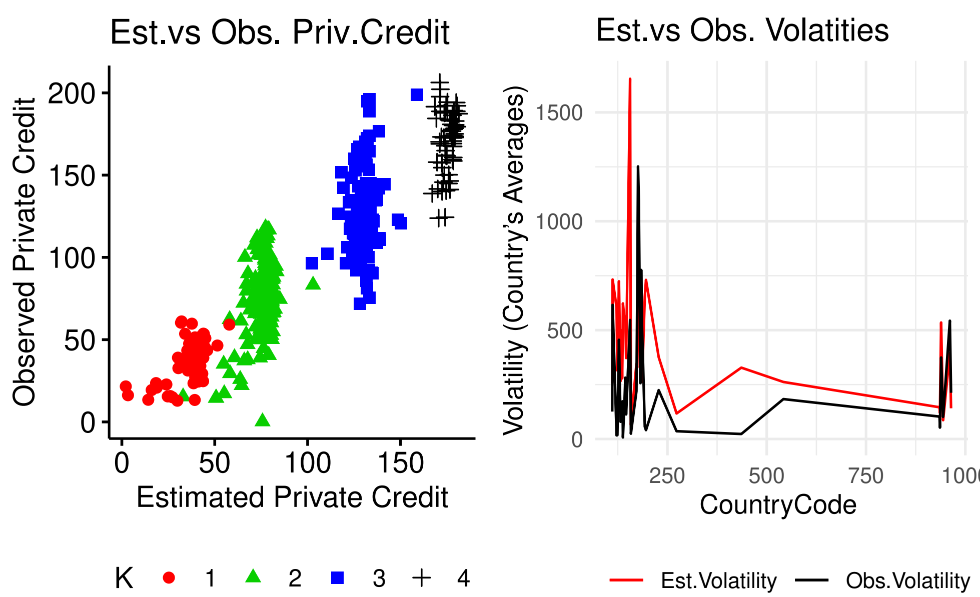

Figure E5: Observed vs. estimated private credit levels by groups and observed vs. estimated volatility, OECD countries. Observed volatility is the variance of private credit (as % of GDP). Estimated volatility is the predicted variance from equation (C.2b).

Model II

F Endogeneity

To account for potential endogeneity, we employ an Arellano-Bond GMM Model[19] with a heteroskedastic and panel-specific AR(1) GLS specification. Results are presented in Table F2 and in Table F1. The coefficients on *FundCost*, for the GMM model, are negative and significant at 5% in the Full Sample (columns 1 and 3), indicating that higher funding costs are associated with a decrease in the private credit to GDP ratio. However, this relationship might not hold in OECD countries. The borrower-targeted MaPP (λ) appears to have a positive impact, whereas the counting index *MPI* shows a negative effect in OECD countries. Interaction terms between the skewness of the distribution of leverage of banks and MaPPs do not show significant effects. The diagnostic tests indicate some concerns with instrument validity, particularly with the Sargan test, suggesting that the results should be interpreted with caution. The model is also unable to identify either the country-specific effects of MaPPs or the heterogeneity of their associated effects on credit volatility.

The GLS estimates confirm the negative effect of funding costs on credit growth in the Full Sample, with coefficients consistently significant across specifications. The interaction between funding costs and leverage is negative and significant, indicating that banks with higher leverage are more sensitive to funding shocks. In contrast, in the OECD subset, the direct effect of funding costs is smaller and not statistically significant, reflecting differences in market structure and access to liquidity.

Borrower-targeted MaPPs (λ) appear largely non-significant in this specification, while financial institution-targeted policies (ϕ_1 and ϕ_2) display heterogeneous effects. Specifically, ϕ_1, associated with concentration limits, tends to stabilize credit in the Full Sample but shows weaker or even negative effects in some OECD clusters. ϕ_2, reflecting levies or taxes on intermediaries, is generally destabilizing, particularly in advanced economies, consistent with the notion that such measures can amplify volatility in highly leveraged and mature financial systems. The MPI index, when interacted with leverage, is only marginally significant in OECD countries, suggesting that broader MaPP intensity has a limited direct impact on credit growth once leverage is accounted for.

Overall, the GLS results support the main insights from the GAMLSS and GMM analy-

[19] Endogeneity may arise from omitted variables, measurement error, or simultaneity between credit growth and MaPPs. The Arellano-Bond GMM estimator addresses this issue by using lagged levels and differences of the explanatory variables as instruments, thereby providing consistent and efficient estimates even in the presence of endogenous regressors. Moreover, it is particularly well suited to dynamic panel settings characterized by short time spans and unobserved country-specific heterogeneity, such as those analyzed in this paper.

Table F1: Heteroschedastic and panel specific AR(1) GLS Model

	(1) Full Sample	(2) OECD	(3) Full Sample	(4) OECD
Dependent variable: *DCredit*				
FundCost	-0.103***	0.110	-0.115***	0.092
	(-3.98)	(0.90)	(-4.40)	(0.82)
Leverage	0.145	0.350*	0.197**	0.055***
	(1.94)	(2.05)	(3.04)	(4.12)
Leverage × *FundCost*	-0.033*	-0.085*	-0.031*	-0.083*
	(-2.43)	(-2.25)	(-2.23)	(-2.21)
Leverage × λ	0.010	0.114		
	(0.18)	(0.75)		
λ (borrower-targeted MaPP)	-0.235	-0.472		
	(-1.55)	(-0.71)		
ϕ_1 (financial institution-targeted MaPP)	0.512*	-0.612		
	(2.53)	(-0.99)		
ϕ_2 (financial institution-targeted MaPP)	-0.305	-2.194		
	(-1.24)	(-1.74)		
Leverage × *MPI*			-0.027	-0.141**
			(-1.51)	(-3.21)
MPI			0.152**	0.244
			(2.95)	(1.34)
Intercept	1.184***	0.195	1.102***	0.057
	(7.98)	(0.30)	(7.83)	(0.10)
Observations	1811	489	1811	489

All variables are one period lagged; t statistics in parentheses.
* p-value<0.05, ** p-value<0.01, *** p-value<0.001.

Table F2: Dynamic panel-data estimation, one-step difference GMM

	(1) Full Sample	(2) OECD	(3) Full Sample	(4) OECD
Dependent variable: *DCredit*				
FundCost	-0.218*	-0.131	-0.190*	-0.273
	(-2.23)	(-0.57)	(-2.32)	(-1.10)
Leverage	-0.693*	-0.836	-0.293	-0.550
	(-2.36)	(-1.52)	(-1.70)	(-1.59)
FundCost $\times$ *Leverage*	0.034	-0.034	0.030	-0.016
	(0.99)	(-0.43)	(1.03)	(-0.23)
Leverage $\times$ λ	-0.372	-0.555		
	(-1.60)	(-1.27)		
λ (borrower-targeted MaPP)	3.845*	4.689*		
	(2.24)	(2.28)		
ϕ_1 (financial institution-targeted MaPP)	0.621	-0.259		
	(0.46)	(-0.18)		
ϕ_2	2.049	0.859		
	(1.30)	(0.41)		
Leverage $\times$ *MPI*			0.029	0.071
			(0.58)	(0.66)
MPI			-0.749	-1.267*
			(-1.70)	(-2.13)
Observations	1650	452	1650	452
Arellano-Bond test for AR(1) z	-3.13	-1.73	-3.13	-1.73
$Pr > z$	0.002	0.083	0.003	
Arellano-Bond test for AR(2) z	-1.44	-0.95	-1.44	-0.98
$Pr > z$	0.150	0.345	0.150	0.326
Sargan test of overid. χ^2	1393.43	563.81	797.27	507.33
Hansen test of overid. χ^2	128.81	28.67	131.16	32.60

All variables are one period lagged; t statistics in parentheses.
* p-value<0.05, ** p-value<0.01, *** p-value<0.001.

ses: funding costs exert a systematic influence on credit, borrower-targeted instruments have limited direct effects, and institution-targeted measures produce heterogeneous outcomes depending on financial development and leverage. Unlike the GMM estimator, GLS provides a continuous measure of policy effects across countries while accommodating serial correlation, offering complementary evidence on the stability and sensitivity of credit dynamics to macroprudential interventions.