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Granular Bank Shocks and Financial Intermediation in a Low-Income Economy*

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Abstract

This paper studies how granular bank shocks propagate to aggregate credit in Mauritania's banking system. Using confidential monthly data, we extract size-weighted innovations to lending growth and profitability. At the aggregate level, lending shocks are large and exhibit a near one-for-one mapping into monthly credit growth, accounting for roughly 80 percent of its short-run fluctuations. By contrast, profitability shocks are small, statistically insignificant, and contribute almost nothing to explaining aggregate credit. This pattern suggests that fluctuations in intermediation are driven by shifts in lending at a few dominant banks, while high earnings are largely retained as buffers rather than recycled into new credit, revealing a persistent wedge between profitability and the provision of financial services. The results have direct policy relevance for Mauritania and, more broadly, for low-income and emerging economies with concentrated and nascent banking sectors.

Keywords: Banking sector granularity, financial intermediation, aggregate credit, idiosyncratic shocks, low-income country, emerging economies.

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1 Introduction

In many emerging markets and developing economies, an imbalance between bank profitability and the level of financial intermediation raises important questions about competitive dynamics, market concentration, and access to credit. This imbalance is particularly problematic in low-income economies, where the financial sector could play a critical role in mobilizing savings and allocating capital to foster inclusive growth. In this context, the Efficiency-Access and Depth Gap (EADG), a measure introduced in IMF (2024b) that captures the discrepancy between the level of banking sector profitability and the financial intermediation or inclusion, serves as a valuable diagnostic tool[1]. A high EADG score indicates that banks generate substantial profits relative to the volume of intermediation they deliver, reflecting potential inefficiencies and market power. In contrast, advanced economies typically exhibit EADG scores near zero or negative, signifying a more competitive and balanced financial system.

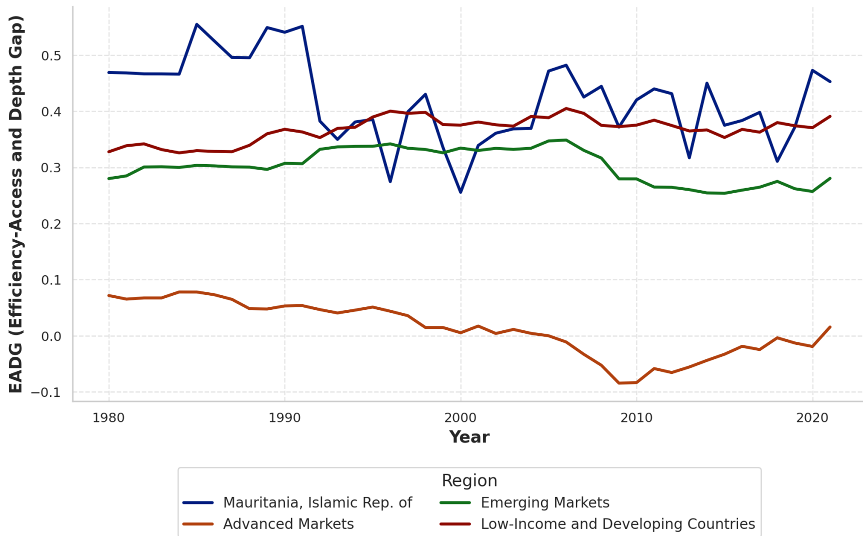
Figure 1 illustrates this striking contrast. Mauritania presents a pronounced imbalance, with an EADG significantly higher than that observed in both advanced and many emerging economies. This finding highlights systemic issues related to market concentration and limited competition, where a few dominant financial institutions generate outsized profits while providing insufficient financial services to the broader economy. In practice, high efficiency scores reflect wide interest rate margins, strong returns on assets and elevated costs rather than deep or inclusive financial intermediation, suggesting that rents are being captured rather than competed away. Such dynamics are not unique to Mauritania but are common in low-income and emerging economies with nascent financial sectors, where smaller banks often struggle to compete and play a more limited role in facilitating intermediation.

This concentration of financial intermediation is further illustrated in Figure 2, which compares total loan volume at the systemwide level with that of the five largest banks and the remaining institutions. The data reveal that aggregate lending in Mauritania is overwhelmingly driven by the

[1] This paper relates to recent work documenting how financial development and intermediation constraints—especially access to credit for firms—shape growth outcomes in emerging and low-income settings. IMF evidence in Blancher et al. (2019) highlights persistent gaps in SME access to finance and the macro-financial benefits of closing them, broader inclusive-growth agendas in the Caucasus and Central Asia in which financial sector policies are a key lever (see Vera-Martín et al. (2019)), and empirical links between financial development and growth in the same region (see Poghosyan (2022)). Complementary cross-country evidence also stresses that the effects of financial opening on credit depth and efficiency depend critically on regulatory quality (see Zhu et al. (2023)).

five dominant banks, underscoring the overwhelming influence of a small number of institutions on credit allocation. Similar patterns are observed in other low-income countries, where concentrated banking systems heighten systematic risks and limit access to credit for underserved segments of the economy, including small and medium-sized enterprises (SMEs) and rural sectors.

Figure 1: EADG (Efficiency–Access and Depth Gap) for Selected Regions

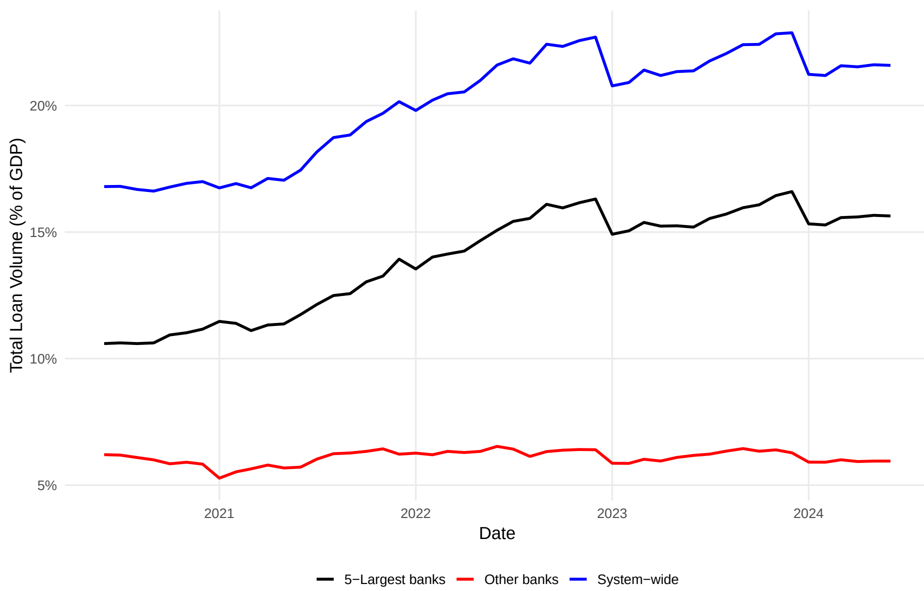


Note: The Efficiency–Access and Depth Gap (EADG) is defined as $\text{EADG} = \text{FI\_Efficiency} - \frac{\text{FI\_Access}+\text{FI\_Depth}}{2}$ and is computed from the Financial Institutions sub-indices of the IMF Financial Development Database (see Svirydzenka (2016) for detailed indices methodology). It compares banks' profitability (efficiency) with their contribution to inclusion (access) and intermediation (depth): an EADG $>>0$ indicates that profits are running ahead of outreach and intermediation, whereas an EADG around 0 signals a more balanced or inclusion-oriented system. Methodology adapted from IMF Country Report (Selected Issues Paper, in IMF (2024b)).

Understanding the dynamics of these concentrated banking systems is crucial because shocks to the largest financial institutions can have disproportionately large effects on overall financial intermediation. When a few dominant banks experience disturbances—such as sudden shifts in credit demand, regulatory changes, or external economic shocks—their predominant role in the market implies that the resulting disruptions can quickly propagate through the financial system, influencing aggregate lending and credit allocation. In a granular sense, idiosyncratic shocks at the level of a handful of large institutions need not wash out in the aggregate when the size distribution of banks is highly skewed. Such shocks can dampen overall credit supply, exacerbate liquidity constraints, or even trigger broader financial instability, thereby affecting economic growth and the transmission of macroeconomic policy.

Furthermore, the persistent dominance of these few large banks often creates an uneven playing field, leaving smaller banks struggling to compete. Many small institutions lack the scale, market influence, or resilience to replicate the performance dynamics of their larger counterparts, while others adopt narrower, relationship-based business models that do little to expand outreach. This configuration further accentuates the imbalance captured by the EADG; access and depth remain limited whereas profits are high but not channeled to greater credit provision. These imbalances not only limit the ability of the system to expand financial services, but also weaken its capacity to stabilise credit provision during periods of stress.

Figure 2: Total Bank Credit (percent of GDP): System−wide vs. 5 Largest Banks vs. Other Banks



Note: Total loan volumes are divided by GDP amounts (both denominated in Mauritanian Ouguiya) and expressed in percentage points on the figure. The blue line represents system-wide credit to the economy; the black line isolates lending by the five largest banks (ranked by balance-sheet size); the red line shows lending by all remaining banks. GDP is available at an annual frequency and the denominator is updated once new annual data are released; as a result, some sharp movements in the credit-to-GDP series reflect changes in the GDP denominator rather than abrupt shifts in underlying credit volumes.

For Mauritania, a country with an over-banked sector and a high EADG as noted in IMF (2024b), these patterns raise a central question; to what extent do shocks hitting a few dominant banks drive aggregate intermediation, and through which balance-sheet channels? Policy debates have so far relied mainly on aggregate indicators and cross-country diagnostics, which are informative about levels but largely silent on the mechanisms through which bank-specific disturbances shape credit outcomes. Yet understanding whether high profits are recycled into lending, or whether lending dynamics are instead governed by discrete, bank-specific shocks that are only weakly related to profitability, is key for designing effective prudential and competition policies. While it is almost mechanical that size-weighted lending shocks at dominant banks should move system-wide credit, there is little systematic evidence on whether size-weighted shocks to bank profitability translate into stronger intermediation. While our focus is Mauritania, similar issues arise in many low-income and developing economies with concentrated, high-margin banking systems, where balanced intermediation is essential for inclusive growth and systemic resilience.

Motivated by these observations, this paper studies how granular bank shocks shape financial intermediation in Mauritania. We estimate bank-level shock-extraction regressions for lending growth and profitability that strip out common macroeconomic conditions and selected bank observables. The residuals from these regressions are interpreted as idiosyncratic innovations and are aggregated using lagged lending shares to obtain size-weighted granular shocks. We then examine how these granular series co-move with monthly aggregate credit growth, controlling again for macro conditions in an aggregate regression framework.

Our main findings are stark. Lending-based granular shocks exhibit a near one-for-one contemporaneous association with aggregate credit growth and raise the explanatory power of aggregate regressions from roughly 10 percent with macro controls alone to about 90 percent once the granular term is included. At the same time, the inclusion of granular lending shocks restores macro coefficients to economically standard signs and magnitudes, revealing the *true* macro pass-through that is otherwise obscured by omitted bank-level heterogeneity. By contrast, profitability-based granular shocks are small, statistically insignificant, and add almost no explanatory power for aggregate credit growth; macro coefficients remain close to their baseline values when they are included. In a high-EADG system such as Mauritania, granular lending shocks (not profitability shocks) are therefore the primary drivers of short-run intermediation dynamics.

As a robustness check, we also implement a placebo exercise in which size-weighted granular lending shocks are replaced with simple cross-bank averages of the idiosyncratic lending residuals. These unweighted shocks display only weak co-movement with aggregate credit growth and load with coefficients that are small and statistically insignificant, while the explanatory power of the regression hardly improves relative to the macro-only baseline. This contrast confirms that our results are genuinely driven by *granularity*, the interaction between idiosyncratic lending shocks and the highly skewed bank-size distribution, rather than by undifferentiated residual noise.

Statistically, a granular bank shock is a size-weighted idiosyncratic innovation at the individual-bank level. In our setting, an idiosyncratic shock is the component of lending growth or profitability that remains after accounting for common macroeconomic conditions and a set of bank-specific characteristics. To fix ideas, a granular lending growth shock can be interpreted as an unexpected change in the pace of credit expansion by a given bank, net of macro trends and observable balance-sheet features. Such shocks may originate from bank-specific decisions to tighten or relax lending standards, internal reassessments of credit risk, shifts in portfolio strategy, or localised developments, such as changes in the composition of the client base or the approval of a lumpy project, that influence credit supply at that bank without necessarily affecting others.

In contrast, a granular profitability shock captures unexpected fluctuations in a bank's net income that are not attributable to systemic trends or observed balance-sheet characteristics. These may arise from changes in operating costs (for instance, due to regulatory compliance or technology investments), fee and commission income, or the performance of large, concentrated loan exposures, including those linked to foreign exchange or trade finance. When such shocks hit the largest institutions, their footprint is large enough that, in principle, they could alter aggregate credit by tightening or relaxing internal risk limits. Our results, however, suggest that in Mauritania these profitability shocks are largely absorbed through buffers—liquidity, provisioning, or capital compliance—rather than being systematically recycled into new lending at the monthly frequency.

By combining detailed bank-level data with macroeconomic controls, our methodology builds on granular macro-finance frameworks such as Gabaix (2011) and Gabaix and Koijen (2024), but adapts them to the context of banking systems in low-income economies. Conceptually, the paper links two strands of work that have largely evolved separately: macro-level diagnostics of banking sector intermediation and profitability, and second, with micro-founded granular models of how individual institutions move the aggregate outcomes. Empirically, we provide, to our knowledge, the first evidence for a low-income country that size-weighted idiosyncratic lending shocks almost fully account for high-frequency movements in aggregate credit, while profitability shocks play a negligible role.

From a macro-critical policy perspective, these findings have three implications. First, policies that mechanically boost bank profitability, through wider spreads or one-off valuation gains, cannot be expected to deliver stronger intermediation unless they also relax constraints on the lending channel at dominant banks. Second, monitoring and mitigating granular lending shocks at the largest institutions is essential for stabilising aggregate credit in concentrated systems, calling for enhanced supervisory focus on their credit standards, concentration risks, and governance. Third, by clarifying the respective roles of bank-specific and macro shocks, our granular approach provides a template for other low-income and developing economies to diagnose whether high EADG scores reflect genuine intermediation constraints or simply the dominance of a few large lenders. In this way, the paper contributes to ongoing debates on market concentration, competition, and financial inclusion in low-income financial systems.

2 Literature Review

A large empirical and policy literature shows that banks in many emerging and low-income economies are highly profitable while providing shallow and costly intermediation. Cross-country and regional studies document that elevated net interest margins and returns on assets in developing countries often reflect operating costs, macroeconomic risk, and market power rather than pure efficiency gains, and tend to coexist with low private credit-to-GDP and limited access (Demirgüç-Kunt and Huizinga (1999); Flamini et al. (2009); Ahokpossi (2013); Beck and Hesse (2009)). Building on multidimensional indices of financial depth, access, and efficiency (Svirydzenka (2016)), recent IMF work documents that many EMDEs combine high banking-sector "efficiency" scores, driven by wide spreads and strong profits, with weak depth and access, and that reforms fostering competition and reducing the sovereign–bank nexus boost private credit and GDP (see IMF (2024a), Chapter 3 of the October 2024 MCD *Regional Economic Outlook*). The Mauritania Selected Issues paper formalizes this imbalance through the Efficiency–Access and Depth Gap (EADG) and shows that Mauritania is an appropriate case study with similar features to other emerging and low-income countries, with profitability far outpacing intermediation and inclusion (see IMF (2024b) and Figure 1).

The existing literature on banking performance, economic activity, and financial stability highlights an ambiguous relationship between competition, concentration, and risk-taking. Early theoretical and empirical work (e.g., Boyd and Nicoló (2005); Claessens and Laeven (2004)) emphasizes that greater competition may erode banks' franchise values and encourage riskier asset portfolios, but subsequent studies stress that the empirical evidence is mixed. Some contributions find that competitive pressure is associated with higher risk-taking, while others argue that concentrated markets can also foster risk through market power and moral hazard. In terms of stability and growth, Beck et al. (2006) show that more concentrated banking systems are not necessarily more crisis-prone, whereas Cetorelli and Gambera (2001) document that concentration can both ease financing constraints for financially dependent sectors and weigh on overall growth. Regional and historical work (e.g., Yildirim and Philippatos (2007); Carlson et al. (2022)) further underscores that deregulation, foreign bank entry, and consolidation reshape competition and credit supply in complex ways. This body of evidence motivates our focus on how shocks originating in a few dominant banks transmit to aggregate credit in a concentrated, low-income banking system.

Related work highlights the macro-critical role of large banks through "too big to fail" (TBTF) incentives and systemic spillovers. Theoretical contributions such as Zhu et al. (2017) show that banks may engage in mergers, even absent scale economies, to increase the likelihood of public support in distress, which can lead to inefficiently concentrated market structures. Empirical evidence further suggests that perceived TBTF status lowers funding costs and encourages leverage and risk-taking at the largest institutions (Strahan (2013); Kaufman (2014)). Recent episodes such as the failure of Silicon Valley Bank illustrate how shocks at a single large institution can generate sizeable losses for depositors and borrowers and trigger broader policy responses (Liu et al. (2024)). Although Mauritania does not operate a formal TBTF regime, these insights underscore that large banks can influence aggregate credit and systemic risk in ways that are disproportionate to their number.

A burgeoning strand of the literature focuses directly on granular shocks as drivers of aggregate fluctuations. Gabaix (2011) shows that when the firm-size distribution is sufficiently fat-tailed, idiosyncratic shocks to a small number of large firms need not wash out in the aggregate and can account for a substantial share of output volatility. Building on this insight, Gabaix and Koijen (2024) propose a systematic way to construct size-weighted idiosyncratic shocks and use them as granular instruments for macro-financial variables. We adapt their residual-then-weighting methodology to the banking context by constructing granular measures of lending and profitability shocks at the bank level.

The granular perspective has since been applied to the financial sector and to both emerging and advanced economies. Blank et al. (2009) extend the granular framework to the German banking system by constructing a "banking granular residual" and find that positive idiosyncratic shocks at large banks can, somewhat counterintuitively, reduce the distress probability of smaller banks through stabilizing spillovers. In an emerging-market setting, Grigoli et al. (2021) document that firm-level idiosyncratic shocks account for over 40 percent of aggregate sales volatility in Chile, though somewhat less than in advanced economies, partly due to weaker propagation mechanisms. Similarly, Ebeke and Eklou (2017) show that granular shocks affecting the largest 100 firms in Europe explain about 40 percent of GDP variance, with significant spillover effects on small and medium-sized enterprises, particularly in the manufacturing and services sectors. Complementing these studies, Amiti and Weinstein (2018) apply the granular framework to bank–firm loan data in Japan. By decomposing movements in aggregate bank credit into a granular supply component and other factors, they find that idiosyncratic bank supply shocks explain roughly 30–40 percent of fluctuations in aggregate loans and investment, underscoring the macroeconomic importance of shocks originating in large banks even in advanced economies.

While the granular approach has been widely applied to advanced economies and, to a lesser extent, to emerging markets, its application to low-income and developing economies remains largely unexplored. Existing work on bank granularity has primarily focused on the United States, Europe, Japan, and a few middle-income countries such as Chile. To the best of our knowledge, this paper is the first to apply a granular framework to the banking system of a low-income country. Focusing on Mauritania, a low competitive banking sector with high profitability and shallow intermediation, we ask whether idiosyncratic shocks at large banks can explain a substantial share of aggregate credit fluctuations, and whether granular shocks to lending and to profitability have symmetric pass-through to aggregate credit.

Our contribution is to connect the profitability–intermediation literature with the granular macro-finance literature in a low-income setting. We move beyond representative-bank, cross-country approaches by combining EADG-style macro diagnostics with a bank-level identification strategy that isolates size-weighted innovations in lending growth and profitability. This allows us to show that granular lending shocks at a few dominant banks map almost one-for-one into aggregate credit, whereas granular profitability shocks have virtually no incremental explanatory power. From a policy perspective, this micro-founded evidence speaks directly to debates on market power, financial inclusion, and macroprudential oversight in low-income economies, where high profitability does not necessarily translate into expanded intermediation and where shocks at a small number of large institutions can have outsized macro-financial effects.

3 Methodology

In this study, we follow the granular framework pioneered by Gabaix (2011) and Gabaix and Koijen (2024) to examine how idiosyncratic bank shocks, not only to bank lending growth but also to profitability, affect aggregate financial intermediation in Mauritania. By integrating monthly bank-level data with macroeconomic controls, observable bank-level characteristics, and bank-specific fixed effects, we isolate idiosyncratic shocks and assess their role in driving system-wide fluctuations.

3.1 Bank-Level Analysis and Idiosyncratic Shocks

Let $Z_{i,t}$ denote a generic bank-level variable of interest for bank i at time t. We define its growth rate as:

$$g_{i,t}^{Z} \;=\; \frac{Z_{i,t} - Z_{i,t-1}}{Z_{i,t-1}}, \tag{1}$$

which measures the proportional change in $Z_{i,t}$ relative to the preceding period. For our level variable (*i.e.* loans), we use this proportional growth. For profitability ratios, we instead use levels as described in section 4.1 table 1, to avoid division by small/negative bases.

To control for both common macroeconomic influences and bank-specific characteristics, we estimate the following regression specification:

$$g_{i,t}^{Z} \;=\; \boldsymbol{\beta}^{Z\prime}\mathbf{X}_t \;+\; \boldsymbol{\gamma}^{Z\prime}\mathbf{W}_{i,t} \;+\; \mu_i \;+\; \varepsilon_{i,t}^{Z}. \tag{2}$$

where $\mathbf{X}_t$ is a vector of macroeconomic controls (e.g., monetary policy rate, inflation, broad money M3 growth and foreign exchange) common to all banks, with $\boldsymbol{\beta}^{Z}$ denoting the corresponding coefficient vector. $\mathbf{W}_{i,t}$ is a vector of observable bank-level control variables (such as bank liquidity, lending-deposit spread, or depositor concentration) that capture heterogeneous characteristics across banks, with $\boldsymbol{\gamma}^Z$ as the associated coefficient vector. μ_i represents bank-specific fixed effects, which control for unobserved time-invariant heterogeneity across banks. $\varepsilon_{i,t}^Z$ is the error term, capturing the idiosyncratic shock to bank i that is not explained by the macroeconomic controls, bank-level characteristics, or fixed effects. This specification can be interpreted as a simple factor model, where $\mathbf{X}_t$ spans common aggregate shocks and $\mathbf{W}_{i,t}$ and μ_i capture differential loadings across banks[2].

The inclusion of both $\mathbf{W}_{i,t}$ and μ_i is critical. The observable bank-level controls $\mathbf{W}_{i,t}$ help mitigate omitted variable bias by accounting for measurable differences in bank operations that may influence $g_{i,t}^Z$. Meanwhile, the fixed effects μ_i capture unobservable, time-invariant attributes of each bank (such as management quality or institutional characteristics), ensuring that the residual $\varepsilon_{i,t}^Z$ represents only the idiosyncratic shocks. This dual-control strategy enhances the credibility of our subsequent analysis on the propagation of micro-level shocks to macro-level outcomes.

3.2 Granular Shocks and Aggregation to the Macro Level

To assess the aggregate impact of these idiosyncratic shocks, each bank's relative importance $s_{i,t-1}$ is measured by its weight in the previous period:

$$s_{i,t-1} = \frac{\Theta_{i,t-1}}{\sum_{j=1}^{N} \Theta_{j,t-1}}, \tag{3}$$

where N denotes the total number of banks and $\Theta_{i,t-1}$ denotes the total assets of bank i at time $t-1$ (alternatively, total loans). Our baseline uses total assets; results are robust to using total loans as the size measure.

The granular shock for the variable Z is then constructed as:

$$\Gamma_t^Z = \sum_{i=1}^{N} s_{i,t-1}\, \varepsilon_{i,t}^Z. \tag{4}$$

This weighted sum emphasizes the contribution of larger banks in driving aggregate fluctuations.

[2] We assume that, conditional on $\mathbf{X}_t, \mathbf{W}_{i,t}$ and μ_i, the idiosyncratic shocks $\varepsilon_{i,t}^Z$ are weakly correlated across banks. This the usual "no strong cross-sectional correlation" granular assumption.

Under a Hulten-style aggregation, the aggregate growth rate of the banking system is approximately a size-weighted sum of bank-level growth rates. This motivates the use of Γ_t^Z as a granular residual capturing the contribution of large-bank idiosyncratic shocks to aggregate fluctuations.

We measure aggregate financial intermediation G_t^{FI} using the official series on aggregate bank credit, which is itself an aggregate over bank balance sheets and therefore consistent with the granular aggregation logic.

To evaluate how granular shocks influence system-wide outcomes, we regress the aggregate credit growth on the granular shock:

$$G_t^{FI} \; = \; \delta_0^Z \; + \; \delta_1^Z \, \Gamma_t^Z \; + \; \delta_2^{Z\,\prime} \mathbf{X}_t \; + \; u_t^Z, \tag{5}$$

where δ_0^Z, δ_1^Z and δ_2^Z are parameters to be estimated, and u_t^Z is the residual capturing other macro-level disturbances. A significant and positive estimate of δ_1^Z would suggest that idiosyncratic shocks, especially those emanating from banks with a larger presence, systematically contribute to aggregate fluctuations in financial intermediation G_t^{FI}. In line with Gabaix (2011), we treat the granular shock Γ_t^Z as a direct predictor of aggregate financial intermediation, rather than as an instrument in a 2SLS framework. Extending the analysis to full GIV-style IV estimation is left for future work.

3.3 Granular Shocks Validity and Diagnostic Testing

For the granular shock Γ_t^Z to be valid, it is imperative that the underlying idiosyncratic shocks $\varepsilon_{i,t}^Z$ satisfy certain conditions:

1. **Orthogonality:** The idiosyncratic shocks must be uncorrelated with both the macroeconomic and bank-level controls:

$$E\big(\varepsilon_{i,t}^Z \mid \mathbf{X}_t, \mathbf{W}_{i,t}\big) \; = \; 0, \tag{6}$$

implying

$$\mathrm{Cov}\big(\varepsilon_{i,t}^Z, \mathbf{X}_t\big) \; = \; 0 \quad \text{and} \quad \mathrm{Cov}\big(\varepsilon_{i,t}^Z, \mathbf{W}_{i,t}\big) \; = \; 0. \tag{7}$$

2. **Granularity:** The size distribution of banks must be sufficiently fat-tailed such that Γ_t^Z exhibits non-trivial variance. If all banks were small and identical ($s_{i,t-1} \approx 1/N$), Γ_t^Z would converge to zero by the Law of Large Numbers. In the Mauritanian context, the distribution of bank size is highly right-skewed and ensures this condition is met (see subsection 4.1), giving the granular shock statistical power. Another argument for granularity is illustrated by figure 2 where most of lending dynamic is driven only by the five largest banks.

These assumptions ensure that the residuals and, by extension, the granular shocks are not contaminated by systematic influences from either the macroeconomic environment or observable bank-specific characteristics. Following Gabaix and Koijen (2024), the main threat to identification is misspecification of the common factors. if $\mathbf{X}_t$ and $\mathbf{W}_{i,t}$ do not fully absorb aggregate shocks, $\varepsilon_{i,t}^Z$ may still contain common components, biasing Γ_t^Z. For this, we add as much aggregate controls as possible to insure the stability of δ_1^Z.

We employ standard diagnostic tests for exogeneity, to confirm these conditions and reinforce the robustness of our estimates. We allow for heteroskedasticity in $\varepsilon_{i,t}^Z$. As emphasized by Gabaix and Koijen (2024), heteroskedasticity primarily affects the efficiency of the granular estimator rather than its consistency. However, we repport White's test for heteroskedasticity for illustration in appendix 6.

Our methodological framework utilizes the granular approach to encompass a variety of bank-level shocks, including lending growth, profitability, and other key performance indicators that may influence aggregate financial intermediation. By combining detailed bank-level data with both macroeconomic and bank-specific controls, as well as incorporating bank-level fixed effects, we ensure that the idiosyncratic shocks captured in our analysis are both precise and exogenous. This specification allows us to credibly assess whether a small number of dominant banks can disproportionately shape the dynamics of the Mauritanian credit market.

4 Data

The empirical analysis in this paper is based on confidential, bank-level data collected by the Banque Centrale de Mauritanie (BCM)[3]. The dataset comprises monthly balance sheet components and prudential ratios for all active banks in Mauritania over the post-COVID period (June 2020 to June 2024). As the data cover the entire population of Mauritanian banks, no sampling procedure was employed. For the purposes of this study, focusing on financial intermediation, aggregate lending, concentration, and profitability, we emphasize (but do not exclusively rely on) the following balance sheet components: Top Five Depositor Amounts, Top Five Borrower Loan Amounts, Average Loan Interest Rate, Average Deposit Interest Rate, Total Loan Volume, Total Bank Capital, Total Deposits, Total Assets, Net Income, Cash And Cash Equivalents.

Two banks were excluded from the sample. One because its operations commenced in November 2023 (leading to missing values for preceding periods), and the other due to inconsistencies and a high incidence of outliers. Data quality is further ensured by cross-validating the aggregated figures against the macro-level aggregates reported by the International Monetary Fund (IMF). Additionally, macro-level data are complemented with macroeconomic indicators (inflation, policy rate, aggregate lending, spot exchange rate, and broad money supply) sourced from IMF country-level data for Mauritania.

4.1 Data Description

Tables 1 and 2 summarize the construction and distribution of the variables used in the empirical analysis. The supervisory panel covers $I = 15$ banks over $T = 49$ monthly observations (June 2020–June 2024), yielding $N = 735$ bank–months. Variables that require lags naturally have fewer observations (e.g., *Lending Growth* has $N = 720$).

Panel A reports variables directly tied to financial intermediation. *Lending Growth* captures the intensive margin of credit supply; *Profitability* measures earnings relative to capital *(netIncome*

[3] Although the dataset covers loan volumes for all active banks, the reported breakdown of credit between Islamic and conventional instruments is not consistently reliable across institutions and time. We therefore do not exploit this dimension in the empirical analysis, even though it is an important feature of Mauritania's banking sector.

/ totalBankCapital); and *liquidity* proxies buffer capacity through the ratio of cash and equivalents to total assets. Concentration on both sides of the balance sheet is summarized by the *Top 5 Depositor Concentration* and *Top 5 Borrower Concentration* ratios, while pricing is captured by the *Lending-Deposit Spread*, the difference between average loan and deposit rates.

The distribution of bank size is highly right-skewed. Median total assets are MRU 6.55 billion versus a mean of MRU 8.76 billion, with a maximum exceeding MRU 33.6 billion. Loans and deposits display similar dispersion (median loans MRU 4.20 billion vs. mean MRU 4.85 billion; median deposits MRU 4.38 billion vs. mean MRU 5.85 billion). This dispersion implies that a small number of large institutions account for a large share of system assets and credit, a feature that is consequential for the aggregate impact of idiosyncratic bank shocks.

Funding is concentrated in a relatively small number of large depositors. The *Top 5 Depositor Concentration* averages 15 percent with an interquartile range from 8 to 21 percent, and reaches as high as 50 percent in some bank–months. In a shallow deposit market, such concentration can heighten sensitivity to large-depositor behavior and shape banks' liquidity management. This motivates treating depositor concentration as a key state variable when interpreting the propagation of idiosyncratic shocks to lending.

Borrower concentration is also material. The median *Top 5 Borrower Concentration* is 21 percent (P75 = 31 percent), indicating that many banks' loan books are anchored by a handful of large obligors. The mean 24 percent and the extreme upper tail (maximum 1) reflect occasional months in which the reported numerator is as large as the contemporaneous total loan amount.

Average loan and deposit rates cluster around 11 percent [4] and 6 percent, respectively, implying a lending–deposit spread near 600 basis points. This margin is economically sizable and consistent with both elevated credit and operating risk and with limited competition in intermediation. The dispersion in spreads across banks provides a natural lens to discuss whether earnings buffers attenuate or amplify the transmission of bank-specific shocks.

Lending Growth has a median close to zero with substantial dispersion (standard deviation 1.42) and a long right tail (maximum 23.31), patterns that are consistent with base effects when loan levels are small and with episodic large disbursements. *Profitability* is volatile at monthly frequency

[4] The Mauritanian Central Bank (BCM) imposes a maximum loan rate equal to the policy rate plus five percentage points *i.e.* $policyRate + 5$ percent. This is verified in our data.

(mean 5 percent of capital; standard deviation 9 percent; range -39 to 51 percent), suggesting that earnings capacity fluctuates meaningfully within the sample. Liquidity ratios average 20 percent of assets with an interquartile range from 9 to 31 percent, indicating heterogeneous ability to absorb funding pressures or accommodate credit demand.

Table 1: Construction of Key Variables

Panel A. Bank-Level Variables		
Variable	**Formula**	**Description**
Lending Growth	$\text{lending Growth}_{i,t} = \frac{\text{totalLoanVolume}_{i,t} - \text{totalLoanVolume}_{i,t-1}}{\text{totalLoanVolume}_{i,t-1}}$	Measures the percentage change in total loan volume from the previous period.
Profitability	$\text{Profitability}_{it} = \frac{\text{netIncome}_{it}}{\text{totalBankCapital}_{it}}$	Reflects the return on bank capital.
Liquidity	$\text{Liquidity}_{it} = \frac{\text{cashAndCashEquivalents}_{it}}{\text{totalAssets}_{it}}$	Indicates the share of liquid assets in total assets.
Top 5 Borrower Concentration	$\text{T5BC}_{it} = \frac{\text{topFiveBorrowerLoanAmounts}_{it}}{\text{totalLoanVolume}_{it}}$	Captures the concentration of loans among the five largest borrowers.
Top 5 Depositor Concentration	$\text{T5DC}_{it} = \frac{\text{topFiveDepositorAmounts}_{it}}{\text{totalDeposits}_{it}}$	Measures the concentration of deposits among the five largest depositors.
Lending-Deposit Spread	$\text{LDS}_{it} = \text{averageLoanInterestRate}_{it} - \text{averageDepositInterestRate}_{it}$	Represents the net interest margin at the bank level.
Panel B. Macro-Level Variables		
Variable	**Formula**	**Description**
Inflation	$\text{Inflation}_t = \frac{\text{headlineCPI}_t - \text{headlineCPI}_{t-1}}{\text{headlineCPI}_{t-1}}$	Computed as the growth rate of the headline consumer price index.
Change in FX Rate (Δ FX)	$\Delta\text{FXRate}_t = \text{SpotFXRate}_t - \text{SpotFXRate}_{t-1}$	Period-to-period change in the nominal USD/MRU exchange rate.
M3 Growth	$\text{M3Growth}_t = \frac{\text{broadMoney}_t - \text{broadMoney}_{t-1}}{\text{broadMoney}_{t-1}}$	Growth rate of broad money (M3), capturing liquidity expansion in the economy.

Note: All variables are expressed at monthly frequency unless otherwise specified. Bank-level indicators are computed from supervisory central bank data, while macroeconomic variables are sourced from IMF datasets.

Panel B shows stable macro conditions with episodic pressures. The policy rate averages 6 percent (P25 = 5 percent, P75 = 8 percent) over the period. The USD/MRU spot rate averages 37 with occasional monthly changes up to 3.5 MRU. Broad money (M3) grows by about 1 percent per month on average, while monthly inflation fluctuates modestly around 0.4 percent monthly. These series provide common controls that shape banks' operating environment over the sample.

Table 2: Descriptive Statistics: Bank- and Macro-Level Variables

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Panel A. Bank-level variables								
topFiveDepositorAmounts	735.00	715,795,718.98	664,207,487.75	46,269,070.60	349,637,380.25	548,063,523.05	939,690,222.87	5,368,238,500.41
topFiveBorrowerLoanAmounts	735.00	986,040,804.61	1,277,875,472.00	3,767,600.00	62,626,914.00	451,713,269.55	1,478,913,740.39	5,657,157,400.02
averageLoanInterestRate	735.00	0.11	0.01	0.09	0.10	0.11	0.12	0.14
averageDepositInterestRate	735.00	0.06	0.01	0.03	0.05	0.06	0.06	0.09
totalLoanVolume	735.00	4,846,436,495.10	4,599,517,144.40	7,138,737.77	319,148,079.09	4,204,917,995.86	7,698,868,555.22	17,608,054,818.24
totalBankCapital	735.00	1,013,683,813.03	132,007,119.89	600,000,000.00	1,000,000,000.00	1,000,000,000.00	1,000,031,375.00	1,520,001,000.00
totalDeposits	735.00	5,852,971,180.55	4,609,363,682.95	609,541,744.60	2,314,234,491.78	4,384,228,716.02	8,432,063,300.62	26,732,142,586.82
totalAssets	735.00	8,759,585,215.94	6,933,544,554.37	1,890,258,585.80	3,270,736,852.05	6,545,739,384.72	12,055,526,107.55	33,618,075,975.69
netIncome	735.00	52,536,380.21	92,995,275.70	-389,707,344.72	8,914,008.64	40,721,866.00	88,661,089.17	511,083,134.51
cashAndCashEquivalents	735.00	1,531,696,087.37	1,383,977,527.80	0.00	540,208,681.32	1,139,970,839.99	2,134,017,289.65	7,412,890,050.27
lendingGrowth	720.00	0.17	1.42	-0.95	-0.01	0.00	0.03	23.31
liquidity	735.00	0.20	0.13	0.00	0.09	0.18	0.31	0.52
profitability	735.00	0.05	0.09	-0.39	0.01	0.04	0.09	0.51
top5DepositorConcentration	735.00	0.15	0.10	0.01	0.08	0.14	0.21	0.50
top5BorrowerConcentration	735.00	0.24	0.24	0.00	0.03	0.21	0.31	1.00
lendingDepositSpread	735.00	0.06	0.01	0.02	0.04	0.06	0.07	0.09
Panel B. Macro-level variables								
policyRate	49.00	0.06	0.01	0.05	0.05	0.05	0.08	0.08
broadMoney	49.00	110,362.31	12,141.39	85,550.31	101,761.30	112,537.55	118,874.11	131,323.49
headlineCPI	49.00	114.14	8.33	102.12	105.14	115.18	121.64	124.84
inflation	49.00	0.0041	0.0047	-0.0066	0.0008	0.0030	0.0077	0.0150
SpotFXRate	49.00	37.01	1.55	34.05	36.00	36.30	37.88	40.00
FXRateChange	49.00	0.03	0.73	-2.10	-0.11	0.00	0.10	3.50
M3Growth	49.00	0.01	0.02	-0.03	-0.00	0.01	0.02	0.07

Notes: Bank-level variables are observed at the bank–month level ($N = 735$; with $T = 49$ and $I = 15$), however the descriptive statistics are reported ; macro-level variables are monthly aggregates ($T = 49$). FX variables are USD/MRU. Values with large magnitudes are printed with thousands separators for readability.

Three empirical features of the data are salient for the analysis that follows: (i) a fat-tailed size distribution, (ii) economically large depositor and borrower concentration, and (iii) wide intermediation margins with meaningful month-to-month variability. Together, these characteristics create conditions under which shocks originating in a small number of banks can affect system-wide lending and profitability, aligning with the granular mechanism investigated in the paper.

5 Main Results

This section implements the granular framework to quantify how bank-specific shocks propagate to aggregate credit in Mauritania and to recover the underlying macro pass-through. We proceed in two steps. First, we estimate bank-level *shock-extraction* regressions for lending growth and profitability that partial out common macro conditions and observable bank characteristics while controlling for time-invariant bank heterogeneity. The residuals from these specifications are interpreted as idiosyncratic innovations at the bank level. Second, we aggregate these innovations into monthly granular series using lagged lending shares as weights, so that movements at larger institutions receive more weight in the aggregate shock. This delivers two objects of interest: a granular lending shock, Γ_t^L, and a granular profitability shock, Γ_t^P, which we then relate to aggregate credit growth.

We use these objects in two complementary ways. We first document how the granular series co-move with aggregate credit growth in simple time-series plots, providing a visual sense of whether size-weighted bank-level innovations track turning points in system credit. We then estimate aggregate-level regressions of credit growth on macro controls alone and on macro controls augmented with the granular shocks. Comparing these specifications allows us to assess (i) how much of the high-frequency variation in aggregate credit is accounted for by granular lending versus profitability shocks, and (ii) whether including Γ_t^L and Γ_t^P restores standard signs and magnitudes for the macro coefficients. Throughout, the focus is not on forecasting performance per se but on decomposing aggregate credit dynamics into a macro component and a granular component driven by a small set of large banks.

Table 3 reports eight parsimonious bank-level shock-extraction specifications in which lending growth is regressed on a common set of macro controls (Inflation, Policy Rate, M3 Growth, and ΔFX), selected bank observables (Liquidity, Profitability, Top 5 Borrower Concentration (T5BC), Top 5 Depositor Concentration (T5DC), and the Lending–Deposit Spread (LDS)), and bank fixed effects. The sequence of models adds blocks of bank observables one at a time to gauge robustness while limiting overfitting and collinearity. We intentionally refrain from including time fixed effects in this monthly panel, they absorb most common variation without materially improving explanatory power, and crucially for our purpose, would attenuate the residual variation we require to construct idiosyncratic shocks.

Table 3: Extracting Idiosyncratic Lending Shock

This table reports panel regressions designed to extract idiosyncratic lending shocks by purging common macroeconomic influences and observable bank characteristics. Each column presents a fixed-effects specification of the form:

$$\text{Lending Growth}_{i,t} = \alpha_i + \boldsymbol{\beta}'\mathbf{X}_t + \boldsymbol{\gamma}'\mathbf{Z}_{i,t} + \varepsilon_{i,t},$$

where α_i denotes bank fixed effects, $\mathbf{X}_t$ includes macroeconomic controls (Inflation, Policy Rate, M3 Growth, and ΔFX), and $\mathbf{Z}_{i,t}$ represents bank-specific observables. The specifications progressively add bank-level controls. This builds on Vo (2018) where bank-level lending is mainly driven by banks characteristics and macroeconomic conditions. We employ eight different specifications **(columns (1)-(8))** by systematically including various combinations of key bank-specific observables, $\text{Profitability}_{i,t}$, $\text{T5DC}_{i,t}$, and $\text{LDS}_{i,t}$, to assess the stability of the common factors and the orthogonality of the resulting residuals. The idiosyncratic residuals $\varepsilon_{i,t}$ are used to build our granular lending shocks $\Gamma_t^{L-spec(k)}$, where k refers to the specific model (1)-(8) (see Table 5).

Dependent Variable:				Lending Growth$_{i,t}$				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Inflation$_t$	14.85	15.09	14.62	14.89	15.02	15.21	14.67	15.13
	(16.72)	(16.80)	(16.43)	(16.66)	(16.69)	(16.90)	(16.43)	(16.80)
Policy Rate$_t$	-1.205*	-1.020	-1.850	-1.175	-1.572	-0.9207	-1.753	-1.431
	(0.6775)	(0.7381)	(1.123)	(0.7979)	(1.042)	(0.8633)	(1.146)	(1.072)
M3 Growth$_t$	-0.2916	-0.2736	-0.2555	-0.3034	-0.2200	-0.2790	-0.2701	-0.2300
	(0.9117)	(0.9303)	(0.9357)	(0.8882)	(0.9740)	(0.9205)	(0.9103)	(0.9592)
ΔFX_t	-0.0580	-0.0578	-0.0599	-0.0583	-0.0596	-0.0579	-0.0599	-0.0596
	(0.0688)	(0.0688)	(0.0705)	(0.0699)	(0.0704)	(0.0698)	(0.0712)	(0.0710)
T5BC$_{i,t}$	-0.0023	-0.0024	-0.0022	-0.0022	-0.0022	-0.0023	-0.0021	-0.0022
	(0.0053)	(0.0053)	(0.0053)	(0.0054)	(0.0053)	(0.0054)	(0.0054)	(0.0054)
Liquidity$_{i,t}$	-0.0401	-0.0306	-0.2676	-0.0571	-0.2700	-0.0448	-0.2581	-0.2604
	(0.1192)	(0.1224)	(0.2776)	(0.1258)	(0.2821)	(0.1257)	(0.2584)	(0.2646)
Profitability$_{i,t}$		-0.1044			-0.1879	-0.1430		-0.2151
		(0.0725)			(0.1355)	(0.1305)		(0.1825)
T5DC$_{i,t}$			0.5720		0.6205		0.5096	0.5627
			(0.5563)		(0.5781)		(0.4804)	(0.5062)
LDS$_{i,t}$				-3.748		-3.859	-3.366	-3.493
				(5.584)		(5.706)	(5.199)	(5.340)
Fixed-effects								
bankID	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	720	720	720	720	720	720	720	720
R^2	0.12455	0.12458	0.12494	0.12496	0.12501	0.12500	0.12526	0.12536
Within R^2	0.00387	0.00389	0.00430	0.00433	0.00439	0.00438	0.00467	0.00478

*Clustered (bankID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*
Note: *The variables $T5BC_{i,t}$, $T5DC_{i,t}$, and $LDS_{i,t}$ correspond to Top 5 Borrower Concentration$_{i,t}$, Top 5 Depositor Concentration$_{i,t}$, and Lending-Deposit Spread$_{i,t}$, respectively.*

Point estimates are stable across specifications and broadly consistent with priors on signs, though imprecise at conventional levels. The policy rate enters with a negative sign in all models and reaches marginal significance in (1); economically, a 100 basis point (henceforth bp) increase in the policy rate (+0.01) is associated with roughly a 1.2 percentage point (henceforth pp) lower monthly lending growth in (1), but the estimate becomes imprecise once additional bank observables are introduced. Inflation loads positively (models (1)–(8)), implying that a one-percentage-point increase in monthly inflation (+0.01) would correspond to about +15 pp in lending growth based on the point estimate; this magnitude should be interpreted cautiously given the wide standard errors and the rarity of such monthly changes. M3 growth and ΔFX carry small coefficients close to zero in economic terms. On bank characteristics, liquidity and profitability coefficients are not statistically different from zero; T5BC loads slightly negatively (around -0.002), implying that even a large +10 pp increase in borrower concentration would be associated with only -0.02 pp in lending growth, an economically minor effect. T5DC is positive (about 0.5–0.6), suggesting that a +10 pp rise in depositor concentration would correspond to +5–6 pp higher lending growth on the point estimates, but again these coefficients are imprecisely estimated. The lending–deposit spread enters negatively across the specifications where it appears, consistent with tighter pricing correlating with slower loan expansion, yet estimates are not statistically significant.

The models exhibit a sizable gap between the overall R^2 (about 12.5 percent) and the within-bank R^2 (about 0.4 percent). The overall R^2 largely reflects bank fixed effects absorbing persistent cross-bank differences, whereas the very low within-bank R^2 indicates that our observed macro controls and bank characteristics explain little of the month-to-month variation in lending growth within a given bank. This is consistent with our design; the bank-level shock-extraction specifications are not meant to forecast lending growth but to purge observables so that the residuals $\hat{\varepsilon}_{i,t}$ isolate idiosyncratic innovations. A low within-bank R^2 therefore does *not* undermine our approach; it implies that most high-frequency movements remain in the residual, providing the variation we need to construct the granular series. Because the granular shock is a size-weighted aggregation of these innovations, $\Gamma_t^{L-spec(k)} = \sum_i s_{i,t-1}\,\hat{\varepsilon}_{i,t}$, its relevance at the aggregate level comes from (i) the non-trivial variance of $\hat{\varepsilon}_{i,t}$ left after conditioning on observables and (ii) the dispersion in bank sizes that gives the weighted sum bite. In short, the shock-extraction regression's low within-bank fit is a feature for identifying idiosyncratic shocks, not necessarily a flaw.

Table 8, reported in Appendix 6, presents standard diagnostic checks for the lending-growth regressions. Breusch–Pagan statistics do not reject homoskedasticity at the 5 percent level in most specifications (p-values 0.05–0.11), and residual–fitted correlations are essentially zero, supporting the orthogonality conditions discussed in section 3.3 and the assumptions in Equation (6). The reported F-statistics measure the joint significance of the macro and bank-level regressors in the within-bank dimension and are around 4.5–4.9, reflecting the limited predictive power of observables for monthly lending growth at the bank level. Importantly, we refer to these regressions as shock-extraction regressions only in the granular sense of constructing residual shocks; they are not part of a 2SLS/IV system, and the F-statistics should not be interpreted as tests of instrument strength. Adding further controls (including time fixed effects) does not materially raise explanatory power and risks overfitting, while also eroding the residual variation that defines the idiosyncratic shocks. Given the diagnostics, the residuals remain (i) orthogonal to included observables and (ii) sufficiently variable to construct Γ_t^L. Consequently, the granular lending-shock series we build from these residuals is valid for our purpose: tracing how bank-specific, size-weighted innovations map into aggregate credit dynamics.

Table 4 reports eight bank-level shock-extraction specifications in which Profitability is regressed on macro controls (Inflation, Policy Rate, M3 Growth, and ΔFX), selected bank observables (Liquidity, Lending Growth, Top 5 Borrower Concentration (T5BC), Top 5 Depositor Concentration (T5DC), and the Lending–Deposit Spread (LDS)), and bank fixed effects. The sequence adds blocks of bank covariates across columns to assess robustness and avoid overfitting. The goal is not to forecast profitability, but to purge common macro influences and observed bank characteristics so that the residuals capture bank-specific innovations in profitability.

Two macro variables load positively and significantly across all models. First, Inflation_t is robustly positive at the 5 percent level (coefficients about 2.13–2.25): a 1 pp monthly increase in inflation (+0.01) is associated with roughly +2.1–2.3 pp higher profitability. Second, Policy Rate_t is also positive and significant (about 1.48–1.78), implying that a 100 bp policy-rate increase corresponds to +1.5–1.8 pp higher profitability. These magnitudes are economically meaningful and consistent with banks' rapid pass-through on asset yields (and valuation/pricing effects) at the monthly frequency. This pattern suggests that banks are major beneficiaries of inflationary environments and that monetary tightening tends to raise bank profitability. In contrast, M3 Growth_t

Table 4: Extracting Idiosyncratic Profitability Shock

This table reports panel regressions designed to extract the idiosyncratic profitability shock by purging common macroeconomic influences and observable bank characteristics. Each column presents a fixed-effects specification of the form:

$$\text{Profitability}_{i,t} = \alpha_i + \boldsymbol{\beta}'\mathbf{X}_t + \boldsymbol{\gamma}'\mathbf{Z}_{i,t} + \varepsilon_{i,t},$$

where α_i denotes bank fixed effects, $\mathbf{X}_t$ includes macroeconomic controls (Inflation, Policy Rate, M3 Growth, and ΔFX), and $\mathbf{Z}_{i,t}$ represents bank-specific observables. This builds on Demirgüç-Kunt and Huizinga (1999) where bank characteristics and macroeconomic conditions are the main drivers of bank profitability. The specifications progressively add bank-level controls. We employ eight different specifications **(columns (1)-(8))** by systematically including various combinations of key bank-specific observables, Lending Growth$_{i,t}$, T5DC$_{i,t}$, and LDS$_{i,t}$, to assess the stability of the common factors and the orthogonality of the resulting residuals. The idiosyncratic residuals $\varepsilon_{i,t}$ are used to build our granular profitability shocks $\Gamma_t^{P-spec(k)}$, where k refers to the specific model (1)-(8) (see Table 6).

Dependent Variable:	Profitability$_{i,t}$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Inflation$_t$	2.234**	2.238**	2.127**	2.241**	2.134**	2.246**	2.137**	2.145**
	(0.8894)	(0.8895)	(0.9714)	(0.8712)	(0.9708)	(0.8717)	(0.9531)	(0.9526)
Policy Rate$_t$	1.771**	1.771**	1.480**	1.777**	1.479**	1.777**	1.497**	1.496**
	(0.6724)	(0.6728)	(0.5541)	(0.6547)	(0.5546)	(0.6550)	(0.5549)	(0.5554)
M3 Growth$_t$	0.1727	0.1726	0.1890	0.1703	0.1889	0.1702	0.1864	0.1863
	(0.2064)	(0.2068)	(0.1980)	(0.2045)	(0.1985)	(0.2049)	(0.1964)	(0.1970)
ΔFX_t	0.0023	0.0022	0.0014	0.0022	0.0014	0.0022	0.0014	0.0014
	(0.0027)	(0.0027)	(0.0024)	(0.0027)	(0.0024)	(0.0027)	(0.0025)	(0.0025)
T5BC$_{i,t}$	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Liquidity$_{i,t}$	0.0900	0.0900	-0.0126	0.0865	-0.0127	0.0865	-0.0109	-0.0110
	(0.1415)	(0.1416)	(0.0910)	(0.1373)	(0.0911)	(0.1374)	(0.0943)	(0.0944)
Lending Growth$_{i,t}$		-0.0003			-0.0005	-0.0004		-0.0005
		(0.0003)			(0.0004)	(0.0003)		(0.0004)
T5DC$_{i,t}$			0.2579		0.2582		0.2469	0.2472
			(0.1514)		(0.1516)		(0.1445)	(0.1446)
LDS$_{i,t}$				-0.7754		-0.7768	-0.5901	-0.5918
				(0.7355)		(0.7377)	(0.5488)	(0.5510)
Fixed-effects								
bankID	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	720	720	720	720	720	720	720	720
R^2	0.44322	0.44323	0.46255	0.44754	0.46260	0.44757	0.46502	0.46508
Within R^2	0.10211	0.10213	0.13328	0.10907	0.13336	0.10912	0.13726	0.13736

*Clustered (bankID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*
Note: *The variables T5BC$_{i,t}$, T5DC$_{i,t}$, and LDS$_{i,t}$ correspond to Top 5 Borrower Concentration$_{i,t}$, Top 5 Depositor Concentration$_{i,t}$, and Lending-Deposit Spread$_{i,t}$, respectively.*

and ΔFX_t are small and not statistically different from zero.

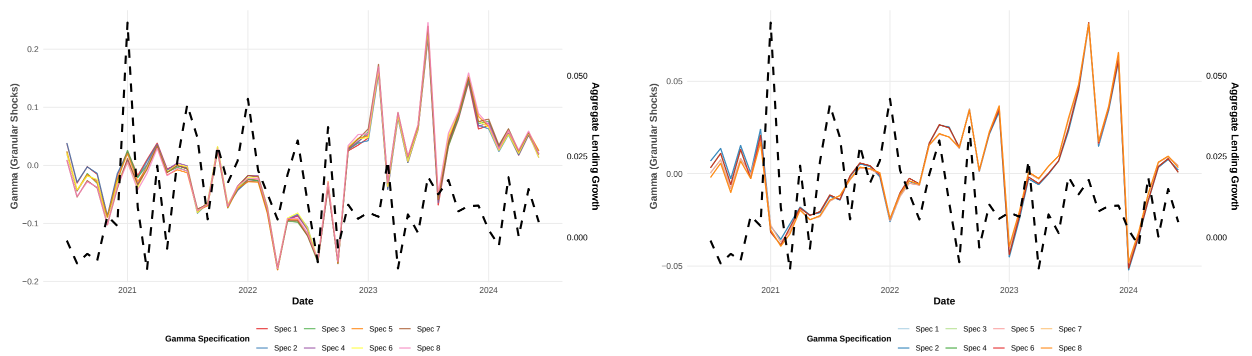
At the bank level, coefficients are generally imprecise. Liquidity shows mixed signs across columns and is not significant. The coefficient on Lending $\text{Growth}_{i,t}$ is small in absolute value (around $|3\text{–}5| \times 10^{-4}$) and statistically indistinguishable from zero, indicating that month-to-month lending expansions do not systematically translate into contemporaneous profitability at this frequency. Concentration measures have limited explanatory content: $\text{T5BC}_{i,t}$ is near zero and negative, while $\text{T5DC}_{i,t}$ is positive (about 0.25) but imprecisely estimated; economically, even a +10 pp change in depositor concentration would imply roughly +2.5 pp profitability on the point estimate, but the uncertainty bands are wide. The lending–deposit spread enters with a negative sign where included, though not significantly so; this may reflect that higher spreads coincide with periods of elevated funding or credit costs that compress net income contemporaneously.

The profitability shock-extraction regressions exhibit moderate overall fit ($\text{R}^2 \approx 0.44\text{–}0.47$), largely because bank fixed effects capture persistent cross-bank differences in profitability levels. The within-bank R^2 is materially higher than in lending-growth models but remains modest (about 0.10–0.14), indicating that macro conditions and observed bank characteristics explain only a limited share of month-to-month profitability movements within a given bank. This is appropriate for our design: we require residual variation after conditioning on observables so that $\hat{\varepsilon}_{i,t}$ isolates idiosyncratic profitability innovations. The granular profitability shock is then formed as a size-weighted aggregation of these innovations, $\Gamma_t = \sum_i s_{i,t-1}\,\hat{\varepsilon}_{i,t}$, so its aggregate relevance follows from (i) the non-trivial variance in $\hat{\varepsilon}_{i,t}$ and (ii) the dispersion in bank sizes that gives the weighted sum bite.

We report standard checks in table 9 of appendix 6. Breusch–Pagan statistics do not reject homoskedasticity (p-values 0.32–0.69), and residual–fitted correlations are essentially zero, supporting the orthogonality conditions in Section 3.3. Model F-statistics are high (about 30–35), confirming that the included regressors have explanatory power for profitability at the monthly frequency. Importantly, our empirical objective is the residual series itself *i.e.* these diagnostics indicate that the residuals are well behaved, uncorrelated with observables and sufficiently variable, so that the resulting $\Gamma_t^{\text{P-spec(k)}}$ is appropriate for the granular propagation step.

The profitability shock-extraction regressions yields stable macro sensitivities and leaves ample residual variation to construct granular profitability shocks. In the next step, we examine whether $\Gamma_t^{\text{P-spec(k)}}$ provides incremental explanatory power for aggregate credit growth beyond macro controls. Anticipating our main hypothesis, we expect any such contribution to be limited relative to granular lending shocks, consistent with profitability gains not being systematically channeled into greater intermediation.

Figure 3: Granular Bank Shocks VS Aggregate Credit Growth



(a) Granular Lending shocks $\Gamma_t^{\text{Lending}}$

(b) Granular Profitability shocks Γ_t^{Profit}

Note: The figure plots the aggregate series of granular bank shocks for lending (left panel) and profitability (right panel) against aggregate credit growth. Granular shocks are computed as size-weighted sums of bank-level idiosyncratic residuals obtained from shock-extraction regressions controlling for macroeconomic and bank-specific factors. first-stage regressions controlling for macroeconomic and bank-specific factors. The dashed black line on both figures refers to aggregate credit growth.

The left panel 3a shows a tight qualitative alignment between granular lending shocks (colored lines) and aggregate credit growth (dashed black line). Major upswings and downswings in $\Gamma_t^{\text{Lending}}$ are mirrored by turning points in aggregate lending growth, and the eight series lie almost on top of each other, indicating that the construction is robust to alternative first-stage controls. Note that the vertical scale is wider than in the profitability panel *i.e.* lending shocks display larger amplitudes and are persistently positive during expansionary phases. This pattern is consistent with a granular transmission mechanism in a concentrated system; when a few large banks experience positive, size-weighted lending innovations (net of macro and bank observables), system credit expands; when they face negative innovations, aggregate credit slows. Given the documented right-skew in bank size and meaningful depositor/borrower concentration, shocks at a small set of institutions naturally propagate to the aggregate.

By contrast, the right panel 3b shows Γ_t^{Profit} fluctuating in a narrow band around zero with much smaller amplitudes and only weak co-movement with aggregate credit growth. Even episodes of stronger profitability shocks coincide with modest or short-lived movements in aggregate lending. The economic interpretation is that profitability improvements—after conditioning on macro factors and bank characteristics—are not systematically recycled into additional intermediation at the monthly horizon. In a market with concentrated funding bases and sizable pricing spreads, profits can reflect margins and valuation effects that bolster buffers without easing credit constraints or lowering the cost of credit. Together, the two panels support our main hypothesis: granular lending shocks matter for aggregate intermediation, whereas granular profitability shocks contribute little, consistent with high earnings not being consistently channeled into greater credit provision.

Table 5 presents the aggregate-level regressions where the dependent variable is Aggregate Credit Growth. Column (Baseline) shows that macro controls alone have limited explanatory power for monthly aggregate credit growth ($R^2 = 0.110$, adjusted $R^2 = 0.028$). Coefficients on Inflation and the Policy Rate are small and imprecise, indicating that common conditions, by themselves, do not account for the pronounced swings in aggregate lending. This sets the stage for testing whether size-weighted idiosyncratic lending shocks can explain the missing variation.

Introducing the granular lending shock Γ_t^L (columns (1)–(8)) yields large, positive, and tightly estimated coefficients, $\hat{\beta}_\Gamma \in [0.63, 0.92]$ with $p < 0.01$. The mapping is economically close to proportional: a +0.01 (1 pp) rise in Γ_t^L is associated with a +0.65–0.92 pp increase in aggregate credit growth in the same month, and a moderate +0.05 shock corresponds to roughly +3.2–4.6 pp. The stability of $\hat{\beta}_\Gamma$ across all eight constructions indicates that this result is not an artifact of the specific first–stage control set used to purge observables.

After adding Γ_t^L, the macro coefficients settle into economically standard signs. *Inflation* turns strongly positive (about 9–14), consistent with nominal expansion and credit demand effects that raise measured credit growth; the *Policy Rate* becomes significantly negative (−1.0 to −1.3 per 100 bp), in line with tighter policy curbing loan supply and demand; *M3 Growth* loads negatively, a puzzling result that may reflect reverse causality (credit slowdowns prompting liquidity expansion), composition effects in broad money, or timing mismatches between supervisory credit and monetary aggregates; and ΔFX is negative, consistent with exchange–rate depreciation tightening balance–sheet constraints and risk management, thereby dampening new lending. In short, once

Table 5: Aggregate Credit Growth and Lending-based Granular Shocks

This table reports aggregate-level regressions of credit growth on lending-based granular shocks. The *baseline* specification includes only macro controls. Columns (1)–(8) add granular shocks $\Gamma_t^{L-\mathrm{spec}(k)}$ constructed from the bank-level shock-extraction regressions for lending growth with progressively richer control sets (see Table 3). Each granular shock is computed as:

$$\Gamma_t^{L-\mathrm{spec}(k)} = \sum_i s_{i,t-1}\,\hat{\varepsilon}_{i,t}^{k},$$

where $s_{i,t-1}$ is bank i's lagged share of total lending and $\hat{\varepsilon}_{i,t}^{k}$ is the residual from bank-level specification k. The aggregate-level equation is:

$$G_t = \alpha + \beta\,\Gamma_t^{L-\mathrm{spec}(k)} + \boldsymbol{\gamma}'\mathbf{X}_t + u_t,$$

where G_t denotes aggregate credit growth, $\mathbf{X}_t$ includes inflation, policy rate, M3 growth, and FX rate changes, and u_t is the error term.

	Dependent variable:								
	Aggregate Credit Growth$_t$								
Specification	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma_t^{L-spec1}$		0.923***							
		(0.021)							
$\Gamma_t^{L-spec2}$			0.891***						
			(0.031)						
$\Gamma_t^{L-spec3}$				0.768***					
				(0.032)					
$\Gamma_t^{L-spec4}$					0.745***				
					(0.041)				
$\Gamma_t^{L-spec5}$						0.748***			
						(0.032)			
$\Gamma_t^{L-spec6}$							0.715***		
							(0.044)		
$\Gamma_t^{L-spec7}$								0.657***	
								(0.041)	
$\Gamma_t^{L-spec8}$									0.634***
									(0.040)
Inflation$_t$	0.120	13.824***	13.201***	11.396***	10.923***	10.874***	10.312***	9.567***	9.010***
	(0.512)	(0.326)	(0.464)	(0.496)	(0.619)	(0.480)	(0.655)	(0.615)	(0.595)
Policy Rate$_t$	−0.241	−1.022***	−1.052***	−1.192***	−1.083***	−1.279***	−1.118***	−1.194***	−1.274***
	(0.161)	(0.030)	(0.045)	(0.059)	(0.072)	(0.062)	(0.081)	(0.084)	(0.090)
M3 Growth$_t$	−0.172	−0.277***	−0.299***	−0.249***	−0.235***	−0.286***	−0.261***	−0.222***	−0.257***
	(0.109)	(0.017)	(0.024)	(0.029)	(0.037)	(0.030)	(0.041)	(0.041)	(0.042)
ΔFX_t	0.0002	−0.054***	−0.052***	−0.045***	−0.044***	−0.044***	−0.042***	−0.039***	−0.037***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Constant	0.028**	0.026***	0.031***	0.046***	0.041***	0.054***	0.046***	0.053***	0.061***
	(0.012)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
With Granular Bank Lending Shocks (Γ_t^L)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48	48	48	48	48	48	48	48	48
R^2	0.110	0.981	0.958	0.938	0.900	0.937	0.878	0.877	0.872
Adjusted R^2	0.028	0.978	0.953	0.930	0.888	0.929	0.864	0.862	0.857

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

bank–specific shocks are accounted for, the "true" macro pass–through emerges cleanly.

Aggregate credit is the sum of banks' outcomes, so omitted bank–level innovations can be spuriously absorbed by macro regressors in a purely aggregate model. The granular term Γ_t^L explicitly captures these size–weighted idiosyncratic movements, removing the confounding micro component from the error term. This separation of micro shocks from common conditions both sharpens the macro coefficients (signs and magnitudes align with standard transmission) and explains the large improvement in fit *i.e.* high–frequency swings in aggregate credit are primarily driven by shocks at a few large lenders, while macro variables set the background against which these granular movements play out.

Model fit improves dramatically once Γ_t^L is introduced. R^2 rises to 0.88–0.98 (adjusted R^2 to 0.86–0.98). The jump from the baseline $R^2 = 0.11$ (adjusted $R^2 = 0.028$) implies that the granular lending term accounts for the bulk of the month-to-month variation in aggregate credit; even under conservative accounting, granular lending shocks account for roughly 70 percent of the explained variation in monthly aggregate credit growth. The stability of $\hat{\beta}_\Gamma$ across all eight constructions indicates that this result is not sensitive to which set of bank observables was partialled out in the bank-level shock-extraction regressions.

The near one-for-one mapping from Γ_t^L to aggregate credit growth is consistent with a granular propagation mechanism in a concentrated banking system. Positive Γ_t^L episodes reflect size-weighted lending innovations at a handful of large institutions, e.g. lumpy project disbursements or shifts in internal risk limits, that move system credit on impact. Negative shocks capture synchronized pullbacks (large-depositor withdrawals, borrower-specific stress, or prudential tightening) that curtail new lending. In short, when the biggest lenders move, the aggregate moves with them. This narrative aligns with our main hypothesis. Bank-level lending shocks, once aggregated by size, are the dominant drivers of short-run intermediation dynamics, whereas macro conditions set the background against which these granular movements play out. Part of the strong fit is mechanical. Under a Hulten-style aggregation, aggregate credit growth is approximately the size-weighted sum of bank-level lending growth. Our contribution is to show that after purging macro and bank observables, the remaining idiosyncratic component at a few large banks, summarized by Γ_t^L, tracks aggregate fluctuations nearly one-for-one, whereas granular profitability shocks do not, as discussed below.

Table 6: Aggregate Credit Growth and Profitability-based Granular Shocks

This table reports aggregate-level regressions of credit growth on profitability-based granular shocks. The *baseline* specification includes only macro controls. Columns (1)–(8) add granular shocks $\Gamma_t^{P-\mathrm{spec}(k)}$ constructed from the bank-level shock-extraction regressions for profitability with progressively richer control sets (see Table 4). Each granular shock is computed as

$$\Gamma_t^{P-\mathrm{spec}(k)} = \sum_i s_{i,t-1}\,\hat{\varepsilon}_{i,t}^k,$$

where $s_{i,t-1}$ is bank i's lagged share of total lending and $\hat{\varepsilon}_{i,t}^k$ is the residual from bank-level profitability specification k. The aggregate-level equation is:

$$G_t = \alpha + \beta\,\Gamma_t^{P-\mathrm{spec}(k)} + \boldsymbol{\gamma}'\mathbf{X}_t + u_t,$$

where G_t denotes aggregate credit growth, $\mathbf{X}_t$ includes inflation, policy rate, M3 growth, and FX rate changes, and u_t is the error term.

	Dependent variable:								
	Aggregate Credit Growth$_t$								
Specification	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma_t^{P-spec1}$		0.031							
		(0.088)							
$\Gamma_t^{P-spec2}$			0.031						
			(0.088)						
$\Gamma_t^{P-spec3}$				0.058					
				(0.091)					
$\Gamma_t^{P-spec4}$					0.040				
					(0.089)				
$\Gamma_t^{P-spec5}$						0.058			
						(0.091)			
$\Gamma_t^{P-spec6}$							0.041		
							(0.089)		
$\Gamma_t^{P-spec7}$								0.064	
								(0.091)	
$\Gamma_t^{P-spec8}$									0.064
									(0.091)
Inflation$_t$	0.120	0.072	0.072	0.027	0.055	0.027	0.055	0.014	0.014
	(0.512)	(0.535)	(0.535)	(0.536)	(0.536)	(0.536)	(0.536)	(0.537)	(0.537)
Policy Rate$_t$	−0.241	−0.261	−0.261	−0.287	−0.269	−0.288	−0.269	−0.295	−0.295
	(0.161)	(0.172)	(0.172)	(0.178)	(0.173)	(0.178)	(0.173)	(0.179)	(0.179)
M3 Growth$_t$	−0.172	−0.181	−0.181	−0.188	−0.183	−0.188	−0.183	−0.189	−0.189
	(0.109)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)	(0.113)
ΔFX_t	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.028**	0.029**	0.029**	0.031**	0.030**	0.031**	0.030**	0.032**	0.032**
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
With Granular Bank Profitability Shocks (Γ_t^P)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48	48	48	48	48	48	48	48	48
R^2	0.110	0.113	0.113	0.119	0.115	0.119	0.115	0.121	0.121
Adjusted R^2	0.028	0.007	0.007	0.014	0.009	0.014	0.009	0.016	0.016

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

As a robustness check on the granularity mechanism, Appendix 6 replaces the size–weighted granular term Γ_t^L with simple cross–bank averages of residual lending innovations, γ_t^L, which give each bank equal weight. This serves as a placebo test to ensure that our results are due to the granularity of the banking sector. Figure 4 shows that these unweighted shocks fluctuate in a narrow band around zero and exhibit only weak co-movement with aggregate credit growth, in sharp contrast to the tight alignment observed for Γ_t^L in Figure 3a. Consistently, Table 7 reports that including γ_t^L in the aggregate regressions leaves the R^2 essentially unchanged relative to the macro-only baseline and yields coefficients that are small and statistically insignificant. Therefore, the explanatory power uncovered in Table 5 does not come from undifferentiated residual noise but from the interaction between non-trivial idiosyncratic lending shocks and the skewed bank-size distribution *i.e.* the core granularity assumption in Mauritania's banking system.

Table 6 presents the second stage regressions with profitability-based Granular shocks. The first column is the same as in lending-based shocks -*(Baseline)*- and shows that macro controls alone explain little of the month–to–month variation in aggregate credit growth ($R^2 = 0.110$, adjusted $R^2 = 0.028$). This serves as a benchmark to assess whether profitability–based granular shocks—size–weighted residual innovations in bank profitability—carry explanatory power for system credit dynamics.

Adding Γ_t^P (columns (1)–(8)) yields small and statistically insignificant coefficients throughout: $\hat{\beta}_{\Gamma^P} \in [0.031, 0.064]$ with standard errors $\approx$ 0.088–0.091. The implied magnitudes are modest; for instance, a +0.05 increase in Γ_t^P corresponds to only +0.16–0.32 percentage points in aggregate credit growth. Model fit barely changes, R^2 moves from 0.110 to 0.113–0.121 (adjusted R^2 to 0.007–0.016), indicating that profitability shocks add negligible explanatory power relative to the baseline. This contrasts sharply with the lending–based granular shocks and is consistent with the idea that bank earnings are not systematically recycled into additional intermediation at the monthly horizon.

Once Γ_t^P is included, macro coefficients remain small and imprecise. *Inflation* hovers around 0.01–0.07, *Policy Rate* around −0.26 to −0.30, *M3 Growth* is mildly negative, and ΔFX is near zero. The lack of change relative to the baseline underscores that profitability innovations do not obscure macro pass–through; rather, they carry little incremental information for aggregate credit.

A plausible mechanism in Mauritania's context is that profitability spikes primarily reflect margin income, fees, or valuation effects that bolster buffers (liquidity, provisioning, capital compliance) or are absorbed by balance–sheet risks linked to concentrated deposit and borrower bases. With limited competitive pressure and meaningful credit risk, banks may not expand lending on impact when profits rise; internal risk limits, pipeline and committee lags, and funding concentration can all delay or mute the translation of earnings into new credit. These results align with our main hypothesis. In a low–income setting with high earnings–to–intermediation (EADG), granular *lending* shocks, not profitability shocks, drive short–run fluctuations in aggregate credit.

Taken together, the lending- and profitability-based granular results show that the granular framework helps uncover the *true* macro pass-through in a low competitive banking system. In a purely aggregate regression, omitted bank-level innovations are mechanically loaded onto macro regressors, muting or distorting their coefficients. By explicitly controlling for size-weighted idiosyncratic lending shocks, Γ_t^L, we separate micro and macro forces. High-frequency swings in aggregate credit are overwhelmingly accounted for by granular lending shocks, while macro variables recover standard signs and magnitudes in the background. In contrast, profitability shocks Γ_t^P neither improve fit nor materially affect macro coefficients, indicating that they carry little information for short-run intermediation once common conditions are controlled for.

The asymmetric role of Γ_t^L and Γ_t^P is consistent with differences in transmission channels. Idiosyncratic lending shocks directly capture shifts in the volume and timing of large credit decisions at the dominant banks, such as lumpy project disbursements, changes in internal risk limits, or borrower-specific events, that immediately alter the flow of new credit in a system with limited borrower and funding diversification. In a granular, weakly competitive market, other banks are unlikely to fully offset these swings on impact, so shocks at a few large institutions propagate almost one-for-one to the aggregate. By contrast, profitability shocks reflect a broader mix of margin income, fee-based revenues, and valuation effects that strengthen balance sheets but do not necessarily relax risk constraints or expand the pipeline of bankable projects within the monthly horizon.

The Mauritanian context amplifies these mechanisms and suggests clear economic implications. With concentrated funding bases, high lending–deposit spreads, and meaningful credit and FX risks, additional profits are more likely to be retained as buffers (liquidity, provisioning, capital compliance) or to offset legacy risks than to be recycled immediately into new lending. Policies that mechanically raise bank profitability, for exemple through wider margins or one-off valuation gains, need not translate into stronger intermediation. By contrast, shocks to lending at the largest banks have disproportionate effects on aggregate credit, highlighting the importance of monitoring their credit policies, concentration risks, and governance. From a policy perspective, improving the resilience and competitive environment of the largest lenders, deepening alternative funding and borrower bases, and aligning prudential tools with concentration risks may be more effective in stabilising and supporting intermediation than interventions focused solely on profitability.

6 Conclusion[5]

This paper has examined the granular dynamics of the Mauritanian banking sector by asking how idiosyncratic shocks at individual banks transmit to aggregate credit in a highly concentrated, high-margin, low-income system. Using confidential monthly bank-level data, we extracted residual innovations in lending growth and profitability after controlling for macroeconomic conditions, observable balance-sheet characteristics, and bank fixed effects, and aggregated them with lagged lending shares to construct granular lending and profitability shocks.

Our main results are stark. Lending-based granular shocks are large and display an almost one-for-one contemporaneous mapping into aggregate credit growth, explaining almost 80 percent of short-run fluctuation of financial intermediation. Placebo specifications that replace size-weighted shocks with simple cross-bank averages of residuals deliver negligible fit and insignificant coefficients, underscoring that it is the interaction between idiosyncratic lending shocks and the skewed bank-size distribution that moves the aggregate. By contrast, profitability-based granular shocks are small, statistically insignificant, and add virtually no explanatory power for aggregate credit. Taken together, the evidence points to a sharp asymmetry: in Mauritania's high-EADG system, short-run movements in financial intermediation are driven by granular lending shocks at a few dominant institutions, while high profits are largely retained as buffers rather than systematically recycled into new lending.

[5] The policy discussions in this section are consistent with the December 2024 IMF Article IV Consultation and February 2026 IMF Staff Report.

From a policy perspective, the findings point to the importance of adopting a comprehensive approach to financial stability that accounts for both the microprudential soundness of individual institutions and the macro-financial externalities arising from concentration and interconnectedness. Consistent with the theoretical literature on financial amplification and systemic risk Bernanke et al.(1999); Brunnermeier and Sannikov (2014); Haldane and May (2011), our results suggest that shocks to the lending behavior of large, interconnected banks can propagate non-linearly through balance-sheet and confidence channels, amplifying the macroeconomic impact of localized disturbances even when aggregate profitability remains strong.

Accordingly, while enhanced supervisory attention to systemically important institutions remains warranted—given their outsized role in transmitting idiosyncratic lending shocks—policy efforts should also address the structural drivers of concentration and systemic vulnerability. In this regard, the introduction or strengthening of macroprudential instruments may be particularly effective in curbing excessive risk concentration and mitigating spillovers. Measures such as caps on large exposures to single borrowers or sectors Basel Committee on Banking Supervision (2014), together with supplementary capital surcharges for global or domestic systemically important institutions Financial Stability Board (2011), can help internalize the externalities associated with scale and interconnectedness. Complementary supervisory practices—regular stress testing, targeted asset-quality reviews, and enhanced forward-looking risk assessments—would further strengthen the prudential framework by enabling the early identification and correction of emerging vulnerabilities. Collectively, these measures could attenuate the amplification of granular credit shocks identified in our empirical results and improve the transmission of monetary policy through a more resilient and diversified banking system.

At the same time, fostering greater competition and diversity within the financial sector could address the underlying structural imbalances that sustain concentration and hinder financial inclusion. Policy initiatives aimed at enhancing access to digital financial services Beck et al. (2010), improving credit information infrastructure—such as through more comprehensive and integrated credit bureaus—and expanding SME refinancing and guarantee schemes may bolster the competitiveness of smaller and mid-sized institutions. By broadening the credit base and improving allocative efficiency, such measures would not only complement macroprudential regulation but also promote a more stable and inclusive financial architecture capable of absorbing shocks without impairing the flow of credit to the real economy. While introduced with the objective of enhanc-ing credit to the private sector, administrative measures to control lending rates, including the imposition of interest rate caps (Taux Effective Global – TEG), distort market-based adjustment mechanisms and undermine credit market efficiency.

The evidence presented contributes to the growing literature on bank granularity and on the profitability–intermediation nexus in emerging and low-income economies. By showing that granular lending shocks, but not granular profitability shocks, drive short-run fluctuations in aggregate credit in a high-EADG system, the paper links macro-diagnostics of banking sector performance with micro-founded granular mechanisms. While our findings are specific to Mauritania, they carry broader implications for other developing economies facing similar structural challenges, emphasiz-ing the importance of designing policies that both contain granular credit risks at dominant banks and foster a more balanced, competitive, and resilient banking sector to support sustainable and inclusive growth.[5]

While a focus on Islamic finance instruments would have added depth to the analysis, inconsistencies in the disaggregation of loan data between Islamic and conventional products do not allow for a meaningful decomposition. This constraint reinforces the importance of strengthening data collection frameworks to ensure high-quality, granular information on loans and other financial assets by financing modality.

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Appendices

A1. Additional Results

Figure 4: Unweighted Bank Idiosyncratic Lending Shocks $\gamma_t^{Lending}$ VS Aggregate Credit Growth

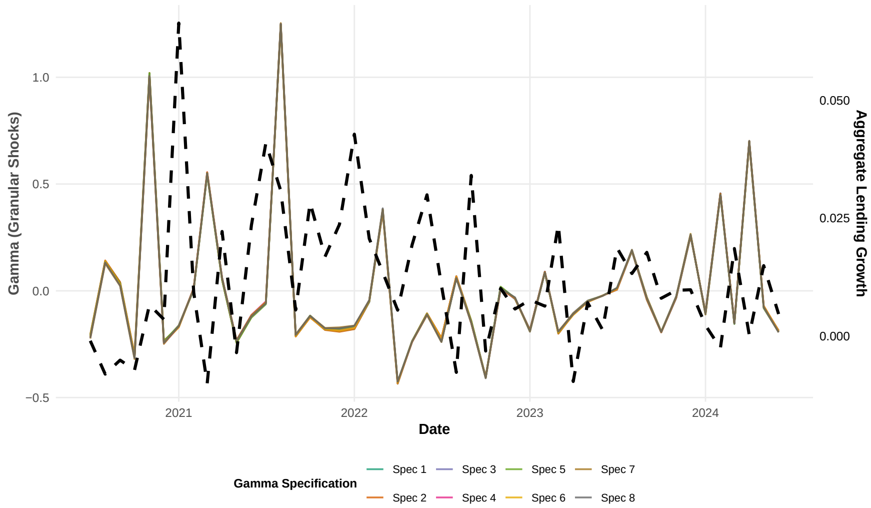


Figure 4 and Table 7 present a complementary placebo exercise using *unweighted* bank idiosyncratic lending shocks. Visually, the coloured lines in Figure 4, the simple cross-bank averages of residual lending innovations from the eight first-stage specifications, fluctuate in a narrow band around zero and display only weak co-movement with aggregate credit growth (black dashed line). Unlike the granular shocks in Figure 3a, the different specifications overlap almost perfectly and rarely line up with turning points in aggregate lending, suggesting that equal-weighted bank shocks have limited aggregate content once common macro conditions are controlled for.

The regression results in Table 7 confirm this visual impression. Across columns (1)–(8), the coefficients on $\gamma_t^{L-\text{spec}(k)}$ are tiny (about -0.003) and statistically indistinguishable from zero, and the inclusion of unweighted shocks barely moves model fit: the R^2 rises only from 0.110 in the macro-only baseline to at most 0.115, while the adjusted R^2 falls slightly because an additional regressor is added without explanatory power. Macro coefficients remain virtually identical to those in the baseline specification, indicating that these unweighted shocks neither help explain aggregate credit nor alter the estimated macro pass-through.

Taken together, these results reinforce the granular interpretation of our main findings. When idiosyncratic lending shocks are averaged across banks with *equal* weights, implicitly adopting a representative-bank view, they wash out and carry no information for aggregate credit dynamics. Only when residual innovations are weighted by bank size, as in our granular shocks Γ_t^L, do they map nearly one-for-one into aggregate credit growth and account for the bulk of its short-run fluctuations. This placebo therefore shows that our main results are not driven by generic residual noise, but by the interaction of non-trivial idiosyncratic shocks with a highly skewed bank-size distribution—the essence of the granularity mechanism in Mauritania's banking system.

Table 7: Aggregate Lending Growth and Unweighted Bank Idiosyncratic Shocks

This table reports aggregate-level regressions of credit growth on *unweighted* bank idiosyncratic lending shocks. Columns (2)–(9) add shocks $\gamma_t^{L-\mathrm{spec}(k)}$ constructed from the bank-level shock-extraction regressions for lending growth with progressively richer control sets (see Table 3). Each unweighted shock is computed as

$$\gamma_t^{L-\mathrm{spec}(k)} = \frac{1}{N}\sum_i \hat{\varepsilon}_{i,t}^k,$$

where N_t is the number of reporting banks in month t and $\hat{\varepsilon}_{i,t}^k$ is the residual from bank-level specification k. The aggregate-level equation is

$$G_t = \alpha + \beta\,\gamma_t^{L-\mathrm{spec}(k)} + \boldsymbol{\gamma}'\mathbf{X}_t + u_t,$$

where G_t denotes aggregate credit growth and $\mathbf{X}_t$ includes inflation, policy rate, M3 growth, and FX rate changes. Unlike the granular shocks $\Gamma_t^{L-\mathrm{spec}(k)}$, which weight residuals by lagged lending shares, these unweighted shocks assign equal weight to all banks and serve as a placebo to assess whether the explanatory power in the main granular regressions is genuinely driven by granularity in the bank-size distribution.

	Dependent variable:								
	Aggregate Credit Growth$_t$								
	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\gamma_t^{L-spec1}$		−0.003							
		(0.007)							
$\gamma_t^{L-spec2}$			−0.003						
			(0.007)						
$\gamma_t^{L-spec3}$				−0.003					
				(0.007)					
$\gamma_t^{L-spec4}$					−0.003				
					(0.007)				
$\gamma_t^{L-spec5}$						−0.003			
						(0.007)			
$\gamma_t^{L-spec6}$							−0.003		
							(0.007)		
$\gamma_t^{L-spec7}$								−0.002	
								(0.007)	
$\gamma_t^{L-spec8}$									−0.003
									(0.007)
Inflation$_t$	0.120	0.120	0.120	0.120	0.120	0.120	0.120	0.120	0.120
	(0.512)	(0.517)	(0.517)	(0.517)	(0.517)	(0.517)	(0.517)	(0.517)	(0.517)
Policy Rate$_t$	−0.241	−0.241	−0.241	−0.241	−0.241	−0.241	−0.241	−0.241	−0.241
	(0.161)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)
M3 Growth$_t$	−0.172	−0.172	−0.172	−0.172	−0.172	−0.172	−0.172	−0.172	−0.172
	(0.109)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
ΔFX_t	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
With Bank Idiosyncratic Lending Shocks (γ_t^L)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48	48	48	48	48	48	48	48	48
R^2	0.110	0.115	0.115	0.115	0.114	0.114	0.114	0.113	0.114
Adjusted R^2	0.028	0.009	0.009	0.009	0.009	0.008	0.009	0.008	0.008

Note: *p<0.1; **p<0.05; ***p<0.01

A2. Statistical Appendix

This appendix reports diagnostic checks for the shock–extraction regressions that underpin our granular lending and profitability shocks. Tables 8 and 9 summarize Breusch–Pagan (BP) statistics for residual variance, correlations between residuals and fitted values, and within–bank F–statistics for each specification. Figures 5 and 6 display residuals versus fitted values for the Lending Growth and Profitability models, respectively. The goal is to verify that the first–stage residuals behave as idiosyncratic innovations that can be meaningfully aggregated into granular shocks, in line with the conditions discussed in Section 3.

Table 8: *Diagnostic Test Results for Lending Growth Models (BP test, Orthogonality, and F-statistic)*

Specification	Statistic	DF	p-value	Correlation	F-statistic
Spec1	8.25	6.00	0.05	0.00	4.83
Spec2	8.30	7.00	0.08	-0.00	4.59
Spec3	9.12	7.00	0.06	-0.00	4.96
Spec4	9.56	7.00	0.05	-0.00	4.59
Spec5	9.12	8.00	0.10	0.00	4.71
Spec6	9.60	8.00	0.09	-0.00	4.38
Spec7	10.31	8.00	0.07	0.00	4.73
Spec8	10.32	9.00	0.11	0.00	4.51

Table 9: *Diagnostic Test Results for Profitability Models (BP test, Orthogonality, and F-statistic)*

Specification	Statistic	DF	p-value	Correlation	F-statistic
Spec1	3.50	6.00	0.32	0.00	34.73
Spec2	4.14	7.00	0.39	-0.00	32.82
Spec3	3.76	7.00	0.44	-0.00	32.92
Spec4	3.61	7.00	0.46	0.00	33.18
Spec5	3.80	8.00	0.58	0.00	31.19
Spec6	4.28	8.00	0.51	0.00	31.45
Spec7	3.83	8.00	0.57	-0.00	31.55
Spec8	3.88	9.00	0.69	-0.00	29.97

The BP statistics in Tables 8–9 do not point to strong, systematic patterns of heteroskedasticity: p–values are comfortably above conventional significance thresholds in almost all specifications. While our granular framework does not require exact homoskedasticity of the residuals, the absence of pronounced scale effects is useful to ensure that a small number of observations with very large variances do not mechanically dominate the size–weighted shocks. In other words, the residual variance appears well–behaved relative to the covariates we condition on.

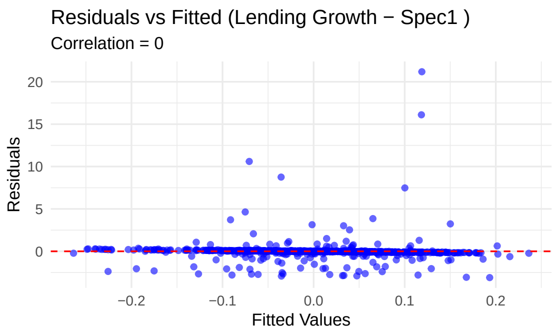
Orthogonality is assessed by examining the correlation between residuals and fitted values. Across all lending and profitability specifications, these correlations are essentially zero (ranging from -0.00 to 0.00 once rounded), indicating that the unexplained component of each model is not systematically related to its linear projection. This is exactly what we require for the residuals to be interpreted as idiosyncratic innovations, conditional on the macro controls and bank characteristics included in the first stage, and for their size–weighted aggregation to satisfy the orthogonality conditions underlying our granular shocks.

The within–bank F–statistics reported in the tables further illustrate the role of observables versus residual variation in the shock–extraction step. For lending growth, F–values around 4–5 indicate that the included regressors have only modest explanatory power in the within–bank dimension, leaving a large share of high–frequency movements in the residuals. This is desirable for our purposes: the first–stage is not meant to forecast lending, but to purge common macro factors and selected bank observables so that the remaining residuals capture bank–specific innovations. For profitability, F–values around 30–35 point to a stronger, but still far from exhaustive, contribution of observables, with ample residual dispersion left to construct granular profitability shocks. These F–statistics should not be interpreted as tests of instrument strength in a 2SLS sense; they are descriptive diagnostics of within–bank fit.

The residual–versus–fitted plots in Figures 5 and 6 visually corroborate these findings. For both lending and profitability, residuals are tightly clustered around zero with no clear trend or curvature relative to fitted values, and no obvious pockets of extreme heteroskedasticity. The absence of discernible structure suggests that the linear specifications capture the systematic variation associated with the included regressors, leaving the residuals to reflect idiosyncratic, bank–specific fluctuations.

Taken together, these diagnostics support three key properties of our first–stage residuals: (i) they are approximately orthogonal to the fitted components, (ii) they retain substantial, well–behaved variation after conditioning on macro and bank–level observables, and (iii) they are not dominated by a few extreme observations. Combined with the strong granularity of the bank size distribution documented in the main text, these features justify the use of size–weighted residuals as granular lending and profitability shocks in the second–stage analysis of aggregate credit dynamics.

Figure 5: Residuals vs Fitted Values for Lending Growth Models (Specs 1–8)



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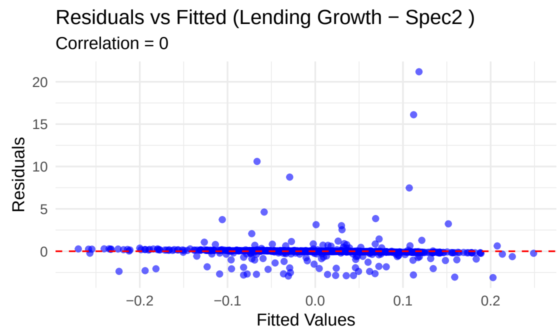
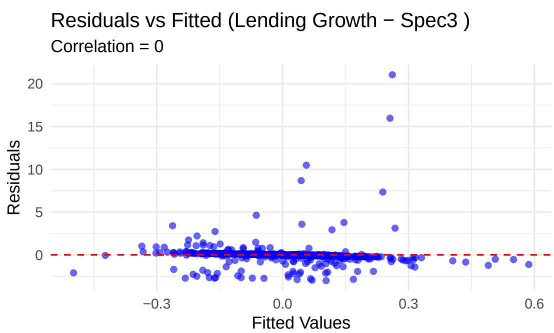
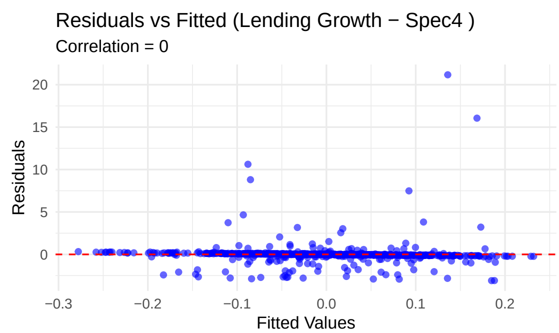


(b) Spec 2



(c) Spec 3



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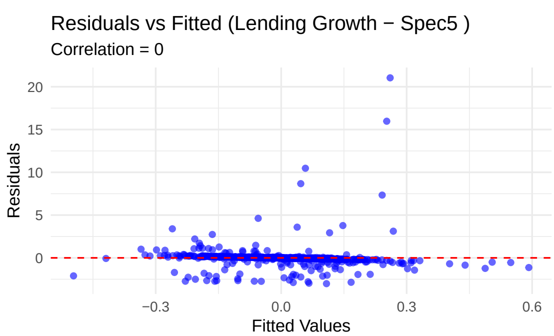

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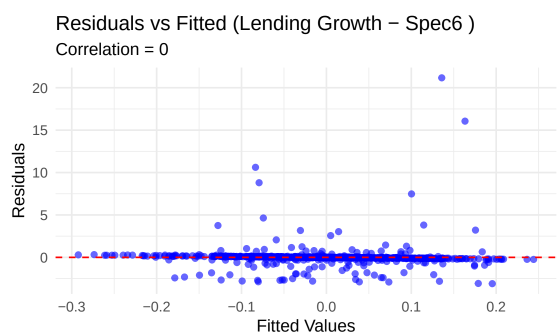
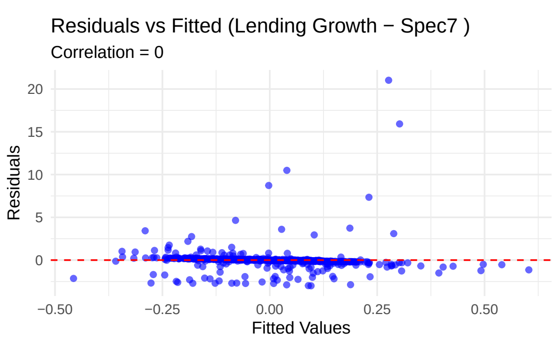
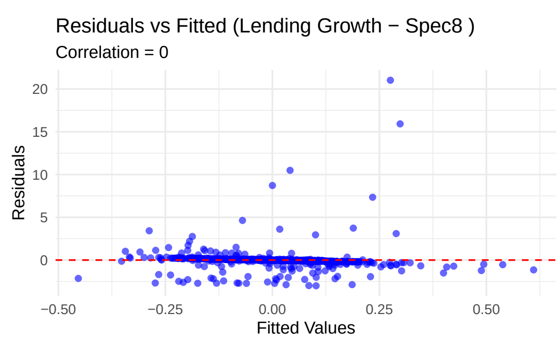


(f) Spec 6

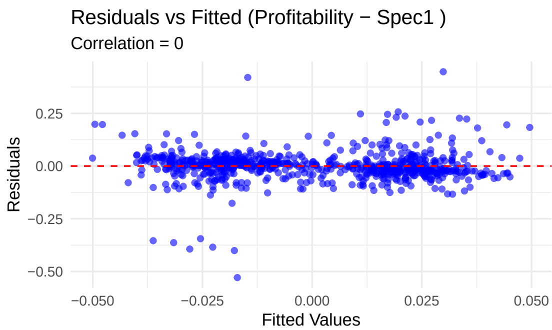


(g) Spec 7



(h) Spec 8

Figure 6: Residuals vs Fitted Values for Profitability Models (Specs 1–8)



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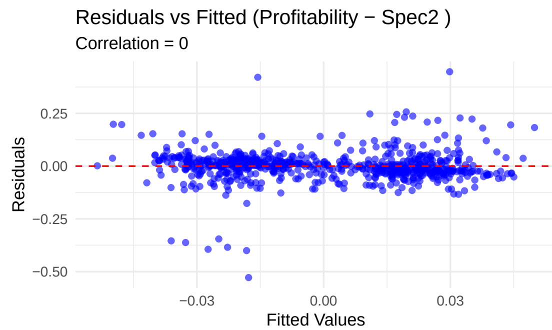
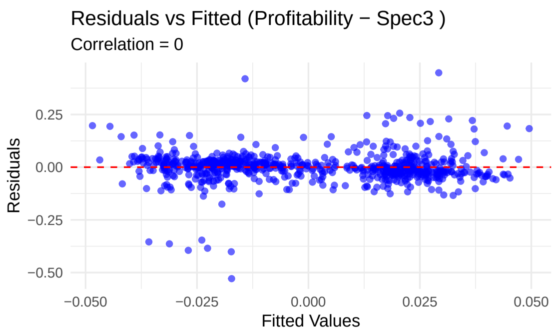


(b) Spec 2



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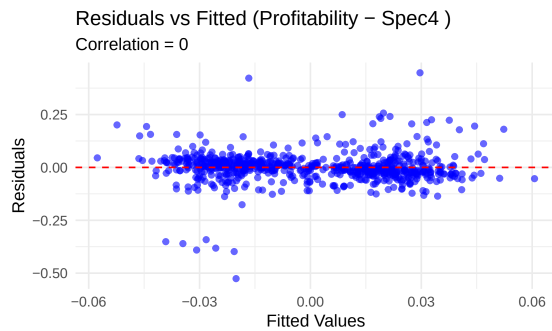

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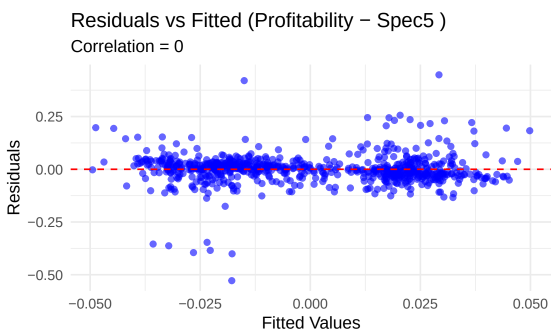

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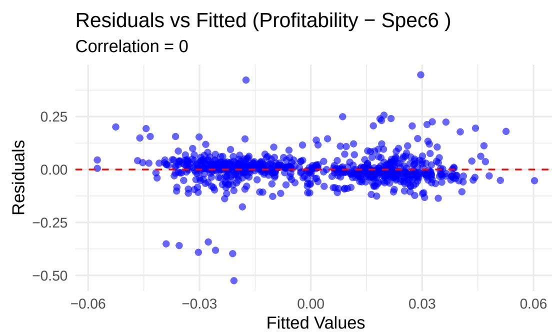

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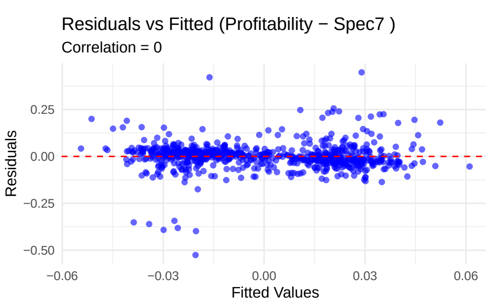
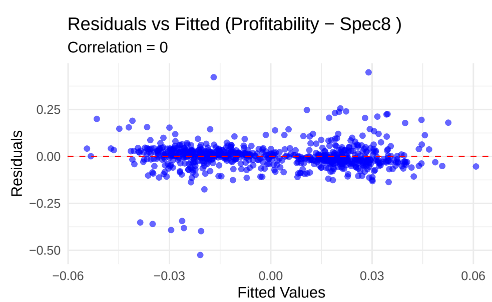


(g) Spec 7



(h) Spec 8

PUBLICATIONS

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