The Effect of Monetary Policy on Systemic Bank Funding Stability*

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Abstract

What is the effect of monetary policy on funding vulnerabilities of banking systems? I construct a novel worldwide macro-financial dataset on the funding structure of banking systems to empirically explore this question. Using an instrumental variable framework, I find that contractionary monetary policy shocks cause an aggregate outflow of retail deposits and an inflow of non-core funding sources. This increasing reliance on market-based funding instruments is associated with a heightened risk of banking panics and crises as well as subsequent contractions in non-core funding, credit, and real activity. I find evidence for a direct chain linking monetary policy, banks' funding structure, and systemic financial stability risk. A model rationalizes the mechanism through which monetary tightening drives retail deposits out of the banking system, prompting banks to increasingly rely on market-based debt, thereby raising funding vulnerabilities.

JEL classification: E44, E52, E58, G01, G21, N10, N20

Keywords: monetary policy, bank funding, banking fragility

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1 Introduction

A broad consensus has emerged that banks' over-reliance on non-core funding was a major factor contributing to the Global Financial Crisis (e.g., IMF, 2013). Yet, despite these lessons learned, a systematic understanding of the relationship between the funding structure of banks and systemic financial stability remains elusive. Moreover, even less is known about the effect of monetary policy on this relationship. This study aims to fill these gaps by investigating two fundamental questions. First, what is the effect of monetary policy on banking systems' dependence on non-core funding? Second, does increased reliance on non-core funding, induced by monetary tightening, lead to a buildup of systemic risk?[1]

Empirically exploring these questions is challenging. The rarity of financial disasters necessitates data on banks' funding structures across a wide range of countries and time periods to systemically examine the determinants of systemic funding vulnerabilities with sufficient statistical power. Such data does not exist. Furthermore, identifying exogenous variations in monetary policy in a historical, global context—where narrative-based or high-frequency identification approaches reach their limits—is complex. I overcome these challenges by (i) constructing a novel dataset that covers the liability structure of banking systems and central bank policy rates for both developed and developing economies at monthly frequency over seven decades and (ii) analyzing the precise timing of central bank actions in floating economies and central bank reactions in pegged economies to identify monetary policy shocks.

I provide evidence of a direct relationship that begins with monetary tightening, operates through the funding structure of banking systems, and culminates in heightened risk of systemic financial instability. This relationship unfolds in two stages. First, monetary tightening leads to a net outflow of retail deposits and a simultaneous inflow of non-core funding, resulting in greater reliance on market-based debt within the banking system. Second, these shifts in bank funding patterns predate and predict systemic banking panics and crises. I further validate these findings at a more granular level using bank-level data from two distinct periods in U.S. financial history.

I build on the model of Drechsler et al. (2017) to rationalize these findings. The economy is populated by a 'sleepy' retail depositor (Hanson et al., 2015), who does not respond to solvency risk, and an uninsured, risk-sensitive non-core investor who provides funds on market-based terms.[2] When interest rates rise, the return on the depositor's initial wealth

[1] Throughout this study, non-core funding refers to *all funding sources other than equity, traditional customer deposits, and those provided by the government or central bank*. After introducing the data, I transform this negative definition of non-core funding into a positive one.

[2] Empirical studies support the existence of heterogeneity in the ability to acquire and process information between retail depositors and other bank lenders (e.g., Davenport and McDill, 2006; Choi and Velasquez, 2016;

increases, raising her demand for liquid deposits for transactional or storage purposes. The preference for liquidity enables the bank to extract part of the additional depositor wealth by raising deposit rates less than one-for-one with policy rates.[3] The bank gains from this widened deposit spread, which offsets mark-to-market losses on long-term assets and thereby serves as a hedge against interest rate risk (Drechsler et al., 2021).

However, rising policy rates also reshape the bank's funding structure. As monetary policy tightens, deposit growth lags behind wealth accumulation due to the rigidity of deposit rates, prompting the bank to increasingly rely on non-core funding sources to finance lending. This behavior is profit-maximizing in the absence of runs. However, the shift toward market-based debt weakens the bank's retail deposit base and, consequently, its hedge against interest rate risk. The resulting book losses create conditions for an insolvency-inducing run, where non-core lenders withdraw their funds upon realizing that a run would render the bank insolvent. I show that such a *wholesale run* emerges as an additional equilibrium when the share of non-core investors becomes sufficiently large and the monetary tightening sufficiently strong.

The first empirical contribution of this study lies in investigating the effect of monetary policy on the liability structure of banking systems. I establish variations in the stance of monetary policy as a statistically significant and economically relevant determinant of banks' reliance on non-core funding. Specifically, following a contractionary monetary policy shock, the ratio between aggregate non-core funding and retail deposits rises, and vice versa for expansionary shocks. This effect is driven by both a net outflow of retail deposits and a net inflow of non-core funding. My baseline specification suggests that if a central bank unexpectedly raises its policy rate by 10 basis points (bps) within a month, the non-core ratio will grow by 1.5% over the following twelve months. This response occurs because non-core funding increases by 0.8%, while funding through retail deposits shrinks by the same magnitude over this period. The identified negative response of aggregate retail deposits contributes to an open debate on aggregate deposit flow sensitivities to policy rate changes (Drechsler et al., 2017; Begenau and Stafford, 2023).

To address endogeneity concerns arising from central banks' systematic response to economic conditions and banks' anticipatory funding adjustments, I employ an instrumental variable approach to estimate these effects. My identification strategy for monetary policy shocks builds on the trilemma of international finance (Obstfeld and Taylor, 2004; Obstfeld et al., 2005), a method pioneered by di Giovanni et al. (2009). This approach has been applied to a historical cross-country setting by Jordà et al. (2020a), Jordà et al. (2020b),

Blickle et al., 2022; Martin et al., 2024).

[3] The empirical literature has long recognized the low interest rate elasticities of retail depositors (e.g., Hannan and Berger, 1991; Amel and Hannan, 1999).

Schularick et al. (2021), Gabriel (2023), Grimm et al. (2023), and Jiménez et al. (2023) using data for advanced economies at annual frequency. Using my novel dataset, I contribute to this literature by refining the so-called *trilemma IV* along three dimensions. First, I proxy the stance of monetary policy with central bank policy rates rather than short-term market rates, which is crucial for emerging and developing economies (De Leo et al., 2022). Second, I safeguard the exclusion restriction by narrowing the time window between actions in base countries and reactions in pegging countries from one year to one month. Third, I regain a strong first stage, despite the conservative identification assumption, through extensive country coverage, even after including time fixed effects that account for common shocks. Ultimately, I identify 29,922 non-zero monetary policy shocks across 145 countries.

Why should researchers and policymakers care about the effect of monetary policy on the funding structure of the banking system? The second key finding of my empirical analysis provides an answer to this question. I uncover a significant shift in the funding structure of banking systems during the months leading up to system-wide financial turmoil. In particular, prior to systemic banking crises and panics, the non-core funding ratio of the banking system rises. Panics and crises can be systematically predicted by rising non-core funding shares and also separately by increasing non-core funding and *decreasing* core funding. In other words, pre-panic and pre-crisis bank funding dynamics mirror those shaped by contractionary monetary policy shocks. These dynamics cannot be explained by surging bank credit, a key predictor of financial crises (Schularick and Taylor, 2012). The pre-crisis rise in banks' non-core funding ratio is as pronounced during credit booms as it is in periods without credit booms. Conversely, during credit booms that do not result in financial disasters, shifts in banks' funding structure are small. Most credit booms do not lead to financial crises (Gourinchas et al., 2001; Dell'Ariccia et al., 2016)—my findings shed light on why some booms bust while others deflate without financial disruptions.

The extensive coverage and relatively high frequency of my dataset also enables me to go beyond binary crisis and panic indicators and construct quantitative measures of (non-systemic) financial market turmoil. I find that a rising non-core reliance of the banking sector increases the volatility of the financial cycle with repercussions for real economic activity. Specifically, a rise in non-core ratios is associated with subsequent outflows of non-core funding, credit crunches, and slowdowns in GDP growth. This result aligns with the finding that sudden stops in non-core funding force banks to cut credit supply (Iyer et al., 2014). Here, too, credit growth—which could explain these dynamics (Mian et al., 2017)—does not serve as an explanation for these associations.

The third and final contribution of my empirical investigation builds on three insights. First, contractionary monetary policy induces an aggregate rise in absolute and relative non-core funding. Second, an absolute and relative increase in non-core funding raises the risk of banking panics and crises. Third, recent studies (Schularick et al., 2021; Acharya et al., 2023; Jiménez et al., 2023) and the evidence presented in this paper demonstrate that monetary tightening poses a short-term threat to financial stability. The synthesis of these findings suggests that monetary policy affects financial stability *directly* through its effect on the funding structure of banking systems. I again use the refined trilemma-based identification of monetary policy shocks and uncover evidence supporting this hypothesis within a unified regression framework. Contractionary monetary policy shocks adversely affect systemic stability of financial markets, but only when they induce a rising non-core funding share within the banking sector.

To verify these macro-level relationships at a more granular level, I analyze bank-level data from two distinct periods in U.S. financial history and document two recurring patterns. First, contractionary monetary policy increases a bank's reliance on non-core funding sources, in line with the results of Drechsler et al. (2017) and Emeksiz (2022). Second, a bank that relies more heavily on non-core funding is more likely to fail, consistent with the findings of Correia et al. (2023). The failure of banks heavily reliant on non-core funding is not necessarily a bad outcome in itself. Such failures may act as a market-disciplining mechanism (Calomiris, 1999), reallocate resources to more efficient banks (Schwartz, 1987), and offer valuable lessons to surviving banks, regulators, and policymakers. However, bank failures come with severe costs when they evolve into system-wide crises (e.g., Cerra and Saxena, 2008; Reinhart and Rogoff, 2009; Jordà et al., 2013; Mian et al., 2014; Funke et al., 2016; Doerr et al., 2022; Jamilov et al., 2024).

Therefore, a critical question remains: do the identified bank-level relationships reflect a disciplining mechanism at the micro level, or does monetary policy affect macro-level financial stability through a shifting funding structure of the banking system? Insights from bank-level data alone are limited in addressing this question. For instance, among the largest U.S. banks holding the majority of deposits, the relationship between monetary policy changes and retail deposit flows disappears, highlighting that "reliable relationships in the cross section of banks may not aggregate" (Begenau and Stafford, 2023, p. 1). Furthermore, to systematically explore the relationship between a banking system's funding structure and rare systemic events such as financial disasters, a long-term, cross-country perspective is needed, which is challenging to achieve with bank-level data alone. Thus far, the lack of existing aggregate data has made a systematic macro-level analysis infeasible as well, leaving the relationship between monetary policy, bank funding structures, and systemic financial stability largely unexplored.

I close this gap by constructing a novel macro-financial dataset. This data collection effort is the result of harmonizing, digitizing, cleaning, and aligning the IMF's International Financial Statistics (henceforth IFS). The IFS provide information on macro-financial variables for nearly all developed and developing economies. However, only a small portion of this data is part of the IMF Online Database. Until now, historical IFS reports have been used only to a limited extent. Monnet and Puy (2021) have digitized five basic macro-financial variables at a quarterly frequency for 49 countries. Other studies have drawn on IFS data to construct time series of bank credit across various countries (Demirgüç-Kunt and Detragiache, 1998; Hardy and Pazarbasioglu, 1999; Hutchison and McDill, 1999; Kaminsky and Reinhart, 1999; Gourinchas et al., 2001; Borio and Lowe, 2002; Bouvatier et al., 2022; Müller and Verner, 2023). No attempt has been made so far to systematically collect long-run cross-country information on the liability structure of banking systems.[4] The process of collecting such data is challenging, as described further below. These challenges explain why our understanding of the causes and consequences of shifting funding structures of banking systems remains limited. The data collection effort of this study overcomes these challenges and compiles data on various bank liability positions for developed and developing economies at monthly frequency, extending back to the 1950s for some countries. For key aggregate bank liability items such as demand deposits, time deposits, foreign liabilities, liabilities to governments and central banks, and capital, the dataset comprises approximately $100,000$ observations.

The mechanism I explore begins with variations in the stance of monetary policy. To quantify these variations, the bank balance sheet data must be supplemented with information on central bank policy rates. Unfortunately, the IFS data availability for monetary policy rates is more limited than for bank balance sheet positions. To address this limitation, I have supplemented the IFS policy rate data with information from the BIS and various historical central bank documents, some of which have been digitized for the first time. The result is a comprehensive dataset of central bank policy rates covering 166 countries and $77,419$ observations at a monthly frequency. This newly constructed monthly policy rate data constitutes the key ingredient of my instrumental variable framework.

Other related literature A growing body of literature has documented the relevance of banks' funding characteristics. The composition of bank funding fluctuates over the financial cycle (Shin and Shin, 2011; Le Leslé, 2012; Vazquez and Federico, 2015; Acharya and Mora, 2015) and is influenced by monetary policy (Bernanke and Blinder, 1992; Drechsler et al., 2017; Choi and Choi, 2021; Supera, 2021; Emeksiz, 2022; Begenau and Stafford, 2023).

[4] Hahm et al. (2013) use the subset of the IFS that is readily available online for emerging and developing economies. Their resulting sample covers a period of 11 years. The IFS are also one of the source that Jamilov et al. (2024) draw upon to construct a cross-country bank deposit database at annual frequency.

Some of these studies (e.g., Choi and Choi, 2021) hypothesize that monetary-policy-induced shifts toward non-core funding sources may increase systemic financial fragility. However, due to the lack of existing macro-financial data, they have not been able to explicitly test this hypothesis. Other recent papers provide bank-level evidence suggesting that a bank's funding mix is informative both for the occurrence of runs and failures (FDIC, 2011; Blickle et al., 2022; Correia et al., 2023) and for the bank's performance during crises and panics (Ratnovski and Huang, 2009; Goldsmith-Pinkham and Yorulmazer, 2010; Ivashina and Scharfstein, 2010; Demirgüç-Kunt and Huizinga, 2010; Cornett et al., 2011; Iyer et al., 2014; Dagher and Kazimov, 2015; Iyer et al., 2016; Federal Reserve, 2023). This study connects these strands of the literature and explicitly analyzes the direct relationship between monetary policy, the funding structure of banking systems, and macro-financial vulnerabilities.

While some studies have analyzed the relationship between specific funding characteristics of the banking system and macro-financial vulnerabilities, they differ from mine in critical respects. Hahm et al. (2013) and de Haan et al. (2020) find that higher exposure to non-core funding, particularly from the foreign sector, has predictive power for (non-systemic) financial market turmoil. These studies are limited to emerging and developing economies and cover a restricted time frame. Moreover, they do not investigate the causes of variations in banks' exposure to non-core funding, which is a key focus of this study. Pereira Pedro et al. (2018) use average annual bank-level data from publicly listed banks across OECD countries and show that the *level* of non-deposit debt to total liabilities and equity of these banks predicts financial crises. Jamilov et al. (2024) study the characteristics and macro-financial consequences of retail deposit runs and Diebold and Richter (2023) highlight the financial stability risks originating from foreign-financed household credit booms. Lastly, Jordà et al. (2021) explore the role of bank capital in 17 advanced economies before and after banking crises. In one specification, they also show an association between the *level* of a residual bank liability variable, capturing all liabilities other than deposits and capital, and banking crises. The exact composition of this variable varies by country; for instance, it sometimes excludes interbank liabilities. Furthermore, it includes positions such as liabilities to governments and central banks, which I can separately isolate. My dataset enables a positive, granular definition of non-core funding and provides the means to analyze individual non-core funding positions across a wide range of developed and developing economies.

Roadmap I proceed by outlining the new macro-financial dataset. Next, I explore the effect of monetary policy shocks on funding structures of banking systems. Section 4 demonstrates that changes in bank funding, akin to those caused by monetary tightening, are informative for systemic financial stability risk. I provide a synthesis of these results in Section 5. Section 6 verifies my main findings for the U.S. using a more granular approach. Section 7 rationalizes these findings within a model and and Section 8 concludes.

2 A new macro-financial dataset

To analyze the relationship between monetary policy, the liability composition of banking systems, and systemic financial stability, data on central bank policy rates and banks' funding structure is essential. This data must cover a sufficiently large number of countries over an extended period to account for the long amplitude of the financial cycle (Claessens et al., 2012; Drehmann et al., 2012) and the rare nature of financial disasters. Ideally, the data should be of high frequency to close the door for potentially confounding factors within my IV framework (discussed in detail below) and to capture short-term variations in banks' funding mix.

Such data does not exist. Therefore, the empirical part of this study begins with the creation of a novel macro-financial dataset that meets the aforementioned requirements. The foundation for this new dataset are the International Financial Statistics (IFS) published by the IMF. I have cleaned the already-existing raw data, digitized additional IFS data, harmonized and aligned various IFS variables, and identified all breaks in the series by reading through all Country Notes provided by the IFS. This process has allowed me to compile a dataset of aggregate bank balance sheet positions, key macroeconomic variables, and central bank policy rates. The resulting dataset forms an unbalanced panel, beginning in the 1950s for some economies and extending to 2022, with monthly frequency and coverage of both developed and developing economies.

The IFS data on central bank policy rates contains significant gaps. Given the critical importance of policy rates for my empirical analysis, I have extended the monthly IFS policy rate data across time and space by merging existing datasets and digitizing additional data from historical documents of national central banks.

Transforming the IFS into a cleaned, harmonized, and break-adjusted dataset is a non-trivial task. Appendix A documents the detailed procedure I followed to create the final macro-financial dataset from the IFS, along with the additional sources used to construct a new monthly monetary policy rate database.

Table 1 presents a stylized bank balance sheet, illustrating the availability of IFS data across countries. For central bank balance sheet positions, the dataset comprises more than 100,000 observations, covering all advanced economies (with the exception of Andorra, Puerto Rico, and Taiwan) and a large number of emerging and developing economies.

Table 1: *Availability of IFS bank balance sheet variables.*

Asset	Countries	Obs.	Liability	Countries	Obs.
Private Credit	190	105,038	Demand Deposits	189	105,305
Public Corporations	178	72,446	Time Deposits	185	102,760
Foreign	188	102,526	Foreign	188	102,174
Central Bank (Reserves)	189	105,590	Central Bank	183	98,227
Central Bank (Other)	174	47,894			
Government	190	104,482	Government	184	97,872
Other Financial Insts.	175	64,487	Other Financial Insts.	175	52,476
			Securities	178	69,451
			Loans	172	38,203
			Derivatives	172	37,940
			Insurance Technical Res.	172	37,907
			Capital	187	98,069
			Other Liabilities (Net)	190	104,677

Given the aggregate bank balance sheet variables listed in Table 1, I now transform the negative definition of non-core funding, provided on page 1, into a positive one.

Definition 1. *Non-core funding is the sum of Foreign Liabilities, Liabilities to Other Financial Institutions, Securities, Loans, Derivatives, and Other Liabilities.*

The *Time Deposits* position is a combination of core and non-core funding since time deposits are provided by both retail depositors and wholesale investors. On one hand, a portion of time deposits, such as large-denomination negotiable certificates of deposits—especially those obtained from institutional investors or acquired via brokers—are wholesale because they are large in volume, negotiated in terms of conditions, and function as "transferable securities that trade in the capital market in competition with other similar instruments like commercial paper and bankers' acceptances" (Fama, 1985, p. 29).[5] As a result, the share of time deposits in total deposits can be considered as measure of *funding vulnerability* in its own right, as in Correia et al. (2023). On the other hand, small-scale time deposits obtained from individual customers are still retail. Unfortunately, the data does not allow me to separate the retail portion of time deposits from the wholesale portion. Bank-level evidence suggests that the wholesale part is more risk-sensitive than the retail part (Martin et al., 2024). To provide a complete picture, I always discuss the responses

[5] Also see the discussion in Shin and Shin (2011, p. 15).

of time deposits in my empirical analysis. These responses typically fall between those of demand deposits and non-core funding, reflecting the mixed nature of time deposits. Furthermore, when classifying *Time Deposits* as an additional non-core funding source, the main findings of the following sections remain unchanged.

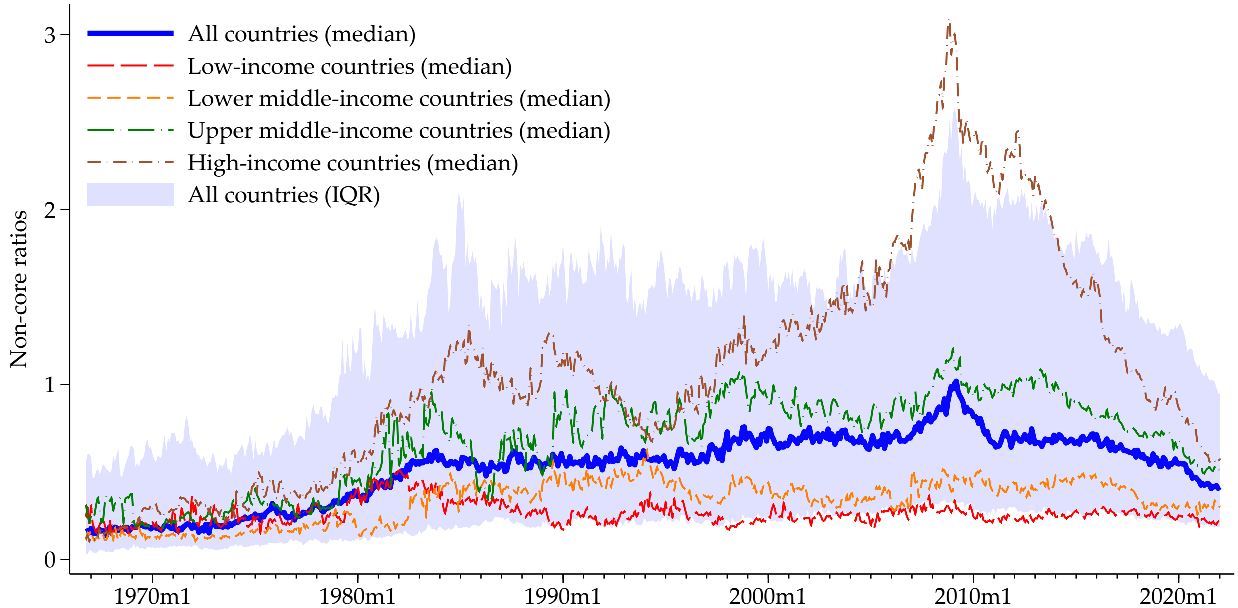
Non-core funding differs from core funding in significant ways. Non-core funding is typically uninsured and provided by risk-sensitive investors on market-based terms. Consequently, non-core funding carries interest rate risk, refinancing risk, liquidity risk, and counterparty risk. However, not all risks apply uniformly to all non-core positions, nor do they affect all countries equally. For example, loans and longer-term securities are generally less prone to sudden withdrawals than interbank liabilities due to their longer maturities. Similarly, the risks associated with foreign liabilities are arguably higher for emerging markets compared to advanced economies (Shin and Shin, 2011). In the main part of this study, I combine various non-core positions. However, the stylized bank balance sheet presented in Table 1 suggests the potential for a more granular analysis. Accordingly, in the following sections, robustness checks and extensions delve into different components of non-core funding, identifying (monetary-tightening-induced) surges in foreign liabilities, interbank liabilities, and short-term securities as the greatest threats to financial stability.

Table 2: *Availability of other used variables.*

Variable	Countries	Obs.	Notes / Sources
Other IFS variables			
Consumer Price Index	188	103,966	
Exchange rate vis-à-vis USD	189	136,832	
Gross Domestic Product	107	32,561	Quarterly, linearly interpolated
Policy rates	166	77,419	Various sources, see Appendix A.2
Financial crisis indicator	162	86,646	Laeven and Valencia (2020)
Banking panic indicator	45	35,597	Baron et al. (2021)
ER regime classification	186	134,057	Ilzetzki et al. (2019, 2022)
Anchor currency classification	184	124,376	Ilzetzki et al. (2019, 2022)
Capital Account openness index	178	99,055	Chinn and Ito (2006) If unavailable: Quinn et al. (2011)

Table 2 lists the other data used throughout the rest of this study, including data drawn from secondary sources. Appendix A.3 summarizes these secondary data sources and provides technical notes.

Figure 1: *Non-core ratios over time.*



Notes: The figure shows the ratio of non-core funding to demand deposits over time for the median country in the full sample (solid blue line) and for the median country within different income groups (other lines). The blue-shaded area shows the interquartile range of this ratio across all countries. *Non-core* is defined in Definition 1. Countries are classified according to the World Bank (2023) Income Classification.

Figure 1 provides an overview of the funding structure of domestic banking systems over more than half a century. The blue solid line represents the non-core ratio, defined as non-core funding relative to retail deposits, for the median country in the database over time.[6,7] This ratio serves as the key measure of funding vulnerabilities throughout this study. The figure highlights three stylized facts about the funding composition of banks, consistent with IMF (2013). First, non-core funding sources constitute an economically relevant portion of bank financing, particularly in high-income countries (brown dash-dotted line), in which non-core funding instruments have exceeded retail deposits in recent decades. Second, there is notable variation in the funding structure of banks over time. Third, there is considerable heterogeneity in the composition of bank liabilities across countries at any given time. The blue-shaded area in the figure illustrates the wide range in

[6]Appendix Figure A5 illustrates that the country coverage increases over time. Some of the large changes in the time series shown in Figure 1 reflect the inclusion of additional countries, which in turn alters the median country.

[7]Appendix Figure C1 provides a more comprehensive overview of the dynamics in private credit and all liability positions listed in Table 1 over time. Appendix Figure C2 offers a similar overview, with an additional breakdown of countries based on their income levels.

the non-core ratio between the 25^{th} and 75^{th} percentile countries.

One explanation for this substantial cross-sectional heterogeneity is differences in the capacity to generate non-core funding products, which, in turn, depends on the development of the domestic financial system. Indeed, when using a simple proxy for the development of the financial system—a country's income level—a clear pecking order emerges. The four dashed lines in Figure 1 show that as a country's level of economic development rises, so does the reliance of its banking sector on market-based funding instruments.

3 The effect of monetary policy on bank funding

3.1 A refined Trilemma IV

To identify monetary policy shocks, I build on the trilemma of international finance (Obstfeld and Taylor, 2004; Obstfeld et al., 2005). It states that a country with an open capital account and a fixed exchange rate system cannot simultaneously conduct independent monetary policy. Rather, the country must adjust its policy rate in accordance with rate changes in its base country. I impose the identification assumption that the base country does not consider domestic macroeconomic conditions of the pegging country when determining its monetary policy stance and interpret policy rate changes in the pegging country induced by (unpredictable) policy rate changes in the base country as exogenous. It is this variation in the pegging countries' policy stance that I exploit to construct measures of monetary policy shocks.

Trilemma-based identification of monetary policy shocks has been used in previous studies, as outlined in the Introduction. These studies use annual data for 17 or 18 advanced economies and proxy the stance of monetary policy using short-term market rates. By leveraging three characteristics of the dataset constructed in this study, I contribute to this literature by refining trilemma-based identification in three dimensions.

I. Data on policy rates Since short-term market rates are arguably risk-free in advanced economies, capturing the monetary policy stance with short-term rates on government debt rather than actual policy rates is of second-order relevance for advanced economies. However, the distinction between central bank policy rates and short-term market rates becomes critical for non-advanced economies. De Leo et al. (2022) identify a disconnect between policy rates and short-term market rates in emerging market economies. They attribute this disconnect to time-varying risk premia driven by global financial conditions, which are themselves influenced by U.S. monetary policy. The U.S. serves as the base country for several emerging markets in my sample. Therefore, using short-term market rates rather than actual policy rates for emerging economies may lead my instrument to capture time-varying risk premia instead of the true stance of monetary policy. Consequently, "the common practice of using short-term market rates to proxy for the stance of monetary policy may lead one to draw inaccurate conclusions about the cyclical properties of the monetary policy in emerging economies as those rates encompass counter-cyclical risk premia—even though this practice appears justified for advanced economies." (De Leo et al., 2022, p. 3)

I have gathered novel information on central bank policy rates. This data allows me to avoid relying on short-term interest rates on government debt or similar short-term market rates as proxies for the stance of monetary policy and ensures that I do not pick up time-varying risk premia.

II. Monthly time window If unexpected monetary tightening in the core country affects the pegging country through channels other than interest rates, the identification assumption is challenged. Such channels may be common shocks (di Giovanni et al., 2009) or spillovers due to trade linkages (Jordà et al., 2020b). The removal of the predictable component of base country policy rate changes sets a high bar for these channels to challenge identification. Furthermore, Shambaugh (2004) and Jordà et al. (2020b) do not find significant effects of common shocks and trade spillovers, respectively.

With the availability of monthly policy rate data comes another method to validate the above-stated identification assumption of the trilemma IV. I impose a significantly tighter time window between monetary policy decisions in the base country and policy responses in the pegging country by requiring that the pegging country reacts within the same month to policy actions in the base country. This conservative and tight time window between base countries' actions and pegging countries' reactions further narrows the door for potentially confounding factors. It safeguards the identification assumption, which now asserts that *within a month*, unpredictable base country policy rate changes affect the pegging country only through policy rates.

III. Extensive country coverage The conservative identification assumption comes at the cost of a weakened first stage, setting a high bar for the relevance condition to be fulfilled. For instance, my instrument disregards policy responses in the pegging country in early February to base country policy actions in late January.

I resolve this issue through a third characteristic of my dataset: its coverage of both developed and developing economies. This broad coverage allows me to exploit numerous relationships between floaters and peggers. As illustrated in Appendix Figure C3, emerging markets often peg their currency to that of an advanced economy. These relationships can only be leveraged in a dataset that includes both types of economies, as mine does. This extensive coverage provides statistical power and ensures that the relevance condition is met, even after including time fixed effects that absorb common shocks, as verified below.

Construction of the instrument The formal construction of the instrument follows Jordà et al. (2020a), adapted to the monthly frequency of my dataset. Let $ER_{i,t} \in \{0,1\}$ be the exchange rate regime indicator derived from Ilzetzki et al. (2019, 2022).[8] It equals 1 if country i has a fixed exchange rate in year-month t, and 0 otherwise. Jordà et al. (2020a) ensure that a peg is well-established by requiring it to be in place both in the current and in the previous year. I adapt this approach to my monthly setting by defining $q_{i,t} = \prod_{k=0}^{23} ER_{i,t-k}$ and classify country i as a pegger if $q_{i,t} = 1$. Similar to Romer and Romer (2004), I first eliminate predictable base country policy rate changes. Let $\Delta r_{b(i,t),t}$ denote policy rate changes in country i's base country b in year-month t. $\Delta \hat{r}_{b(i,t),t}$ represent corresponding predicted changes in $\Delta r_{b(i,t),t}$ using base country observables.[9] Additionally, $k_{i,t} \in [0,1]$ refers to the Chinn and Ito (2006) capital account openness index. Then, I define my final instrument as

$$z_{i,t} = q_{i,t}\, k_{i,t} \left(\Delta r_{b(i,t),t} - \Delta \hat{r}_{b(i,t),t}\right) \quad . \tag{1}$$

This instrument assigns residualized variations in base countries' policy rate changes to corresponding pegging countries, giving greater weight to those peggers with more open capital accounts.

3.2 Econometric setting

Equipped with the instrumental variable z, I examine the effect of monetary policy on the funding structure of banking systems by estimating a Jordà (2005) local projection using instrumental variable methods (LP-IV),

$$\Delta_{h+1} y_{i,t+h} = \alpha_i^h + \beta^h \Delta R_{i,t}^{policy} + \sum_{k=1}^{12} \gamma_k^h \Delta R_{i,t-k}^{policy} + \sum_{k=1}^{12} \delta_k^h \Delta y_{i,t-k} + \sum_{k=0}^{12} \mathbf{\Gamma}_k^h \mathbf{X}_{i,t-k} + e_{i,t+h} \quad , \tag{2}$$

[8] Appendix A.3 explains how I transform the granular Ilzetzki et al. (2019, 2022) exchange rate regime classification into a binary indicator.

[9] To be precise, $\Delta \hat{r}_{b(i,t),t}$ are predicted values from OLS estimates of $\Delta r_{b(i,t),t} = \alpha_i + \sum_{k=1}^{12} \beta_k \Delta r_{b(i,t-k),t-k} + \sum_{k=0}^{12} \gamma_k \left(\Delta \log CPI\right)_{i,t-k} + e_{i,t}$. Here, $\log CPI$ refers to the log-transformed consumer price index and Δ denotes monthly changes. I summarize data availability for these variables in Table 2. In a robustness check below, I additionally control for lags 0 to 12 of monthly changes in log-transformed real GDP. As explained on page 18 below, including these additional control variables reduces the sample size considerably but leaves the basic results intact.

for $h = 0, \dots, H$. Here, $\Delta_{h+1} y_{i,t+h}$ denotes cumulative changes in the response variable y (specified below) from year-month $t-1$ to year-month $t+h$, and α refers to country fixed effects. Figure 1 above highlights the heterogeneity in banking sectors' reliance on non-core funding across countries, underscoring the importance of including country fixed effects. Robustness checks further enrich this model with time fixed effects.

$\boldsymbol{X}_{i,t}$ is a vector of control variables consisting of monthly changes in log exchange rates vis-à-vis the U.S. Dollar, log consumer prices, and log real private credit. I do not control for real economic activity because cross-country monthly GDP data does not exist, and even the quarterly data provided by the IFS is limited, as shown in Table 2. Robustness checks additionally control for linearly interpolated quarterly real GDP growth. Although including this variable reduces the number of observations significantly, the main results presented below remain unchanged. Throughout the rest of this study, I always control for contemporaneous and lagged growth rates of private credit. Therefore, as discussed in more detail in Section 4, all the following estimates can be interpreted as effects that go above and beyond the role played by private credit growth, which is considered "the single best predictor of financial instability" (Jordà et al., 2011, p. 340).

$\Delta R^{policy}_{i,t}$ are monthly monetary policy rate changes in country i in year-month t, which I instrument with $z_{i,t}$. Ultimately, $\{\beta^h\}_{h=0}^{H}$ are the coefficients of interest, tracing the cumulative effect of trilemma-identified monetary policy shocks on the response variables over time. One key response variable is the non-core funding share of the banking system. Here, the mechanisms outlined in the Introduction suggest $\beta > 0$, and I am now prepared to empirically evaluate this hypothesis.

3.3 Empirical results

First stage Table 3 presents the first-stage results and verifies the strength of my instrumental variable. Column (1), for instance, suggests that when the unpredictable component of a base country's policy rate rises by 10 bps, a pegging country with a fully open capital account responds by raising its policy rate by 2.7 bps *within the same month*. I estimate an even stronger association when including control variables, as demonstrated in column (2). Columns (3) and (4) verify that the instrument maintains its relevance when including year fixed effects and year×month fixed effects, respectively.

Pure interest parity, a correlation of 1, is not required for the rank condition to be satisfied; a valid IV only needs a positive correlation to meet the relevance condition, which mine does. In practice, pegging countries may respond with a lag or partially smooth their short-term interest rates (Obstfeld et al., 2005). Additional factors contributing to a correlation below 1 include costs to arbitrage (Shambaugh, 2004) and the fact that some

Table 3: *First stage.*

Dep. var.: $\Delta R^{policy}_{i,t}$	(1)	(2)	(3)	(4)
$z_{i,t}$	0.268***	0.397***	0.360***	0.319***
	(0.058)	(0.065)	(0.062)	(0.075)
Controls	✗	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	Year	Year × Month
KP weak IV	21.47	36.77	33.19	18.37
Countries	157	154	154	154
Observations	46184	36894	36894	36894

Notes: OLS estimates of γ with country-based cluster-robust standard errors of $\Delta R^{policy}_{i,t} = \alpha_i + \alpha_t + \gamma z_{i,t} + \sum_{k=1}^{12} \delta^k \Delta R^{policy}_{i,t-k} + \sum_{k=0}^{12} \mathbf{\Gamma}^k \mathbf{X}_{i,t-k} + e_{i,t}$. $\mathbf{X}$ is defined in Section 3.2. In column (1), $\mathbf{X}$ and α_t are excluded. In column (2), α_t is excluded. In column (3), α_t refers to year fixed effects. In column (4), α_t refers to year×month fixed effects. *KP weak IV*: Kleibergen-Paap (2006) Wald rk F-statistic. *** $p < 0.01$.

central banks do not conduct monetary policy through interest rate targeting. Instead, they may rely on other instruments, such as quantitative controls on money and credit (Monnet, 2014), rendering the policy rate redundant. Indeed, as Shambaugh (2004) points out, some countries have maintained constant interest rates for extended periods. My central bank policy rate dataset reveals that these countries are mostly non-advanced economies. Appendix Table C1 demonstrates that excluding these non-advanced economies strengthens the first stage. I choose not to restrict my dataset in any way and instead use all available observations in my baseline specification.

The trilemma of international finance is alive and well. This would not be the case if the global financial cycle played an all-encompassing role (Rey, 2013), or if a significant number of floating countries were afraid to float (Calvo and Reinhart, 2002). Neither is the case. Appendix Table C2 indicates that central banks of countries classified as floaters maintain independence from monetary policy of their anchor currency countries. Consistent with the findings of Shambaugh (2004), the table shows that peggers and peggers only react to monetary policy actions in their base country within the same month. Conversely, as suggested by uncovered interest parity, policy rate changes in anchor countries pass through to exchange rates only in floating currency countries. Appendix Table C3 shows that while the currencies of floaters weaken significantly against the U.S. Dollar following a tightening in the anchor country, the value of peggers' currencies remains stable.

Table 4: *The effect of monetary policy on bank funding: second-stage results at a 12-month horizon.*

		Real Quantities	
	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Demand Dep.	Non-core
$\Delta R^{policy}_{i,t}$	14.506***	-7.578***	7.718**
	(4.093)	(2.863)	(3.776)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	46.04	51.60	45.11
Countries	151	152	152
Observations	31748	33444	32024

Notes: LP-IV estimates of β^{12} with country-based cluster-robust standard errors of model (2). $\Delta R^{policy}_{i,t}$ is instrumented with $z_{i,t}$. Response variables are log-transformed. *KP weak IV*: Kleibergen-Paap (2006) Wald rk F-statistic. *Non-core* is defined in Definition 1. ** $p < 0.05$, *** $p < 0.01$.

Second stage With the verification that the instrument satisfies the rank condition, I proceed to the second stage, the LP-IV estimation of model (2). To ensure clarity, I begin by presenting the results in a table format for a horizon of $h = 12$ months. This presentation displays the F-statistic from the Kleibergen-Paap (2006) test for weak instruments, as well as the exact number of observations and countries used in each specification.[10]

The first column of Table 4 illustrates the central finding of this section: in the months following a contractionary monetary policy shock, the non-core ratio of the banking system grows.[11] As discussed earlier, existing bank-level evidence and my model constructed below yield ambiguous predictions regarding the directional response of aggregate retail deposits to increasing policy rates. In the model outlined in Section 7, this response will depend on the parameters. Therefore, whether aggregate retail deposits rise or fall after a monetary contraction remains an empirical question that has, until now, gone unanswered.

[10]As illustrated in Tables 1 and 2, data availability varies across the different IFS variables. To maximize the statistical power of my dataset, I avoid equating the sample size across different empirical specifications.

[11]In all specifications, I concentrate on cumulative growth rates rather than cumulative differences in non-core ratios to better account for the large heterogeneity in countries' (or later, banks') non-core funding shares.

The second column of Table 4 addresses this gap, showing that contractionary monetary policy shocks are followed by net outflows of real demand deposits from the banking system. Meanwhile, non-core funding increases, as shown in the third column. As a result, the positive effect of contractionary monetary policy on the non-core ratio, presented in the first column of the table, is driven by both a net outflow of retail deposits and a net inflow of non-traditional funding sources. These findings place the bank-level evidence outlined in the Introduction into a macroeconomic context.

The effects presented in Table 4 are not only statistically significant (and, as shown below, robust to model specification) but also economically meaningful. Column 2 indicates that when an economy experiences a 10 bps contractionary monetary policy shock in year-month t, the cumulative growth of real demand deposits from $t-1$ to $t+12$ is approximately –0.8%.[12] At the same time, non-core funding *grows* by 0.8% in real terms (column (3)). The resulting growth in the non-core ratio, depicted in column (1), is 1.5%. This substantial substitution of deposit contractions with non-core funding sources is consistent with Begenau and Stafford (2023) and Whited et al. (2023).

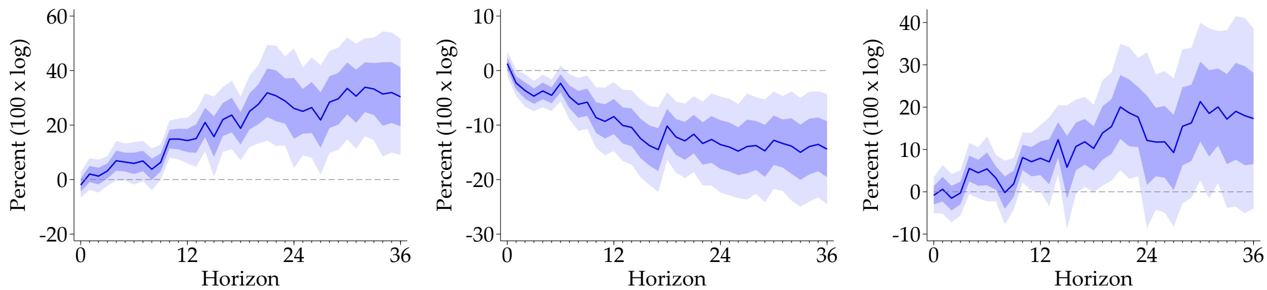
Monetary policy can influence systemic financial stability through banks' funding structure if and only if it exerts strong effects on the funding composition of the banking sector. Table 4 establishes a necessary condition for this mechanism by identifying a sizable effect of contractionary monetary policy shocks on the banking system's reliance on non-core funding. If this shift in funding structure also contributes to macro-level financial instability and volatility, then the estimated effects reported in Table 4 carry implications for policymakers. The documentation of a direct relationship between monetary policy, the funding structure of the banking system, and systemic financial turmoil constitutes the contribution of Sections 4 and 5.

Robustness and Extensions While Table 4 focuses on a specific horizon and summarizes the sample coverage and relevance of the instrument for each specification, Figure 2 displays impulse responses from LP-IV estimation for horizons up to $h = 36$ months. The effect of monetary policy shocks on banks' funding structure are long-lasting, remaining significant even at a three-year horizon. For example, panel (a) of Figure 2 shows that a 10 bps contractionary monetary policy shock induces a cumulative 3% growth in the non-core

[12] At first glance, a reader might wonder why the point estimates in Table 4 appear so large. However, $\Delta R^{policy}_{i,t}$ refers to *monthly* policy rate changes. In most of my sample, $\Delta R^{policy}_{i,t} = 0$, and when there are changes, they are typically small. For instance, $\Delta R^{policy}_{i,t}$ equals –50 bps at the 5^{th} percentile and 32 bps at the 95^{th} percentile of its pooled country-year-month distribution. Therefore, evaluating the effect of a 10 bps change in $\Delta R^{policy}_{i,t}$ serves as a realistic benchmark. Naturally, the point estimates are smaller when responses to 12-month policy rate changes are considered, as illustrated in Appendix Table C4.

Figure 2: *Impulse Response Functions of bank funding to a contractionary monetary policy shock.*

(a) *Non-core/Demand Deposits* (b) *Real Demand Deposits* (c) *Real non-core funding*



Notes: LP-IV estimates of $\{\beta^h\}_{h=0}^{36}$ of model (2). Shaded areas indicate 95% and 68% confidence intervals based on country-based cluster-robust standard errors. $\Delta R_{i,t}^{policy}$ is instrumented with $z_{i,t}$. Response variables are log-transformed. *Non-core* is defined in Definition 1.

ratio over the subsequent three years.

In Appendix Table C5, I include, in addition to the other control variables listed in Section 3.2, lags 0 to 12 of monthly changes in log-transformed real GDP to model (2). In Appendix Table C6, I also use these real activity controls to extract the unpredictable component of base country policy rate changes. Including these controls reduces the number of observations by more than half due to the limited data availability for GDP (and other proxies of real economic activity) in the IFS. Nonetheless, the LP-IV estimates of Appendix Tables C5 and C6 confirm the main findings presented in Table 4. In Appendix Table C7, I take the opposite approach and exclude all control variables. Once again, the simplified model produces results consistent with the economic interpretation outlined above.

The findings of Shambaugh (2004) suggest that common shocks, which could challenge trilemma-based identification, are not of first-order relevance. Shambaugh (2004) uses annual data. My identification of monetary policy shocks exploits the monthly frequency of my dataset, further narrowing the door for a relevant role of common shocks. In my setting, common shocks would need to hit the base and pegging country *within the same month* to pose a challenge to identification. The inclusion of year fixed effects (Appendix Table C8) and year×month fixed effects (Appendix Table C9) higlights the robustness of my results against global shocks. Albeit statistical uncertainty rises, the positive effect of contractionary monetary policy shocks on banks' non-core ratio remains statistically significant at the 5% level.

Furthermore, Appendix Table C10 shows that the results are robust to the inclusion of country×decade fixed effects, which absorb country-specific institutional changes, such as the U.S. repeal of the Glass-Steagall Act in 1999.

Appendix Table C11 sets core and non-core funding in relation to total assets. As expected, following a contractionary monetary policy shock, the share of non-core funding in total assets rises (first column) while the share of demand deposits declines (second column). The third column of the table confirms that the share of time deposits in total assets also decreases slightly (but not significantly), implying a reduction in the total-deposit-to-asset ratio after unexpected monetary tightening (column (4)).

I further illustrate the heterogeneity in the response of time and demand deposits to exogenous variations in the stance of monetary policy in the first two columns of Appendix Table C12. Monetary tightening prompts a shift from demand deposits to time deposits, likely due to the higher interest rate sensitivity of time deposits. This result aligns with the bank-level evidence of Supera (2021). As discussed in Section 2, time deposits are provided by both retail depositors and wholesale investors, but my dataset does not allow for a detailed analysis of the different types of time deposits. The third column of the table verifies that when defining *core funding* as the sum of demand and time deposits—an upper bound for total funding through traditional retail depositors—the central finding of this section remains alive and well; a contractionary monetary policy shock causes a rise in the non-core-to-core funding ratio of banking systems.

Appendix Tables C13, C14, and C15 show that the identified effects are largely unchanged when restricting the sample to advanced economies, pegging countries, or non-euro-area countries, respectively. Appendix Tables C16 and C17 further indicate that the effects are largely symmetric; while contractionary monetary policy increases banks' reliance on non-core funding, expansionary shocks have the opposite effect.

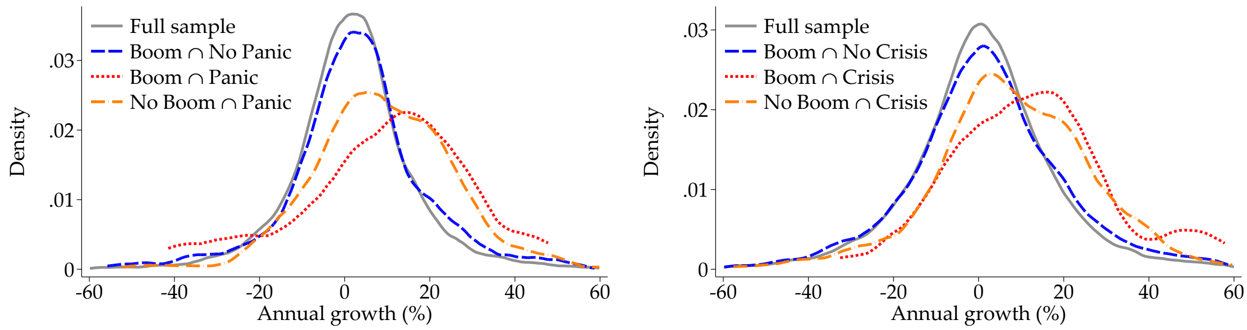
Finally, Appendix Tables C18 to C21 delve into the different non-core positions for both the full set of countries and the sub-sample of advanced economies. The effect of monetary policy is most precisely estimated for foreign liabilities. Additionally, monetary policy has a stronger effect on foreign liabilities in non-advanced economies compared to advanced economies. However, beyond these differences, the estimates indicate that contractionary monetary shocks lead to an inflow of all types of non-core funding sources, in contrast to the negative effect on retail deposits.

4 Macro-level consequences of shifting bank funding

The previous section has established monetary policy as an economically relevant determinant of the funding structure of banking systems across time and space. This uncovered relationship is policy-relevant if such monetary-tightening-induced shifts in bank funding threaten financial stability—a possibility that has largely been overlooked in existing

Figure 3: *Non-core growth before banking panics and financial crises.*

(a) *Non-core ratio before panics* (b) *Non-core ratio before crises*



Notes: I define an economy as *booming* when detrended real private credit exceeds its country-specific standard deviation. Real private credit is detrended based on a two-sided Hamilton (2018) filter. The gray solid lines show the pooled country-year-month distribution of growth rates of the ratio of non-core funding to demand deposits from $t-12$ to t. *Non-core* is defined in Definition 1. The blue dashed line shows corresponding distributions conditional on being in a boom in t and experiencing no banking panic (panel (a)) or financial crisis (panel (b)) within $t+1$ and $t+12$. The red dotted line shows corresponding distributions conditional on being in a boom in t and experiencing a panic or crisis within $t+1$ and $t+12$. The orange dash-dotted line shows corresponding distributions conditional on not being in a boom in t but experiencing a panic or crisis within $t+1$ and $t+12$.

research.

In this section, I temporarily step away from my instrumental variable framework and causal inference. I demonstrate that dynamics in aggregate bank funding akin to those induced by monetary tightening are informative for the risk of system-wide banking panics and crises, as well as for the likelihood of non-core runs, credit crunches, and real contractions. I return to my instrumental variable framework in Section 5 to identify the direct relationship between monetary policy, bank funding, and systemic financial instability risk within a single-regression framework.

4.1 Non-core ratios and credit booms before crises and panics

Figure 3 illustrates the pooled country-year-month distribution of annual growth rates in banks' non-core funding ratios, both for the full sample (gray lines) and during specific episodes (other lines).

The blue dashed lines illustrate these annual growth rates for observations characterized by credit booms that are *not* followed by banking panics (panel (a)) or financial crises (panel (b)).[13] In both panels, the gray solid line and the blue dashed line closely overlap,

[13] I outline the definition of credit booms in the notes of Figure 3. I obtain similar results when employing

suggesting that dynamics in banking systems' non-core ratios do not change during 'good booms'.

This picture changes significantly when I condition the sample on being in a 'bad boom'. During booms that *are* followed by a banking panic or financial crisis, the non-core ratio grows visibly, as illustrated by the dotted red lines. The comparison between the blue dashed and dotted red lines suggests that analyzing aggregate bank funding sources helps distinguish harmless credit booms from those that eventually bust. A Kolmogorov-Smirnov test corroborates this interpretation, rejecting the null hypothesis that the two lines are drawn from the same distribution ($p < 0.001$).

In contrast, the growth distributions shown by the red dotted and orange dash-dotted lines do not significantly differ ($p = 0.37$). Both shift markedly to the right. No matter whether the economy is in a credit boom or not, the growth distribution of non-core ratios exhibits a significant shift when a panic or crisis is imminent. Figure 3 suggests that changes in banks' exposure to non-core funding are a distinct source of macro-level instability on their own and provide valuable information for policymakers.

4.2 Event studies

An event-study approach sheds light on how bank funding structures change before the average banking panic and financial crisis. Panels (a)–(c) of Figure 4 illustrate the cumulative real growth of different bank liability variables from 36 months before the onset of banking panics to $36 - h$ months before panics, relative to other times. Panel (a) shows that in the 3 years leading up to banking panics, the non-core funding ratio grows by more than 30% compared to normal times. The shaded area, representing 95% confidence intervals, indicates that this shift in the funding structure of the banking system is statistically significant. The pre-panic rise in the ratio between non-core funding and demand deposits is due to both the numerator and the denominator. Panel (b) shows a net outflow of real demand deposits in the months leading up to banking panics, while panel (c) reveals a substantial increase in non-core funding.

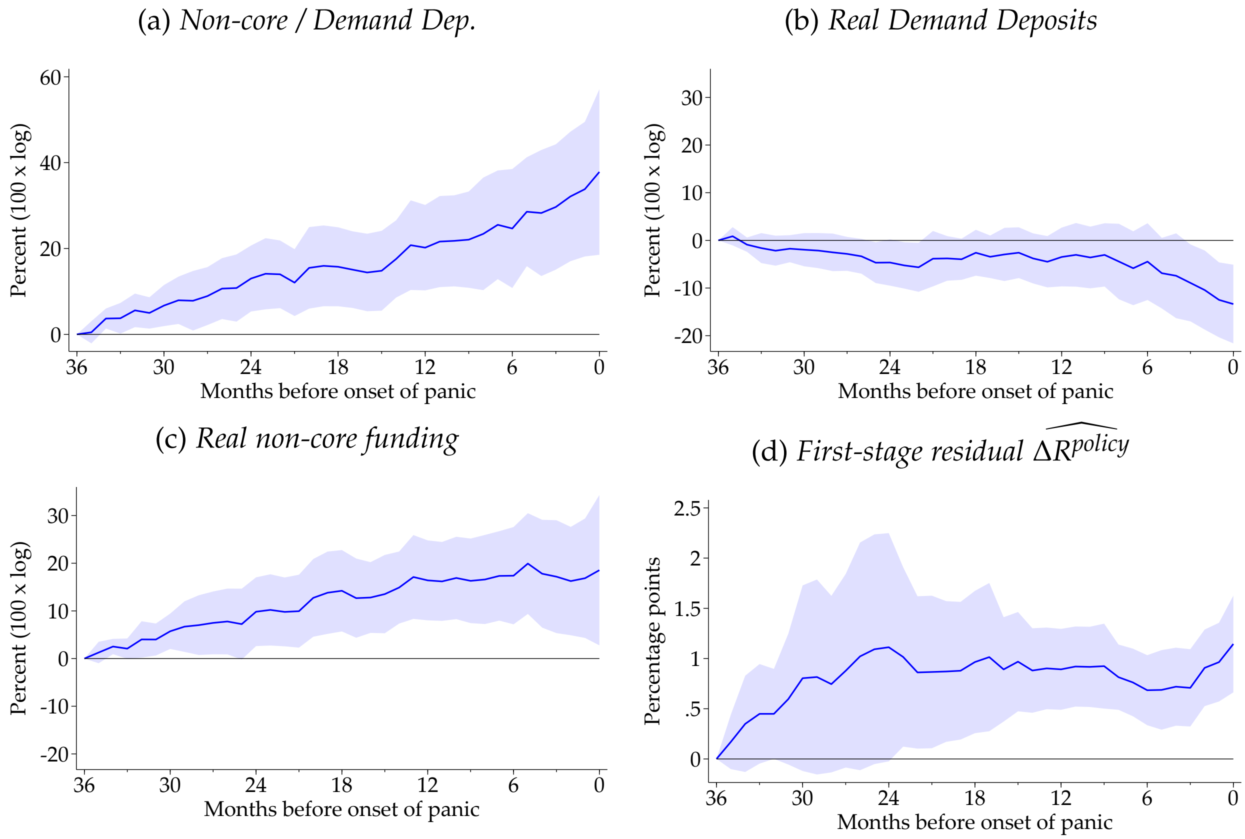
The net outflow of retail deposits during pre-panic periods is striking, as periods of financial disasters are typically preceded by expansions of bank balance sheets.[14] It follows that the proportion of retail deposits within banks' total assets declines sharply, even though the share of non-core funding in total assets increases, as shown in Appendix Figure C7.

Appendix Figure C8 sets non-core funding and demand deposits in relation to total

alternative definitions of credit booms, as shown in Appendix Figures C4 and C5.

[14] Appendix Figure C6 confirms that real private bank credit and real total bank assets increase significantly prior to banking panics.

Figure 4: *Pre-panic paths of bank funding and policy rates.*



Notes: Panels (a)–(c) show OLS estimates of $\{\beta^h\}_{h=0}^{36}$ of $y_{i,t-36+h} - y_{i,t-36} = \alpha_i^h + \beta^h \mathbb{1}\{panic_{i,t} = 1\} + e_{i,t-36+h}$. y is log-transformed and specified in the titles of the panels. *Non-core* is defined in Definition 1. Panel (d) shows OLS estimates of $\{\beta^h\}_{h=0}^{36}$ of $\sum_{k=0}^{h} \widehat{\Delta R_{i,t-36+k}^{policy}} = \alpha_i^h + \beta^h \mathbb{1}\{panic_{i,t} = 1\} + e_{i,t-36+h}$. $\widehat{\Delta R^{policy}}$ are the first-stage residuals from column (2) of Table 3. Shaded areas indicate 95% confidence intervals based on country-based cluster-robust standard errors.

private deposits—defined as the sum of demand deposits and time deposits—and illustrates corresponding pre-panic paths. Although non-core funding rises as a share of total private deposits (panel (a)), this increase is somewhat tempered by a shift within private deposits toward time deposits during pre-panic periods (panel (b)).

Furthermore, the inclusion of year, year×month, or country×decade fixed effects does not significantly alter the pre-panic paths of core and non-core funding, as shown in Appendix Figures C9, C10, and C11, respectively.

The patterns illustrated in Figure 4 (a)–(c) are reminiscent of those that preceded the Global Financial Crisis.[15] However, these patterns also characterize the months and years

[15] Baron et al. (2021) date the U.S. banking panic during the Global Financial Crisis to September 2008. Appendix Figure C12 illustrates the trajectory of the non-core ratio, real demand deposits, and real non-core

before other banking panics. Appendix Figure C13 illustrates these results by presenting estimates from a restricted sample that excludes 2007 and 2008. Finally, Appendix Figure C14 confirms that similar conclusions apply to the path of non-core ratios before financial crises.

Returning to the discussion on the nature of time deposits, Appendix Figure C15 illustrates their behavior before banking panics. Not only do time deposits rise following a contractionary monetary policy shock, as demonstrated in Section 3, but they also show a significant upward trend in the three years preceding the average banking panic. This result supports the view that a portion of time deposits originates from runnable, risk-sensitive, and uninsured wholesale investors. The sharp increase in the time-deposit-to-demand-deposit ratio before financial turmoil echoes the findings of Correia et al. (2023), who interpret and empirically establish a similar ratio as a critical measure of *funding vulnerability* at the bank level.

It is reasonable to expect that funding vulnerabilities are more pronounced in non-core funding sources with shorter maturities, such as repos, which were at the heart of the 2007-08 panic (Gorton and Metrick, 2012). Appendix Figure C16 substantiates this hypothesis, showing that arguably shorter-term non-core funding sources—foreign liabilities, interbank liabilities, and short-term securities—are key drivers of the pre-panic surge in aggregate non-core funding.

A comparison between Figure 4 (a)–(c) and Table 4 reveals that monetary policy induces precisely those movements in the funding structure of banking systems that characterize the months leading up to banking panics. Column (1) of Table 4 shows that contractionary monetary policy shocks result in a significant rise in non-core funding ratios, while Figure 4 (a) documents that non-core funding ratios increase sharply in the months prior to banking panics. Similarly, columns (2) and (3) of Table 4 demonstrate that monetary tightening causes a net outflow of real retail deposits and a net inflow of real non-core funding, while Figure 4 (b)–(c) reveals that these flows predate banking panics. Therefore, the combination of the findings of Figure 4 and Table 4 provides *indirect* evidence that monetary-policy-induced changes in banks' funding structure affect financial system stability. This indirect evidence is further corroborated by the observation that the average panic in my sample is preceded by contractionary monetary policy shocks, as seen in panel (d) of Figure 4. Similar conclusions apply to financial crises (Appendix Figure C14). In Section 5, I provide evidence in favor of a *direct* relationship between monetary policy, bank funding, and financial stability.

funding in the U.S. over the 36 months leading up to September 2008.

4.3 The predictive power of bank funding for financial disasters

I systematically verify the predictive power of the funding structure of banking systems for systemic financial stability risk through the lense of a formal regression framework and a forecasting performance evaluation. Specifically, I estimate a logistic model of the form

$$\log\left(\frac{p_{i,t+1}}{1-p_{i,t+1}}\right) = \alpha_i + \beta\,\Delta_{36}\left(\log\frac{\textit{Non-core}}{\textit{Demand}}\right)_{i,t} + \boldsymbol{\Gamma}\,\boldsymbol{X}_{i,t} + u_{i,t+1} \quad . \tag{3}$$

Here, $p_{i,t+1}$ denotes the probability that the systemic instability event of interest—a banking panic or financial crises—starts in year-month $t+1$. α represents country fixed effects. $\boldsymbol{X}$ includes (i) an indicator equal to 1 if the systemic instability event starts between year-month $t-36$ and t and (ii) 36-month changes in those control variables employed before and outlined in Section 3.2. $\boldsymbol{X}$, in particular, ensures that the maximum likelihood estimates of β capture the predictive power of shifting bank funding for instability risk that goes above and beyond the information contained in credit booms. My motivation to consider growth rates over a three-year horizon stems from three factors. First, credit booms typically last for three to four years (Mian et al., 2017). Second, the shift toward non-core funding following monetary tightening is gradual (Figure 2). Third, the buildup on non-core reliance before crises and panics takes time as well (Figures 4 and C14).

The descriptive evidence provided in the previous two subsections suggest that such predictive power exists. Table 5 provides a final confirmation. Column (1) of this table indicates that the likelihood of a banking panic starting in year-month $t+1$ increases by 24 bps following a 1 standard deviation growth in the non-core ratio between $t-36$ and t. This estimate is economically meaningful, especially when compared to the unconditional full-sample probability of only 0.37% that a banking panic starts in any given year-month. Furthermore, I obtain an even larger point estimate after including control variables (column (2)). Columns (3) and (4) show that rising non-core ratios also predict financial crises with a high degree of statistical precision.

Throughout this paper, I have argued that a rise in the banking system's reliance on non-core funding is a distinct source of instability on its own that cannot be explained by credit booms. Two key arguments for this statement have been provided so far. First, I control for private credit growth in all regression specifications. Second, Figure 3 has demonstrated that a shift toward non-core funding characterizes the months leading up to panics and crises, regardless of whether credit is booming or not.

I now present a third argument in favor of the statement that the asset side of the banking system cannot account for the instability-generating dynamics arising from the liability side. Here, I assess the forecasting performance of different model specifications

Table 5: *Shifts in banks' funding mix predict banking panics and financial crises.*

	Banking panics		Financial crises	
	(1)	(2)	(3)	(4)
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	0.244***	0.253***	0.094***	0.129***
	(0.037)	(0.032)	(0.027)	(0.045)
Controls	✗	✓	✗	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
Countries	33	31	76	60
Observations	10174	9264	25595	17414
AUROC	0.74	0.73	0.70	0.69
p-value	0.00	0.01	0.00	0.18

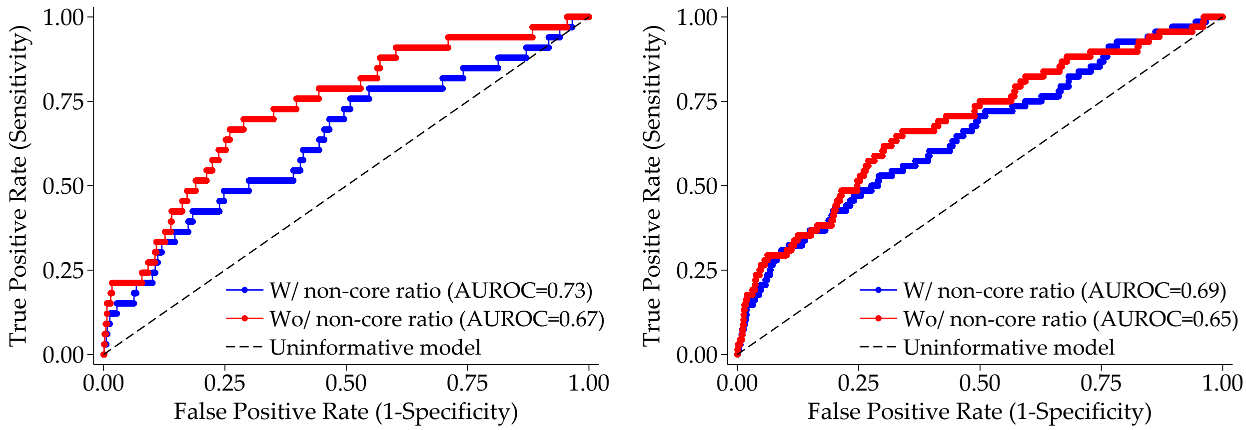
Notes: Maximum likelihood estimates with country-based cluster-robust standard errors of model (3) evaluated at the sample means of the covariates. The independent variables are normalized. *Non-core* is defined in Definition 1. Last row: DeLong et al. (1988) test of equality of ROC areas vis-à-vis a model that excludes $\Delta_{36}\left(\log \frac{Non\text{-}core}{Demand}\right)$. *** $p < 0.01$.

through the lens of the Area under the Receiver Operating Characteristic curve (henceforth AUROC). The Receiver Operating Characteristic (ROC) curve is a tool for evaluating the forecasting ability of a binary classification model within a single value. The ROC curve transforms probabilities into classifications by plotting the true positive rate against the false positive rate for different classification thresholds (Fawcett, 2006; Berge and Jordà, 2011). The AUROC quantifies the model's forecasting performance across all classification thresholds by integrating the area under the ROC curve. A random 'coin-toss' model produces a ROC curve along the 45-degree line, yielding an AUROC of 0.5, while a perfect classification model results in an AUROC of 1. Country fixed effects and control variables already raise the AUROC above 0.5. Therefore, I use model (3) without $\Delta_{36}\left(\log \frac{Non\text{-}core}{Demand}\right)$ as the benchmark. This benchmark model excludes all variables related to bank funding characteristics but includes, among others, real private credit growth. I then test whether adding a *single* variable that captures information on the funding structure of banking systems improves the AUROC.

The last row of Table 5 provides the corresponding p-values of this nonparametric test. The p-values indicate that the inclusion of $\Delta_{36}\left(\log \frac{Non\text{-}core}{Demand}\right)$ significantly enhances the predictive performance of the binary classification model in most specifications. Figure

Figure 5: *ROC curves.*

(a) *Banking panics* (b) *Financial crises*



Notes: ROC curves of model (3) with (red line) and without (blue line) $\Delta_{36}\left(\log \frac{\textit{Non-core}}{\textit{Demand}}\right)$ for banking panics (left panel) and financial crises (right panel).

5 presents the ROC curves for models with and without $\Delta_{36}\left(\log \frac{\textit{Non-core}}{\textit{Demand}}\right)$. This figure visually illustrates that adding this funding vulnerability measure to a model that already includes country fixed effects and controls increases the AUROC.

4.4 Beyond banking panic and financial crisis chronologies

Laeven and Valencia (2020, p. 310) define financial crises as "[s]ignificant signs of financial distress in the banking system", and Baron et al. (2021, p. 53) characterize banking panics as "episodes of severe and sudden withdrawals of funding by bank creditors from a significant part of the banking system". My dataset quantifies the funding structure of banking systems for the near-universe of developed and developing economies at high frequency over many decades. This comprehensive data allows me to go beyond binary indicators of financial instability and assign quantitative measures to concepts such as *financial distress* and *severe and sudden withdrawals*. Using these quantitative measures enables me to objectively (i) capture the severity of financial disruptions, (ii) pinpoint the timing of funding withdrawals, and (iii) extend the analysis to countries that are not part of existing systemic financial instability chronologies.

I employ straightforward quantitative measures of financial distress. The first measure is the 12-month growth rates of key bank balance sheet variables. The second measure is a binary indicator that identifies periods when these 12-month growth rates fall into the left tail of the pooled cross-country-time distribution. While such purely statistical indicators also carry the risk of misidentifying financial disruption (Romer and Romer, 2017), they avoid the "classification uncertainty" (Bordo and Meissner, 2016) present in narratively identified instability chronologies, such as the one provided by Laeven and Valencia (2020).

I explore whether shifts in banks' reliance on non-core funding predict my quantitative measures of financial distress using logistic model (3) when the dependent variable is binary, and linear model

$$\Delta_{12} y_{i,t+12} = \alpha_i + \beta \, \Delta_{36} \left(\log \frac{\textit{Non-core}}{\textit{Demand}} \right)_{i,t} + \boldsymbol{\Gamma} \, \boldsymbol{X}_{i,t} + \gamma \, \Delta_{36} y_{i,t} + u_{i,t+12} \tag{4}$$

when the dependent variable is continuous. Here, $\boldsymbol{X}$ includes again 36-month changes in those variables listed in Section 3.2.

Table 6 presents estimates for various dependent variables[16], starting with real non-core funding in the first two columns of panel (a). A shift toward a higher reliance on non-core funding systemically forecasts significant reversals in non-core funding. The first column shows that a 1 standard deviation growth in the non-core ratio over a three-year horizon is followed by a 4.9% decline in real non-core funding within the next 12 months. Column (2) indicates that a 1 standard deviation growth in the non-core ratio predicts a 1.3 percentage points (pps) increase in the likelihood of a *wholesale run*, which I define as the 12-month growth of real non-core funding being in the lowest decile of its pooled cross-country-time distribution.[17]

A higher reliance on non-core funding sources has broader implications for the volatility of the financial cycle, with implications for real economic activity. The heightened funding vulnerabilities following the shift toward non-core funding spill over to credit markets and, ultimately, the real economy. The third and fourth columns of Table 6 (a) show that a shift in the bank financing structure toward non-core sources is associated with a significantly higher likelihood of subsequent *credit crunches.* Similarly, the first and second columns of Table 6 (b) indicate that *real contractions* are more likely after a period of rising non-core ratios.

However, the final two columns of Table 6 demonstrate that a rise in the non-core funding share does *not* predict subsequent outflows of retail deposits. While increasing reliance on non-core funding is associated with sharp reversals in non-core funding, private credit, and real economic activity, 55,000 observations of macro-financial data do not reveal

[16]Appendix Table C22 replicates the main analysis without including any control variables, while Appendix Tables C23 and C24 incorporate year fixed effects and year×month fixed effects, respectively. The results remain robust across these sensitivity checks.

[17]Appendix Figure C17 illustrates distributions and corresponding values at the 10^{th} percentiles of those response variables used in this section of the study.

Table 6: *Predictive power of shifts in banks' funding mix beyond banking panics and financial crises.*

(a) Non-core funding and private credit

	$y = \log$ *Real Non-core*		$y = \log$ *Real Private Credit*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-4.912***	1.328***	-0.722**	1.249***
	(0.804)	(0.277)	(0.282)	(0.323)
Estimation	OLS	Logit	OLS	Logit
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
Countries	185	159	184	159
Observations	54770	48183	55925	50341

(b) GDP and demand deposits

	$y = \log$ *Real GDP*		$y = \log$ *Real Demand Deposits*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-1.018***	1.379**	-0.377	0.276
	(0.253)	(0.622)	(0.308)	(0.368)
Estimation	OLS	Logit	OLS	Logit
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
Countries	102	100	184	172
Observations	17887	17819	55490	53555

Notes: Maximum likelihood and OLS estimates of model (3) and (4), respectively, with country-based cluster-robust standard errors. The independent variables are normalized. $\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$ equals 1 if $\Delta_{12} y_{i,t+12}$ is in the lowest decile of its pooled cross-country-time distribution and 0 else. y is specified in the table titles. *Non-core* is defined in Definition 1. ** $p < 0.05$, *** $p < 0.01$.

any impact on demand deposits. This finding further strengthens the argument that retail deposits represent a stable funding source with an implicit long duration, which does not strongly react to variations in the degree of funding vulnerability, likely due to their 'sleepy' nature or explicit or implicit insurance.

5 Synthesis

The main findings of the previous sections—monetary policy induces precisely those shifts in the funding structure of banking systems that precede financial disasters—indicate that monetary-policy-induced changes in bank funding impact the stability of the financial system. In this section, I provide direct evidence supporting this hypothesis by returning to my trilemma IV framework and integrating the findings from the earlier sections into a single-regression framework. This framework is a synthesis of models (2) and (3),

$$
\begin{aligned}
y_{i,t+1,t+12} = {} & \alpha_i + \beta\, \Delta R^{policy}_{i,t-12} + \gamma\, \mathbb{1}\{\Delta_{12} \left(\frac{Non-core}{Demand}\right)_{i,t} > 0\} \\
& + \delta\, \Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12} \left(\frac{Non-core}{Demand}\right)_{i,t} > 0\} + \sum_{k=0}^{12} \mathbf{\Gamma}^k \mathbf{X}_{i,t-k} + \sum_{k=0}^{12} \lambda^k y_{i,t-k} + u_{i,t+1}\,.
\end{aligned}
\tag{5}
$$

Here, $y_{t+1,t+12} \in \{0, 1\}$ equals 1 if event y—a banking panic or a financial crisis—occurs between year-month $t+1$ and $t+12$. $\boldsymbol{X}$ includes the same control variables as in Section 3. β measures the effect of trilemma-instrumented variations in the stance of monetary policy on the likelihood that event y materializes. γ estimates the association between rising non-core funding shares and event y. Finally, δ captures the effect of a contractionary monetary policy shock in $t-12$, which is directly followed by an increase in non-core funding shares between $t-12$ and t, on panic or crisis risk within the next year. As before, I instrument $\Delta R^{policy}_{i,t-12}$ with $z_{i,t-12}$. Furthermore, I use $z_{i,t-12} \times \mathbb{1}\{\Delta_{12} \left(\frac{Non-core}{Demand}\right)_{i,t} > 0\}$ as an additional instrument.

As Table 4 suggests, non-core funding usually rises after monetary tightening. However, there are also instances when tightening monetary policy goes hand-in-hand with falling non-core funding ratios, as illustrated in Appendix Table C25. These cases yield the necessary variation in the data to estimate model (5). A comparison of the relative frequencies presented in panels (a) and (b) of Appendix Table C25 already hints toward $\delta > 0$.

Table 7 presents estimation results of model (5) for banking panics, while Appendix Table C26 focuses on financial crises and reaches similar conclusions. Column (1) of Table 7 confirms the finding from the literature, outlined in the Introduction, that contractionary monetary policy has short-term adverse effects on financial stability. A 10 bps contractionary monetary policy shock in year-month $t-12$ increases the likelihood of a banking panic

Table 7: *The effect of monetary-policy-induced changes in bank funding on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	15.587***		5.416
	(5.307)		(3.586)
$\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		1.438*	1.118
		(0.756)	(0.804)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			24.088***
			(9.226)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	53.64		34.26
Countries	41	41	41
Observations	13406	13406	13406

Notes: 2SLS (columns (1) and (3)) and OLS (column (2)) estimates with country-based cluster-robust standard errors of β, γ, and δ of model (5). In column (1), $\Delta R^{policy}_{i,t-12}$ is instrumented with $z_{i,t-12}$. In column (3), the two used instruments are $z_{i,t-12}$ and $z_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$. *Non-core* is defined in Definition 1. * $p < 0.1$, *** $p < 0.01$.

occurring between $t+1$ and $t+12$ by 1.6 pps.

Column (2) verifies the findings of the previous parts; rising non-core funding shares increase financial fragility. An increase in banks' reliance on non-core funding over the past year is associated with a 1.4 pps higher probability of a banking panic in the subsequent year.

Finally, the third column shows that monetary-policy-induced increases in the non-core funding ratio of the banking system have a significant impact on financial stability beyond the individual effects of policy rates and non-core funding. Indeed, the small and insignificant point estimate in the first row of column (3), combined with the large and statistically significant estimate in the third row, strongly suggests that contractionary monetary policy leads to heightened financial instability only when it triggers a shift in banks' funding toward runnable, market-based debt. Specifically, a 10 bps trilemma-identified contractionary monetary policy shock in year-month $t-12$, followed by a rise in non-core ratios between $t-12$ and t, increases the probability of a banking panic within the next 12 months by 2.4 pps—a significant increase given the rare nature of large-scale financial disruptions.

Consistent with the previous findings, Appendix Tables C27 and C28 confirm that these effects are driven by both the numerator (net inflow of non-core funding) and the denominator (net outflow of retail deposits) of the non-core ratio. A contractionary monetary policy shock that induces a rise in real non-core funding leads to a higher likelihood of systemic instability in the subsequent months (Appendix Table C27). The opposite holds true for retail deposits (Appendix Table C28).

I delve one last time into the different non-core positions. In Appendix Tables C29, C30, C31, C32, C33, C34, and C35, I interact monetary policy shocks with foreign liabilities, interbank liabilities, securities, short-term securities, long-term securities, derivatives, and other non-core liabilities, respectively. These tables confirm that non-core sources that have shorter maturities, and are thus more prone to runs, are the key drivers of the relationship between monetary policy, bank funding shifts, and macro-financial instability.

The results presented in Table 7 are robust to different specifications and choices I have made in the process. In particular, Appendix Tables C36 and C37, which include time fixed effects, confirm that these findings are not driven by world shocks or other confounding factors. Moreover, considering non-core funding dynamics over a longer period of time (Appendix Table C38) and examining panic risk over a longer horizon (Appendix Table C39) corroborates the critical role of monetary-policy-induced shifts in bank funding for the buildup of financial vulnerabilities. Finally, in Appendix Table C40, I interact monetary policy shocks with time deposits. The results presented in this table align with (i) the argument that time deposits are at least partially obtained from institutional investors and as such a source of funding vulnerabilities and (ii) the finding that time deposits increase following contractionary policy shocks and prior to systemic instability episodes.

6 A verification at the bank level

My macro-financial dataset and instrumental variable approach enables me to identify 29,922 unique monetary policy shocks across 145 countries. However, the trilemma IV framework does not permit the identification of interest rate shocks within the U.S., which has never operated under a currency peg during the post-WWII period. Hence, $z_{US,t} = 0$ for all time periods covered by my macro-financial dataset. In this section, I adopt a more granular approach, zoom into two distinct periods of U.S. financial history, and verify my main empirical findings using U.S.-specific monetary policy shocks and bank-level data.

The National Banking era, spanning from the passage of the National Banking Acts of 1863 and 1864 to the eve of World War I, offers an ideal laboratory for studying how monetary policy affects the funding vulnerabilities of individual U.S. banks. The pre-WWI decades were a period of relatively free banking: regulation was light, banks were not influenced by (or in anticipation of) government intervention, and unit banking implied that banking markets were mostly local and independent (Carlson et al., 2022). Additionally, banking was not affected by different state regulations, and bank failures and panics remained a recurring phenomenon (Grossman, 1993). Here, I use the National Banks balance sheet data of Carlson et al. (2022), which covers all national banks between 1867 and 1904 (Carlson et al., 2022; Correia et al., 2023) at an annual frequency, and an identification of monetary policy shocks building on the trilemma of international finance.

Fast forward 100 years, with the Federal Reserve now established and Greenbook forecasts regularly published, I can exploit Call Reports data for U.S. commercial banks between 1976 and 2020 at a quarterly frequency, along with the monetary shock series constructed by Romer and Romer (2023), to conduct a similar analysis for a markedly different historical episode.

I describe these two bank-level datasets in Appendix B and illustrate them in Figure 6. The figure displays the ratio of non-core funding, as defined on page 1[18], to private deposits for the median bank as well as for banks at the 5^{th} and 95^{th} percentiles. Panel (a) illustrates that, during the National Banking era, non-core ratios peaked in the early 1890s, just before the 1893 panic, when "failures exceeded both in number and in the amount of liabilities those which had occurred in any other period of equal length in our history" (Sprague, 1910). During this period, the absence of regulatory policies such as nationwide deposit insurance allows us to identify the most turbulent financial market periods by examining the number of bank failures. Panel (b) highlights that bank failures have been far less frequent in recent decades.

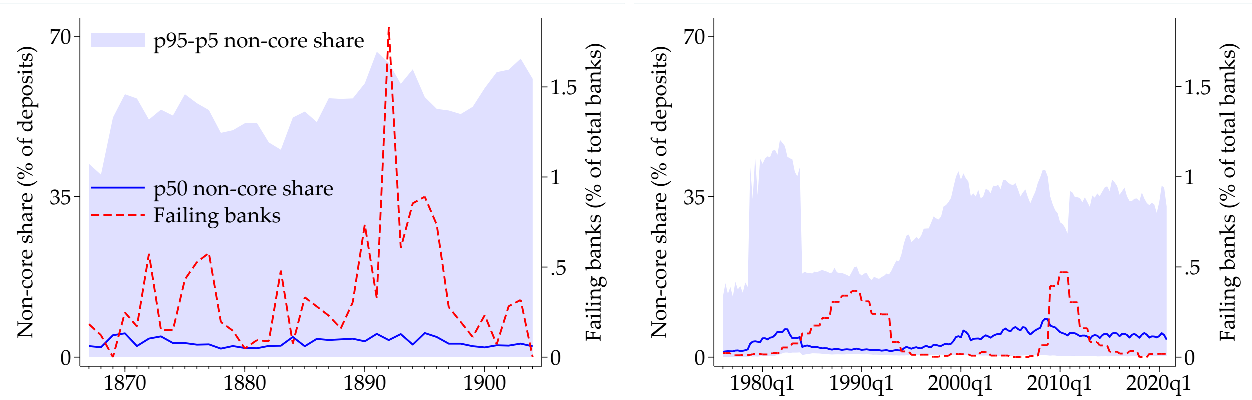
The bank-level effect of monetary policy I focus on the U.S. banking system to understand the effect of monetary policy on the structure of individual bank balance sheets by estimating once more a Jordà (2005) local projection,

$$\begin{aligned}\Delta_h \left(\log \frac{\textit{Non-core}}{\textit{Deposits}}\right)_{b,t+h} = {} & \alpha_b^h + \beta^h \, \Delta R_t + \sum_{k=1}^{4} \gamma_k^h \, \Delta R_{t-k} \\ & + \sum_{k=0}^{4} \delta_k^h \, \Delta \left(\log \frac{\textit{Non-core}}{\textit{Deposits}}\right)_{b,t-k} + \mathbf{\Gamma}^h \mathbf{X}_{b,t} + e_{b,t+h} \quad ,\end{aligned} \tag{6}$$

[18] For both datasets, Appendix B transforms this negative definition of non-core funding into a positive one.

Figure 6: *Non-core ratios and bank failures in the United States.*

(a) *1867–1904* (b) *1976–2020*



Notes: The left y-axes show the ratio between non-core funding and private deposits of the median bank (blue solid lines) and the banks at the 5^{th} and 95^{th} percentile (blue shaded areas). The right y-axes show the percentage of failing banks per year over time (red dashed lines). The data and the definition of non-core funding are explained in Appendix B.

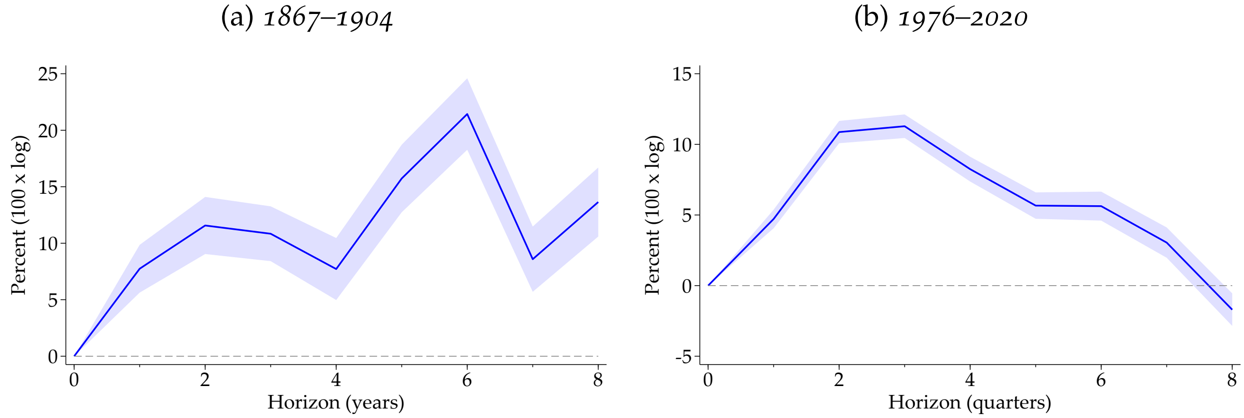
for both the National Banking era and the post-1975 period up to an horizon of 8 periods. α denotes bank-level fixed effects, and $\Delta_h \left(\log \frac{\textit{Non-core}}{\textit{Deposits}}\right)_{b,t+h}$ refers to the log growth in bank b's non-core ratio from t to $t+h$. The vector of control variables $\boldsymbol{X}$ includes lags 0 to 4 of one-period changes in the following log-transformed variables: real total assets, real total deposits, and real non-core funding. Additionally, $\boldsymbol{X}$ includes the log of real total assets as of period t, which serves as a proxy for bank size—a factor that can explain the magnitude of deposit outflows during systemic runs (Jamilov et al., 2024).

Before WWI period, "the influence of London on credit conditions throughout the world was so predominant that the Bank of England could almost have claimed to be the conductor of the international orchestra" (Keynes, 1930, p. 274). The U.S. return to the gold standard in 1879 thus meant that the U.S. had to follow the tune of the Bank of England, effectively pegging its currency to the pound sterling (Bloomfield, 1959; Obstfeld et al., 2005). I assume that the unpredictable component of the Bank of England's policy rate decisions was independent of macro-financial conditions in the U.S. at that time. Exploiting once more the trilemma of international finance, I instrument U.S. short-term market rates ΔR_t with Taylor rule residuals of U.K. monetary policy for the period 1879–1913.[19]

For the post-1975 data, ΔR refers to the Romer and Romer (2023) monetary policy shock

[19] Formally, I define U.K. Taylor rule residuals in year t as predicted values from OLS estimates of $\Delta R_{U.K.,t} = \alpha_{U.K.} + \sum_{k=1}^{4} \beta_k \Delta R_{U.K.,t-k} + \sum_{k=0}^{4} \boldsymbol{\Gamma}_k \mathbf{X}_{U.K.,t-k} + e_{U.K.,t}$. $\boldsymbol{X}$ includes annual changes in log consumer prices and log real GDP per capita. I assign the value 0 to the instrument for observations from the pre-1879 period.

Figure 7: *The bank-level effect of monetary policy on non-core ratios.*



Notes: 2SLS estimates (panel (a)) and OLS estimates (panel (b)) with 95% confidence intervals based on bank-based cluster-robust standard errors of model (6). In panel (a), ΔR refers to annual changes in U.S. short-term interest rates which I instrument with U.K. Taylor rule residuals. In panel (b), ΔR refers to Romer and Romer (2023) monetary policy shocks.

dummy. It equals +1 (–1) whenever the authors identify a contractionary (expansionary) shock based on their readings of the Minutes and Transcripts of Federal Reserve policy-making meetings.[20] Romer and Romer (2023) revisit and refine their earlier work on the narrative identification of monetary policy shocks and extend the sample period. To the best of my knowledge, no other existing U.S. monetary policy shock series spans a larger time frame.

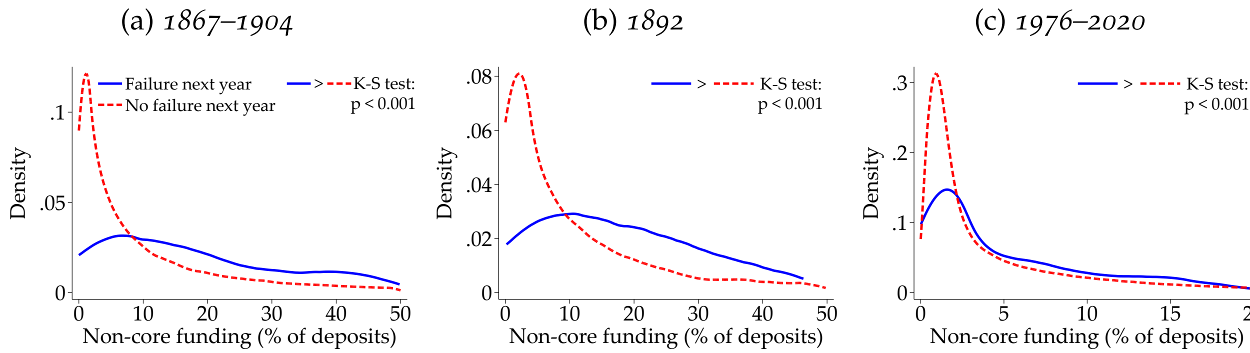
Figure 7 illustrates estimates of $\{\beta\}_{h=1}^{8}$. The estimates suggest that in both episodes, contractionary monetary policy leads to a higher share of funding through non-core sources in subsequent periods. For instance, panel (b) indicates that in the four quarters following a contractionary monetary policy shock, a bank's non-core-to-core ratio grows by 8.3%.

Non-core funding and bank failures Figure 8 highlights a key characteristic of failing banks; in the year preceding their failure, they rely more on non-core funding compared to surviving banks. The significant difference in the non-core funding ratio between surviving banks (red dashed lines) and failing banks (blue solid lines) is evident throughout the entire National Banking era (panel (a)), in the cross-section on the eve of the 1893 crisis (panel (b)), and after 1975 (panel (c)).

A formal regression framework eliminates concerns that this difference could be attributed to other factors such as common shocks, state-specific characteristics, bank size, or balance sheet growth. I evidence this in Table 8, which presents maximum likelihood

[20] I follow Romer and Romer (2023) and directly use the shock dummy in a reduced-form regression rather than using the dummy as an instrument for a quantitative measure of monetary policy.

Figure 8: *Distribution of bank-level non-core ratios of surviving and failing U.S. banks.*



Notes: The blue solid lines show distributions of non-core ratios of banks that fail in the following year (panels (a) and (b)) or in the following four quarters (panel (c)). The red dashed lines show distributions of non-core ratios of banks that do not fail in the following year (panels (a) and (b)) or in the following four quarters (panel (c)). *K-S test* refers to a one-sided Kolmogorov-Smirnov test. The alternative hypothesis is that the CDF of the distribution for failing banks is greater than the CDF of the distribution for surviving banks for at least one value.

estimates of the logistic model

$$\log\left(\frac{p_{b,\text{next year}}}{1-p_{b,\text{next year}}}\right) = \alpha_{state} + \alpha_{year} + \beta \log\left(\frac{\textit{Non-core}}{\textit{Deposits}}\right)_{b,t} + \boldsymbol{\Gamma}\,\boldsymbol{X}_{b,t} + u_{b,\text{next year}} \quad . \tag{7}$$

Here, $p_{b,\text{next year}}$ denotes the probability that bank b fails in the next year (when using the annual National Banking era data) or within the next four quarters (when using the quarterly Call Reports data). α_{state} are state-level fixed effects, and α_{year} are year fixed effects. I exclude bank-level fixed effects due to the incidental parameter problem (Neyman and Scott, 1948). $\boldsymbol{X}$ includes the same control variables as before.

The table shows that, in the cross-section, banks more exposed to non-traditional, market-based, risk-sensitive funding instruments are more susceptible to failure risk. Column (1) suggests that a 1 standard deviation growth of the non-core share predicts a 19 bps higher failure risk in the next year during the National Banking era. Column (2) confirms that this association remains significant after controlling for year fixed effects. The smaller point estimates in columns (3) and (4) must be interpreted in the context of the infrequent occurrence of bank failures in the U.S. in recent decades.

7 Model

7.1 Economy

I build on Drechsler et al. (2017) and consider a static model.

Table 8: *Predicting U.S. bank failures with non-core ratios.*

	1867–1904		*1976—2020*	
Dep. var.: Failure in next year	(1)	(2)	(3)	(4)
$\log\left(\frac{\text{Non-core}}{\text{Deposits}}\right)_{b,t}$	0.193***	0.162***	0.022***	0.011***
	(0.027)	(0.029)	(0.002)	(0.001)
Controls	✓	✓	✓	✓
State FEs	✓	✓	✓	✓
Year FEs	✗	✓	✗	✓
Banks	2890	2839	21499	21477
Observations	39058	34202	1093035	907650
# Bank failures	128	128	361	361

Notes: Maximum likelihood estimates of β with bank-based cluster-robust standard errors of model (7). The independent variables are normalized. The values represent estimates of marginal effects evaluated at the sample means of the covariates. *** $p < 0.01$.

Representative retail depositor A representative retail depositor can (i) invest in risk-free bonds at the policy rate r, (ii) deposit her money at rate $r - s$, and (iii) hold cash, which yields no nominal return. Here, s represents the deposit spread, defined as the difference between the policy rate and the deposit rate. The depositor maximizes her utility according to a CES aggregator. She derives utility from final wealth W and liquidity services ℓ. ρ refers to the elasticity of substitution between these two goods, which are complements such that $\rho \in (0, 1)$. $\lambda > 0$ denotes the relative utility the depositor obtains from liquidity services vis-à-vis final wealth. The depositor derives liquidity services from cash M and retail deposits D, also according to a CES aggregator, with ϵ denoting the elasticity of substitution between cash and deposits. Cash and deposits are substitutes, such that $\epsilon > 1$. The partial liquidity of deposits is captured by the parameter $\delta \in (0, 1)$. Final wealth equals the risk-free return the depositor obtains on initial wealth W_0 minus (i) the return r she forgoes on cash holding and (ii) the return s she forgoes on deposit holdings. Consequently, the problem of the representative retail depositor is

$$\max_{W,M,D} U(W, \ell) = \left(W^{\frac{\rho-1}{\rho}} + (\lambda\ell)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \quad s.t. \quad \ell(M, D) = \left(M^{\frac{\epsilon-1}{\epsilon}} + (\delta D)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \text{ and}$$
$$W = W_0(1 + r) - M\, r - D\, s \quad .$$

Representative bank A representative bank invests in perpetuities B at the risk-free rate r. It finances its long-term investments through deposits D and non-core funding H. $\frac{H}{D}$ serves as the theoretical counterpart to the *non-core ratio* analyzed empirically in the previous sections. If the bank is small relative to (international) capital markets, it can borrow non-core funding sources at a constant marginal cost. Historically, this assumption is common in banking models (Fama, 1985; Hannan and Berger, 1991). Evidence from the U.S. suggests that monetary tightening reduces the supply of retail deposits while increasing funding creation in money markets (Xiao, 2020; Afonso et al., 2023). If some of these funds are recycled back into banks as non-core funding, the marginal cost of non-core funding could even *decrease* with the policy rate. Taking a conservative stance and following Drechsler et al. (2017), I model the marginal cost of non-core funding as linearly increasing with the used quantity.[21] Hence, the bank's profit maximization problem is

$$\max_{s,H} \Pi = rB - \left(h_0 + \frac{h_1}{2}H\right) H - (r-s)D \quad s.t. \quad B = H + D \quad .$$

Here, $h_0 \in [0, r)$ and $h_1 > 0$ are technological parameters that can be interpreted as representing the banking system's capacity to produce non-core funding instruments.

7.2 Equilibrium

The first-order condition of the bank's problem with respect to H directly yields the equilibrium amount of non-core funding, $H^* = \frac{r-h_0}{h_1}$.

Drechsler et al. (2017) concentrate on the limit $\rho \to 1$ and show that, in this case, the equilibrium amount of retail deposits decreases as policy rates rise, i.e. $\frac{\partial D^*}{\partial r} < 0$. However, this conclusion only holds in the limit case $\rho \to 1$. As noted by Repullo (2020), when deviating from this limit case, the equilibrium response of deposits to policy rate changes becomes ambiguous. This ambiguity can be illustrated by deriving a closed-form expression for the equilibrium amount of deposits under two different sets of parameter specifications. If $\rho \to 0$ and $\epsilon = 2$[22],

$$D^* = \frac{(1+r)W_0}{\delta\lambda \left[2 + \sqrt{\frac{\lambda}{r+\lambda}} + \sqrt{\frac{\lambda+r}{\lambda}}\right]} \quad . \tag{8}$$

[21] In this environment, bank lending increases with rising interest rates. Drechsler et al. (2017) additionally model decreasing marginal returns on bank lending. Since my focus lies on the funding composition rather than on the response of total credit, I abstract from this aspect.

[22] Here, the depositor's demand for retail deposits and the profit-maximizing deposit spread are $D = \frac{r\delta W_0(1+r)}{(s^2+r\delta s)\left(1+\frac{\lambda}{r}+\frac{\lambda\delta}{s}\right)}$ and $s^* = r\delta\sqrt{\frac{\lambda}{\lambda+r}}$, respectively.

Here, the equilibrium amount of deposits is *rising* in the policy rate.[23] Similarly, if $\rho \to 0$ and $\epsilon \to \infty$,

$$D^* = \frac{(1+r)W_0}{\lambda + \delta r} \quad , \tag{9}$$

and the equilibrium amount of deposits is rising in the policy rate as soon as $\lambda > \delta$.

The relationship between the equilibrium amount of retail deposits and the policy rate can be positive because, in addition to the negative substitution effect emphasized by Drechsler et al. (2017)[24], there is also a positive income effect. When monetary policy tightens, the return on initial wealth W_0 increases. In response, the depositor raises her deposit balance. In equations (8) and (9), this positive income effect is captured by the numerators. When $\rho \to 0$, the depositor does not substitute from liquidity to bonds as policy rates rise. The absence of this substitution channel increases the bank's retail deposit franchise value. This allows the bank to extract more rent from the depositor by raising deposit spreads, as the opportunity cost of holding cash rise as soon as cash and deposits are substitutable to some degree ($\epsilon > 1$). The limit case—perfect substitutability between cash and deposits—illustrates this mechanism clearly; when $\epsilon \to \infty$, $s^* = \delta r$, leading to equation (9). This *rent extraction effect* is captured by the denominators of equations (8) and (9).

If retail deposit spreads did not respond to changes in the policy rate, the denominators would remain unaffected by policy rate changes. As a result, deposits would increase proportionally to wealth when policy rates rise, keeping the ratio between deposits D and non-core funding H constant. But equilibrium deposit spreads *do* respond to policy rate changes; $\frac{\partial s^*}{\partial r} > 0$. Consequently, the bank extracts part of the policy-tightening-induced rise in wealth. Whether deposits grow or shrink following a change in monetary policy depends on the model's parameters and is, ultimately, an empirical question that was addressed in the previous sections. However, due to the bank's capability to extract a positive amount of retail depositor wealth from any increase in the policy rate, we can make an unambiguous statement regarding the response of funding ratios to rising policy rates.

Implication 1. $\frac{\partial \frac{H^*}{D^*}}{\partial r} > 0$ *for both* $\rho \to 0$ *and* $\rho \to 1$.

[23] $\frac{\partial D^*}{\partial r} = \frac{\delta W_0(\zeta+\delta)(r\zeta+\lambda\zeta+\lambda\delta) - \delta W_0(1+r)\left[\frac{-\zeta}{2(r+\lambda)}(r\zeta+\lambda\zeta+\lambda\delta)+(\zeta+\delta)\left(\frac{-r\zeta}{2(r+\lambda)}+\zeta-\frac{\lambda\zeta}{2(r+\lambda)}\right)\right]}{[(\zeta+\delta)(r\zeta+\lambda\zeta+\lambda\delta)]^2}$ with $\zeta = \delta\sqrt{\frac{\lambda}{\lambda+r}}$. This expression is positive if $h(\lambda) := 2\lambda(\zeta+\delta)(r\zeta+\lambda\zeta+\lambda\delta) + 2r^2\zeta^2 + 2r\lambda\zeta^2 + 4r\delta\lambda\zeta + 2r\delta^2\lambda - \zeta\gamma r > 0$. Since $h(0) = 0$ and $\frac{\partial h(\lambda)}{\partial \lambda} > 0$, $h(\lambda) > 0 \; \forall \; \lambda > 0$.

[24] After showing that deposits decrease in the policy rate, the authors conclude: "When the central bank raises the Fed funds rate, cash becomes more expensive to hold, and this allows banks to raise deposit spreads without losing deposits to cash. Households respond by reducing their deposit holdings, and deposits flow out of the banking system and into bonds." (p. 1820)

Non-core funding makes up an ever-increasing share of total funding as policy rates rise, regardless of whether the substitutability between final wealth and liquidity services is high or low.

7.3 Bank failure equilibrium

I use the model to illustrate how non-core funding creates financial fragility in the presence of mark-to-market losses on long-term assets induced by tightening monetary policy.[25] While the representative retail depositor is insured or 'sleepy' (Hanson et al., 2015) and keeps her deposits in the bank regardless of the bank's fundamentals, non-core lenders are risk-sensitive and withdraw their funds as soon as they anticipate a collective withdrawal that would render the bank insolvent. Non-core lenders behave symmetrically, either remaining with the bank ($\theta = 0$) or running the bank by withdrawing all their funds ($\theta = 1$).

In this environment, an unexpected rise in the policy rate of size Δ has several effects on the mark-to-market valuation of the bank. On the asset side, the bank incurs mark-to-market losses on its long-term investments. On the liability side, there is a positive net inflow of non-core funding. Additionally, there is a net inflow of retail deposits, which may be positive or negative depending on the model parameters, as discussed earlier. Notably, the bank raises the deposit spread on retail deposits, which provides a partial, though incomplete, hedge against unexpected monetary tightening. Whether this hedge is sufficient to prevent run-induced failure critically depends on the share and behavior of the bank's non-core lenders. Consequently, the net present value of the remaining assets of the bank after the unexpected monetary tightening can be expressed as

$$A = \frac{1+r}{1+r+\Delta}B(r) + H(r+\Delta) - H(r) + D(r+\Delta) - D(r) - \theta H(r+\Delta) \quad .$$

Here, $D(r)$ and $H(r)$ denote equilibrium values of the two funding sources under the old interest rate regime while $D(r+\Delta)$ and $H(r+\Delta)$ refer to equilibrium levels after the unexpected policy rate change (the "*" is omitted for ease of exposition). $B(r)$ represents the amount of perpetuities the bank purchased before the interest rate shock. Similarly, the net present value of the remaining external liabilities of the bank is

$$L^{ex} = \frac{1}{1+r+\Delta}\left[(1+r+\Delta-s(r+\Delta))D(r+\Delta) + (1+h_0+\frac{h_1}{2}H(r+\Delta))(1-\theta)H(r+\Delta)\right] \quad .$$

Here, $s(r+\Delta)$ is the equilibrium deposit spread the bank charges after the central bank has

[25]This exercise is related to Jiang et al. (2023). However, Jiang et al. (2023) endogenize neither banks' funding mix nor banks' funding cost.

unexpectedly raised its rate. When $\Delta = 0$, i.e. in the absence of the interest rate shock,

$$A - L^{ex} = s(r)D(r) + \frac{(r - h_0)^2}{2h_1} > 0 \quad .$$

The bank is *solvent* due to its retail deposit franchise value (first term on right-hand side) and its positive net interest margin on non-core funding (second term). The bank is *insolvent*, and thus fails, if its assets A fall below its external liabilities L^{ex}. In the absence of a bank run, bank failure occurs if

$$s(r + \Delta)D(r + \Delta) + \frac{(r + \Delta - h_0)^2}{2h_1} < \Delta B(r) \quad . \tag{10}$$

The bank is insolvent if its available resources are insufficient to cover the mark-to-market losses on its long-term investments. A sufficiently high level of policy rates, a strong enough response of the equilibrium deposit spread to rising policy rates, and a relatively small unexpected rise in policy rates ensure that inequality (10) does *not* hold, allowing the bank to remain solvent and avoid failure.

If the sensitivity of retail deposit rates to policy rate changes is sufficiently low, the bank's profitability may even increase following monetary tightening. This study does not claim that rising policy rates *per se* increase financial vulnerabilities. In fact, the recent tightening cycle has coincided with surging bank profits (e.g., Bank of England, 2023; OCC, 2023; ECB, 2024), consistent with studies highlighting the positive effect of higher policy rates on banks' profitability and net worth (Samuelson, 1945; Borio et al., 2017; Heider et al., 2019; Ulate, 2021; Abadi et al., 2023; Eggertsson et al., 2024).[26] The empirical evidence presented above confirms that rising policy rates alone do not create instability risk. However, I find that tightening monetary policy increases the likelihood of systemic financial instability if it leads to a rise in the share of non-core funding.

To rationalize this finding, I consider now the scenario in which non-core lenders run the bank and withdraw all their funds after an unexpected hike in policy rates. A non-core run increases the likelihood of bank failure, as the bank loses the spread income derived from its non-core funding business. Consequently, $A < L^{ex}$ as soon as the bank's retail deposit franchise value under the new interest rate falls below the mark-to-market losses

[26] Samuelson (1945) argues that "a rise in interest rates hurts the banking system if the average time period of its inpayments exceeds that of its outpayments" (p. 24). He contends that this situation is unlikely since deposits are a stable funding source in the presence of deposit insurance. However, the post-1945 period saw a significant shift away from deposit funding (Jordà et al., 2021). This study argues that the time period of outpayments can decrease significantly as banks shift to uninsured, non-core funding sources, which are more sensitive to interest rate changes and risk perceptions.

on its long-term assets,

$$s(r+\Delta)D(r+\Delta) \; < \; \Delta B(r) \quad .$$

When policy rates rise, the deposit spread widens, providing a hedge against interest rate risk. Whether this hedge is sufficient to prevent an insolvency-inducing non-core run depends on the bank's reliance on non-core funding, which in turn fluctuates with the stance of monetary policy. In the absence of a run, the spread income from non-core funding also rises with policy rates. This heightened spread income incentivizes the bank to shift towards market-based debt as monetary policy tightens. However, it is precisely too high a reliance on non-core funding that creates run risk, which fully erodes the value of non-core funding. If non-core lenders run rather than stay after a monetary tightening, the spread income from non-core funding does not rise but instread drops to zero. The interest rate hedging quality of retail deposits arises from their insensity to risk, giving them an implicit long duration. Non-core funding, on the other hand, provides the weakest possible hedge against interest rate risk—its value becomes maximally risky precisely when interest rate risk materializes.

As a result, a 'good' equilibrium, in which no run occurs and the bank remains solvent, and a 'bad' equilibrium, in which non-core lenders run and the bank fails, co-exist if

$$s(r+\Delta)D(r+\Delta) \; \in \; \left[\Delta D(r) - \frac{(r-h_0)^2}{2h_1} - \frac{\Delta^2}{2h_1} \; , \; \Delta\frac{(r-h_0)}{h_1} + \Delta D(r)\right) \quad ,$$

which leads to a second implication.

Implication 2. *A non-degenerate interval in which both solvency and run-induced insolvency co-exist is possible if policy tightens ($\Delta > 0$) and the amount of non-core funding is positive ($H > 0$). This interval widens as r or Δ increases.*

This exercise underscores that while a bank's retail deposit franchise value acts a hedge against interest rate risk, protecting it against mark-to-market losses on long-term assets, the combination of contractionary monetary policy shocks and high and rising exposure to market-based funding erodes this protection, opening the door for run-induced bank failure.

8 Conclusion

The contribution of this study lies in the identification of a fundamental mechanism through which monetary policy shapes the stability of financial systems. Using novel macro-financial data and instrumental variable methods, I demonstrate that monetary policy impacts systemic financial risk by influencing the funding structure of banking systems.

Contractionary monetary policy leads to a shift toward non-traditional, market-based, risk-sensitive funding sources. High non-core funding ratios predict individual bank failures across two distinct periods of U.S. banking history. Policymakers cannot dismiss these failures as merely a disciplining mechanism for other financial institutions, since rising non-core ratios precede and predict systemic financial instability throughout time and space.

By integrating these results into a unified regression framework, I find evidence for a direct relationship that begins with a contractionary monetary policy shock, shifts the funding structure of banks toward market-based debt, and ultimately raises the likelihood of large-scale financial disruptions. The information contained in credit growth cannot explain these effects. Therefore, the way expansions are financed is crucial to understanding their broader consequences. I rationalize these findings within a model that emphasizes the destabilizing effect of monetary tightening in the presence of risk-sensitive and uninsured non-core investors.

The results of this study reaffirm the lessons drawn from the regional banking distress in the U.S. in 2023; a changing funding structure of the banking system is a source of financial instability during periods of sharp monetary contraction. My findings call for the implementation of well-considered macro-prudential policies that limit excessive non-core growth and internalize the negative externalities banks impose on the financial system by over-relying on non-core funding sources. This study suggests that such policies, as proposed after the Global Financial Crisis (Shin, 2011; IMF, 2011), can play a crucial role in enhancing financial system stability, especially during monetary tightening cycles.

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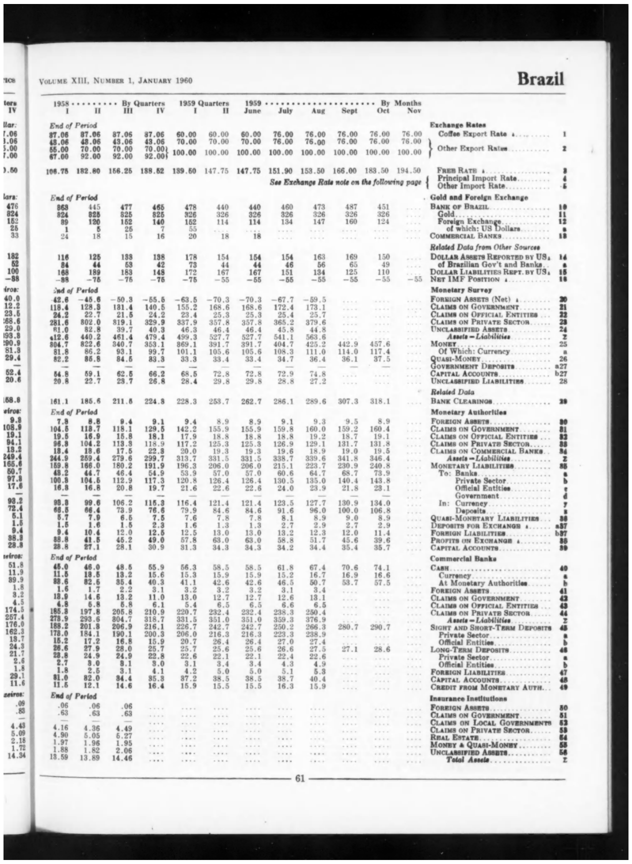
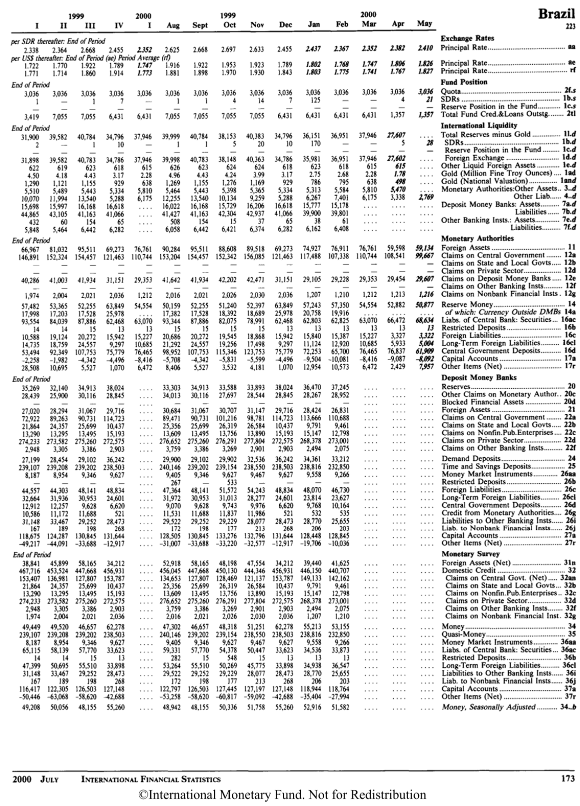
Appendices

Figure A1: *Examples of reported IFS bank balance sheet data.*

(a) *Brazil, 1960*



(b) *Brazil, 2000*



Sources: IMF (1960, p. 61) (left) and IMF (2000, p. 173) (right).

A Description of the new macro-financial dataset

A.1 The International Financial Statistics

The backbone of the new dataset constructed in this study are the International Financial Statistics (IFS), published by the IMF at monthly frequency since January 1948. The IFS, in turn, draw on various national sources, including Central Bank Bulletins, Statistical Office Bulletins, and Central Bank Monthly and Annual Reports.

The IFS reported no data on banks' liability positions in the late 1940s and early 1950s. Information on the liability composition of banks began to emerge in the mid-1950s, with the precise starting date varying across countries, and became more comprehensive and detailed over time. Similarly, data on different types of interest rates were scarce in the immediate post-WWII years but became more extensive as time progressed.

Scanned versions of a fraction of the IFS reports are available online, though the majority

Figure A2: *Examples of reported IFS interest rate data.*

Brazil, 1960

End of Period												**Interest, Prices, Production**	
6.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	**REDISCOUNT RATE**	60

Brazil, 2000

Interest Rates																*Percent Per Annum*
Discount Rate *(End of Period)*	**60**	....	....	....	25.34	45.09	39.41	21.37	23.87	23.58	23.58	45.09	38.54	29.41	42.34	39.41
Money Market Rate	**60b**	3,284.44	4,820.64	53.37	27.45	25.00	29.50	26.26	22.13	21.22	20.89	35.77	33.28	22.93	24.62	37.18
Treasury Bill Rate	**60c**	....	....	49.93	25.73	24.79	28.57	***26.23***	22.09	21.55	21.49	34.04	34.01	23.13	....	....
Treasury Bill Rate (Fgn.Currency)	**60c.f**	....	....	17.78	15.13	11.60	15.04	....	11.42	11.38	10.29	13.29	14.85	13.92	15.78	15.59
Savings Rate	**60k**	2,743.33	4,206.04	40.26	16.39	16.62	14.48	12.31	15.12	14.57	14.66	22.14	17.31	12.35	12.16	16.12
Deposit Rate	**60l**	3,293.50	5,175.24	52.25	26.45	24.35	28.00	26.02	22.86	21.08	20.79	32.67	32.27	22.65	23.78	33.31

Sources: IMF (1960, p. 63) (top) and IMF (2000, p. 174) (bottom).

Figure A3: *Example of IFS Country Notes: Banking variables.*

Deposit Money Banks: Comprises commercial banks and other monetary institutions. Other monetary institutions include the major savings bank and accounts of the postal checking system. Excluded accounts of small savings banks, which are only available annually, are minor.

I Beginning December 1987, the accounts of the deposit money banks exclude the accounts of their nonresident branches.

I Through December 1990, deposit money banks' claims on other banking institutions and local governments are included in *Claims on Private Sector (line 22d)*. The accounts of the deposit money banks were completely restructured from January 1991. I From June 1991, the accounts of the deposit money banks include the postal giro system.

Source: IMF (2000, p. 270) (Country Notes for Denmark).

of reports only exist as physical copies. Figure A1 illustrates the structure of the IFS reports for one country, Brazil, at two points in time: 1960 and 2000. The *Commercial Banks* section in the 1960 report and the *Deposit Money Banks* section in the 2000 report list the available bank balance sheet variables at annual, quarterly, and monthly frequencies. Information on interest rates is reported on a different page, as shown in Figure A2.

A subset of the raw data reported in the IFS is available online.[27] Using this raw data as a starting point, I apply a three-step procedure, outlined below, to obtain a final, harmonized, and break-adjusted dataset. I trim all variables in this final dataset at the 0.1^{th} and 99.9^{th} percentiles, and use all remaining observations in the empirical analysis.

Step I: Cleaning of already digitized raw data Figure A1 exemplifies how the IFS presentation of bank balance sheet items changes over time. For instance, the January 1960

[27] See `https://data.imf.org/ifs`. This data was originally collected on CD-ROMs.

Figure A4: *Example of IFS Country Notes: Interest rates.*

Interest Rates: All rates are converted into annual rates by compounding the simple arithmetic averages of the monthly rates applicable on each day in the month.

Discount Rate: Average rate on monetary loans offered by tender by the Bank of Israel to commercial banks. Prior to October 1987, the maximum rate charged by the Bank on discount window loans to commercial banks. Prior to September 1983, this was a single rate.

Treasury Bill Rate: Yield to maturity on short-term treasury bills.

Deposit Rate: Average rate offered by commercial banks on all short-term deposits up to one year. Prior to September 1988, the rate offered by commercial banks on 14-day fixed deposits of NIS 20,000 was used.

Lending Rate: Average effective cost of all unindexed credit in Israeli currency, including overdraft credit. Prior to January 1989, the average rate charged by commercial banks on overdrafts.

Source: IMF (2000, p. 421) (Country Notes for Israel).

Report lists the two categories *SIGHT AND SHORT-TERM DEPOSITS* and *LONG-TERM DEPOSITS*, which are further divided into *Private Sector* and *Official Entities*. The July 2000 Report, however, lists the positions *Demand Deposits*, *Time and Savings Deposits*, and *Central Government Deposits*. In the late 1990s and early 2000s, the bank balance sheet data changed from a "old presentation" format to a "new presentation" format, with the exact timing varying across countries. Changes in data presentation necessitate careful alignment of the old-presentation variables and new-presentation variables. Sometimes, these changes create breaks, which are documented in the *Country Notes*. Below, I explain how I address these breaks.

The raw data, initially collected on CD-ROMs and now available online, assigns codes to each variable. These codes differ between the old and new presentation formats for the bank balance sheet variables. In Table A1, I document how I transform the raw IFS data into the final bank balance sheet variables shown in Tables 1 and 2. Table A1 is not an exhaustive list of bank balance sheet positions reported in the IFS. I have combined some positions; for instance, for some countries, there is a distinction between *Securities other than Shares Included In Broad Money* and *Securities other than Shares Excluded from Broad Money* which I group together under the *Securities* position in Table 1.

All countries except for the U.S. report bank balance sheet data on a monthly basis. The U.S., however, reports this data only at the quarterly level. To create monthly time series from this quarterly data, I linearly interpolate the bank balance sheet data (and only bank balance sheet data) for the U.S. (and only for the U.S.).

Table A1: *Transformation of IFS variables into final variables.*

Final variable	IFS variable codes Old presentation	New presentation
Total Assets	20RA	FODA
Private Credit	22D	FOSAOP
Claims on Public Corporations	22C	FOSAON
Foreign Claims	21	FOSAF
Claims on Central Bank (Reserves)	20C+20	FOSAAR+FOSAAC
Claims on Central Bank (Other)	20N	FOSAAO
Claims on Government	22A+22B+22BX	FOSAG+FOSAOG
Claims on Other Financial Inst.	22G+22F	FOSAOF
Demand Deposits	24	FOST
Time Deposits	25	FOSD
Foreign Liabilities	26C+26CL	FOSLF
Liabilities to Central Bank	26G	FOSLA
Liabilities to Government	26D+26DA+26DG+26F+25A	FOSLG
Liabilities to Other Financial Inst.	26J+26I	FOSDX
Securities	26AA+26AB	FOSS + FOSSX
Loans	Not available	FOSL
Derivatives	Not available	FOSFD
Insurance Technical Reserves	Not available	FOSI
Capital	27A	FOSE
Other (net)	27R	FOSO
Consumer Price Index	PCPI_IX	
Exchange rate vis-à-vis USD	ENDE_XDC_USD_RATE	
Gross Domestic Product	NGDP_NSA_XDC	

Step II: Digitization of additional IFS print versions The online-available raw data is incomplete, with a significant gap in bank balance sheet data for Euro Area countries during the late 1990s and early 2000s, spanning several years. To address this issue, I used physical copies of the IFS reports and state-of-the-art text digitization methods (Correia and Luck, 2023) to extend the IFS coverage back to the beginning of 1999. This effort produces a dataset that encompasses, for some variables, more than 100,000 observations. I would like to emphasize that I did *not* digitize additional pre-1999 bank balance sheet data. Scanning and digitizing *all* monthly pre-1999 IFS reports would require substantial effort, with limited benefits for this study. Much of the pre-1999 bank balance sheet data is already available on CD-ROMs and used in the empirical analysis of this study. Missing pre-1999 data usually concerns policy rates rather than bank balance sheet data. I have, therefore, focused on digitizing additional policy rate data, as documented in part A.2.

Step III: Identification of breaks The time series of the bank balance sheet positions are subject to infrequent breaks. These breaks occur for various reasons, such as the inclusion of savings banks or other institutions, the reclassification of certain balance sheet items, or the implementation of an improved sectorization of accounts. Although breaks are rare, ignoring them renders the raw IFS data practically unusable.

Fortunately, the *Country Notes* of the various IFS reports document the precise month of *each* break. These reports document breaks in all data series over the last years. Figure A3 provides a scan of the Country Notes for Denmark's banking sector variables from the July 2000 IFS report, and Figure A4 shows an example of documented breaks in interest rate variables.

I have meticulously identified all breaks in all IFS series used throughout this study and excluded from my empirical analysis any observations characterized by a break, regardless of its source.[28] Here, the advantage of my dataset becomes apparent: because my dataset is monthly, and breaks are identified at the monthly level, excluding break-affected variables impacts only a small portion of the final dataset.

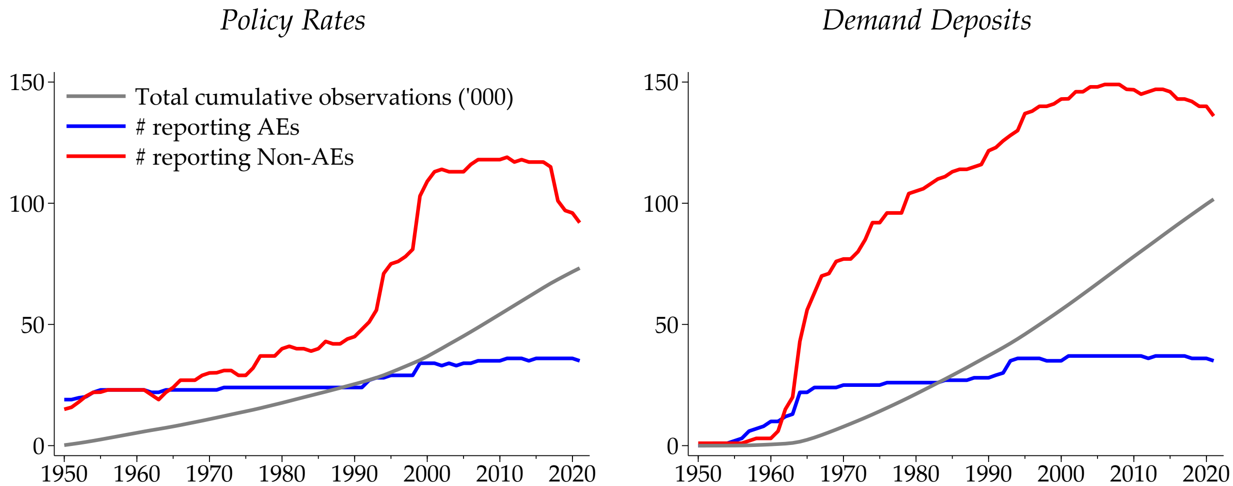
Data overview Table 1 of the main text presents a stylized balance sheet of the banking system, along with the number of available observations for each balance sheet item.

Figure A5 illustrates the unbalanced nature of the final dataset for two key variables of my empirical analysis—policy rates (panel (a)) and demand deposits (panel (b)).

One of the balance sheet items is *Private Credit*. There is nothing peculiar about the *Private Credit* data in the IFS; as with the other balance sheet items, I applied the three-

[28]To be clear, as for the bank-level data, when I consider the growth rate of or change in a variable from period t to period $t+h$, I exclude corresponding observations as soon as there is a break between t and $t+h$.

Figure A5: *Overview of data availability for policy rates and demand deposits.*



step procedure outlined above to obtain cleaned and harmonized time series for all 190 countries. Dynamics of credit aggregates are not the primary focus of this paper.[29] However, information on bank lending has been gathered in several other studies, which allows me to compare my *Private Credit* series with existing ones compiled from other sources. Does the carefully implemented three-step procedure yield data series that align with those from existing studies? Figure A6 shows that the answer is 'yes'. The figure plots time series of log-transformed bank credit to the private sector for the largest economies on each continent[30] in local currency[31] and compares this data with that collected in four other studies. For each country shown in the figure, the data series closely overlap. The newly created monthly bank credit data from this study aligns with the quarterly data from Dembiermont, Drehmann, and Muksakunratana (2013), Monnet and Puy (2021), and Müller and Verner (2023), and with the annual data from Jordà, Schularick, and Taylor (2017). One clarification for the Euro Area countries is necessary. For those countries, two different sets of statistics are reported: one based on a euro-area-wide residency criterion and another based on a national residency criterion.[32] The IFS provide a more detailed

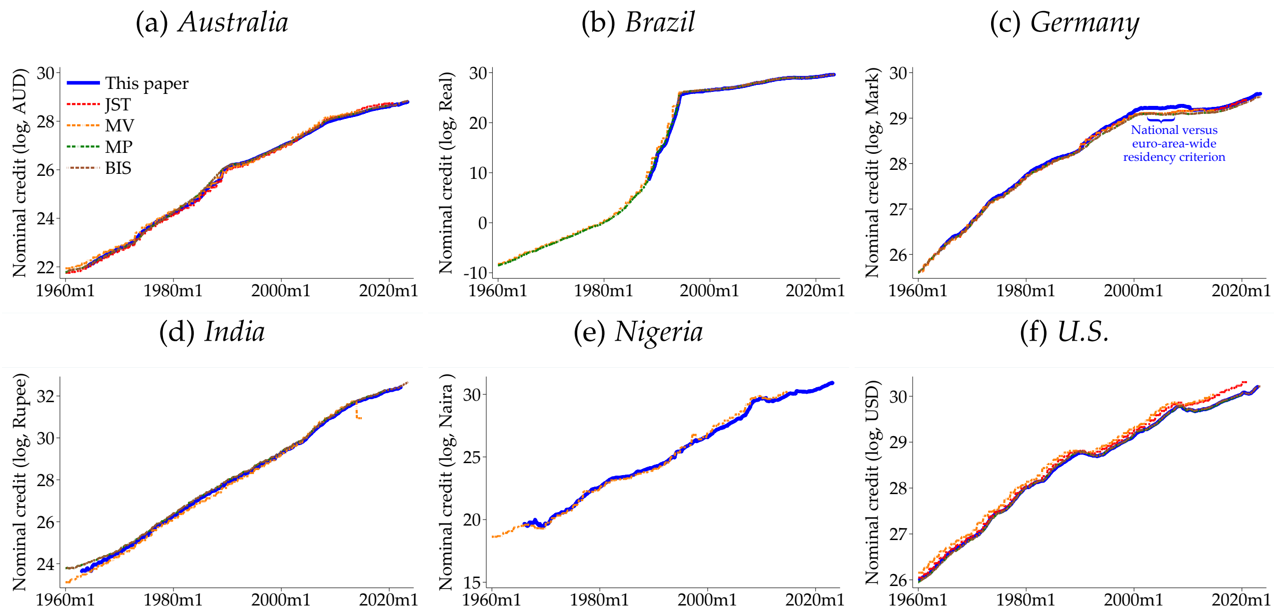
[29]It is nevertheless worthwhile to notice that, to the best of my knowledge, no other dataset on bank credit covers as many countries over such an extended period at a monthly frequency as the dataset used in this study.

[30]The International Financial Statistics for Russia are only available from 1992 onwards. Hence, I show data for Germany.

[31]All balance sheet data is in local currency. I have converted euro-denominated data to local currencies using the exchange rates listed in IMF (2023b).

[32]"In the application of the euro area-wide residency criterion, all institutional units that are resident in the euro area (but not necessarily in the same country) are treated as domestic residents, while all units outside the euro area are treated as nonresidents. For example, claims on government under the national residency criterion include only claims on the government of the same country, whereas claims on government under the euro area-wide residency criterion include claims on the governments of all euro area countries." (IMF,

Figure A6: *Private credit: comparison with other datasets.*



Notes: Log-transformed private credit data from the new dataset constructed in this study (blue), Jordà, Schularick, and Taylor (2017) (red), Müller and Verner (2023) (orange), Monnet and Puy (2021) (green), and the BIS Credit Database (Dembiermont, Drehmann, and Muksakunratana, 2013) (brown).

decomposition of banks' balance sheets for the euro-area-wide residency criterion. For this reason, I use the euro-area wide residency criterion for the Euro Area countries. This decision explains the small discrepancy in the time series of private credit for Germany illustrated in panel (c) of Figure A6.

A.2 Additional policy rate data

I fill policy rate data consecutively from the following IFS variables and secondary sources. Whenever the underlying source of the final policy rate variable changes, I flag the observation as a break observation, as in the IFS data outlined above.

1. I use the IFS Monetary Policy-Related Interest Rate data (IFS code FPOLM_PA). As outlined in IMF (2023a, p. 23), the "Central Bank Policy Rate is the target rate used by the central bank to conduct monetary policy. The monetary policy instrument varies across countries and is described in the Country Notes."

2. If data is still missing, I use the IFS Discount Rate data (IFS code FID_PA).

2023a, p. 19)

Figure A7: *Example of central bank discount rates reported by the Bundesbank.*

7. Central Bank discount rates in foreign countries *)

Country	Rate on 31 December 1969: % p. a.	Rate on 31 December 1969: Applicable from	Previous rate: % p. a.	Previous rate: Applicable from
I. European countries				
1. EEC member countries				
Belgium-Luxembourg	7 1/2	18 Sep. '69	7	31 July '69
France	8	9 Oct. '69	7	13 June '69
Italy	4	14 Aug. '69	3 1/2	7 June '58
Netherlands	6	4 Aug. '69	5 1/2	9 Apr. '69
2. EFTA member countries				
Austria	4 3/4	11 Sep. '69	3 3/4	27 Oct. '67
Denmark	9	12 May '69	7	31 Mar. '69
Norway	4 1/2	27 Sep. '69	3 1/2	14 Feb. '55
Portugal	2 3/4	8 Jan. '69	2 1/2	1 Sep. '65
Sweden 1)	7	11 July '69	6	28 Feb. '69
Switzerland	3 3/4	15 Sep. '69	3	10 July '67
United Kingdom	8	27 Feb. '69	7	19 Sep. '68
3. Other European countries				
Finland	7	28 Apr. '62	8	30 Mar. '62
Greece	6 1/2	15 Sep. '69	6	1 July '69
Iceland	5 1/4	1 Jan. '66	5	1 Jan. '65
Spain	5 1/2	22 July '69	4 1/2	27 Nov. '67
Turkey	7 1/2	1 July '61	9	29 Nov. '60

Country	Rate on 31 December 1969: % p. a.	Rate on 31 December 1969: Applicable from	Previous rate: % p. a.	Previous rate: Applicable from
II. Non-European industrial countries				
Canada	8	16 July '69	7 1/2	11 June '69
Japan	6.25	1 Sep. '69	5.84	7 Aug. '68
New Zealand	7	23 Mar. '61	6	19 Oct. '59
South Africa	5 1/2	27 Aug. '68	6	8 July '66
United States 2)	6	4 Apr. '69	5 1/2	18 Dec. '68
III. Non-European developing countries				
Ceylon 3)	5 1/2	May '68	5	28 May '65
Chile	19.09	1 Jan. '69	16.61	1 Jan. '68
Colombia	8	30 Apr. '63	7	11 Mar. '63
Costa Rica	5	Sep. '66	4	1 July '64
Ecuador	5	22 Nov. '56	6	19 July '51
El Salvador	4	24 Aug. '64	6	24 June '61
Ghana	5 1/2	30 Mar. '68	6	8 May '67
India	5	4 Mar. '68	6	17 Feb. '65
Iran	8	7 Aug. '69	7	26 Nov. '68
Korea, South	23	1 Oct. '68	21	1 Mar. '68
Nicaragua	8	4 Feb. '65	6	1 Apr. '54
Pakistan	5	15 June '65	4	15 Jan. '59
United Arab Republic (Egypt)	5	15 May '62	3	13 Nov. '52

* Discount rates applied by central banks in transactions with commercial banks; excluding special terms for certain finance transactions (e. g., rediscount of export bills). — 1 Discount rate of the central bank in transactions with non-banks. Since 5 June 1952 the rate governing transactions with banks has been currently adapted to market conditions. — 2 Discount rate of the Federal Reserve Bank of New York. — 3 Rate for advances against government securities.

Source: Bundesbank (1970, p. 45).

3. If data is still missing, I use the IFS Refinancing Rate data (IFS code FIR_PA).

4. If data is still missing, I use the IFS Central Bank Borrowing Facility Rate data (IFS code FIBFR_PA).

5. If data is still missing, I use data from the BIS central bank policy rates database.[33]

6. For a handful of countries, I have found new central bank policy rate data. If data is still missing, I use such information from national central bank documents. I outline the precise sources below.

7. If data is still missing, I use the central bank discount rate data from the German central bank's monthly reports. Starting with Bundesbank (1956, p. 88), the statistical appendices of these reports contain this information for various countries. I show an example of the reported data in Figure A7.

Austria. I have collected monthly data for the central bank discount rate from April 1945 to December 1998 from Oesterreichischen Nationalbank (1999, p. 23*)

[33] https://data.bis.org/topics/CBPOL.

Finland. Here, I have filled gaps in the policy rate series by digitizing data on the base rate of interest applied by the Bank of Finland from January 1950 to December 1998 from various Year Books of the Bank of Finland, which are available online on the website of the Bank of Finland.[34]

Greece. I have extended the policy rate data using the series *Interest rates and volumes of monetary policy operations – Standing Facilities Interest Rates before the Bank of Greece joined the Eurosystem – Overnight Deposit Facility Tranches - Basic Tranche* documented on the website of the Bank of Greece for the period 1997M3–2000M12.[35]

Norway. If the above-outlined sources contain gaps, I use data on end-of-month Norges Bank's discount rates from Eitrheim and Klovland (2007), which covers the full post-WWII period until the end of 1986.

A.3 Secondary data sources

Table 2 in the main text lists secondary data sources that complement the new macro-financial dataset in the empirical analysis.

To identify periods of large-scale financial disruptions, I exploit existing historical chronologies of systemic financial instability events. These chronologies are typically available only at an annual frequency (e.g., Reinhart and Rogoff, 2009; Jordà, Schularick, and Taylor, 2017). Laeven and Valencia (2020) also construct a narrative chronology of the starting year of banking crises for the period 1970–2017. However, in their Appendix, they additionally identify the precise starting *month* for a subset of these banking crises. I combine my dataset with this monthly crisis chronology, assuming that crises start in January when Laeven and Valencia do not identify the precise starting month. Baron, Verner, and Xiong (2021) provide an alternative chronology of systemic financial instability events, focusing on narratively identified banking panics. Their database documents the starting months of banking panics for 46 countries from 1870 to 2016. Taiwan is part of the database of Baron, Verner, and Xiong (2021) but not of the IFS. Hence, as reported in Table 2, I use the information on the onset of banking panics for 45 countries.

The construction of the trilemma IV, described in Section 3.2, requires information on countries' degree of capital account openness. I obtain this information from the indices constructed by Chinn and Ito (2006) and Quinn, Schindler, and Toyoda (2011). I use the Quinn-Schindler-Toyoda Index whenever the Chinn-Ito Index is unavailable. The Chinn-Ito

[34] https://www.suomenpankki.fi/en/media-and-publications/publications/annual-report/.
[35] https://www.bankofgreece.gr/en/statistics/financial-markets-and-interest-rates/interest-rates-and-volumes-of-nonetary-policy-operations.

Index starts in 1970. The Quinn-Schindler-Toyoda Index enables me to define the trilemma IV for the pre-1970 period as well. Quinn, Schindler, and Toyoda (2011) and Chinn and Ito (2006) sometimes disagree on a country's degree of capital account openness, which could create a break in the final combined index when switching from the Quinn-Schindler-Toyoda Index to the Chinn-Ito Index. Such breaks do not create issues for constructing the trilemma IV. The two indices are only available at an annual frequency. I assign the index values to all months within a given year. This procedure is reasonable since changes in *de-jure* capital account restrictions tend to be slow-moving.

The construction of the trilemma IV also requires information on countries' exchange rate classification and the anchor currency of pegging countries. Here, I use the monthly datasets constructed by Ilzetzki, Reinhart, and Rogoff (2019, 2022). Ilzetzki, Reinhart, and Rogoff provide a granular classification of exchange rate regimes. They define 14 different exchange rate arrangements, ranging from hard pegs to free floats. I transform this granular classification into a binary variable by defining exchange rate regimes as *fixed* when Ilzetzki, Reinhart, and Rogoff classify them as (i) *No separate legal tender or currency union*, (ii) *Pre announced peg or currency board arrangement*, (iii) *Pre announced horizontal band that is narrower than or equal to* $\pm 2\%$, (iv) *De facto peg*, (v) *Pre announced crawling peg; de facto moving band narrower than or equal to* $\pm 1\%$, or (vi) *Pre announced crawling band that is narrower than or equal to* $\pm 2\%$ *or de facto horizontal band that is narrower than or equal to* $\pm 2\%$. I have verified that the empirical results of this study do not depend on the precise threshold I choose. In particular, when I also classify the regimes (vii) *De facto crawling peg*, (viii) *De facto crawling band that is narrower than or equal to* $\pm 2\%$, and (ix) *Pre announced crawling band that is wider than or equal to* $\pm 2\%$ as pegging, as done by Jordà, Schularick, and Taylor (2020a), the results remain similar. However, these intermediate regimes often do not react to base country rate changes within the same month, reducing the strength of my instrument. For this reason, I only include countries with a stricter peg in my treatment group. In line with Jordà, Schularick, and Taylor (2020a), I assume that eurozone countries (with the exception of Germany) have a hard peg vis-à-vis Germany. The assumption that Germany acts as the base country for the other eurozone countries is supported by evidence indicating that at least until the Global Financial Crisis, "the ECB followed Germany's "Taylor rule" with a remarkable degree of precision" (Ilzetzki, Reinhart, and Rogoff, 2019, Appendix 5; also see Smant, 2002). A robustness check on page 19 of the main text confirms that rejecting the assumption that eurozone countries have a hard peg vis-à-vis Germany does not significantly affect the main results.

Table 2 shows that all these secondary data sources cover a large number of countries over an extended period of time, similar to my newly constructed macro-financial dataset.

B Description of the bank-level data

B.1 National Banking era data

Carlson, Correia, and Luck (2022) have digitized balance sheet data of *all* national banks for the period from 1867 to 1904 at annual frequency. The authors have kindly made their dataset publicly available.[36] Carlson, Correia, and Luck (2022) and Correia and Luck (2023) document this dataset in more detail. Given the bank balance sheet variables of this dataset, I transform the negative definition of non-core funding provided on page 1 of the main part into a positive one. Here, I define non-core funding as the sum of the following liability positions: *Due to national banks*, *Due to state banks and bankers*, *Due to trust companies and savings banks*, *Due to approved reserve agents*, *Notes and bills rediscounted*, *Bills payable*, and *Liabilities other than those stated above*. The data also contains information on bank failures, defined as the year in which the bank was placed in receivership. The sample consists of $110,965$ observations and $7,109$ banks.

I trim all first-differenced variables and growth rates at the 0.5^{th} and 99.5^{th} percentiles. Whenever one of the above-listed non-core items is missing in year $t+k-1$ and non-missing in $t+k$ or vice versa for a bank, I ignore growth rates and changes in a variable from t to $t+h$ for that bank in the empirical analysis if $h \geq k$.

I construct real variables based on annual CPI data from the Macrohistory Database (Jordà, Schularick, and Taylor, 2017).[37] Annual data on short-term interest rates, which I denote as R in the main text, and real GDP per capita also come from this database.

B.2 Post-1975 data

I source quarterly bank-level data, including information on bank failures, from the U.S. Commercial Bank Call Reports. The Wharton Research Data Services (WRDS) provides these Call Reports for the period from 1976Q1 to 2020Q4. As with the National Banking era data and the macro-financial data, the Call Reports allow for the transformation of the negative definition of non-core funding provided on page 1 into a positive one. Accordingly, I define non-core funding as the sum of the following items: *Federal funds purchased and securities sold under agreements to repurchase*, *Trading liabilities*, *Subordinated notes and debentures*, *Other borrowed money*, *Deposits of commercial banks and other depository institutions in the U.S.*, *Deposits of banks in foreign countries*, and *Other liabilities*. Table B1 lists the corresponding codes of these variables, as well as the codes for other variables used in the empirical

[36] https://scorreia.com/data/call-reports.html.

[37] https://www.macrohistory.net/database/.

Table B1: *Transformation of Call Report variables into final variables.*

Final Variable	Variable Codes
Federal funds purchased and securities sold under agreements to repurchase	RCON2800 (RCONB993+RCONB995 if missing)
Trading liabilities	RCON3548
Subordinated notes and debentures	RCON3200
Other borrowed money	RCON3190 (RCON2850 if missing)
Deposits of commercial banks and other depository institutions in the U.S.	RCON2188+RCON2189 (RCON2660 if missing)
Deposits of banks in foreign countries	RCON2190 (RCON2660 if missing)
Other liabilities	RCON2930
Private deposits	RCON2615 (RCON2187 if missing, RCONB549+ RCONB550 if still missing)
Total Assets	RCON2170
Total Deposits	RCON2200

analysis.[38] The sample consists of $1,939,187$ observations and $24,045$ banks.

I trim the variables and handle missing values in the same way as with the National Banking data. I exclude a few dozen balance sheet variables with negative entries, assuming they are errors. This issue does not arise in the National Banking era data.

I construct real variables based on quarterly CPI data.[39] Quarterly U.S. policy rates, which I denote in the main text as R, come from my new dataset outlined in Section 2 and Appendix A.

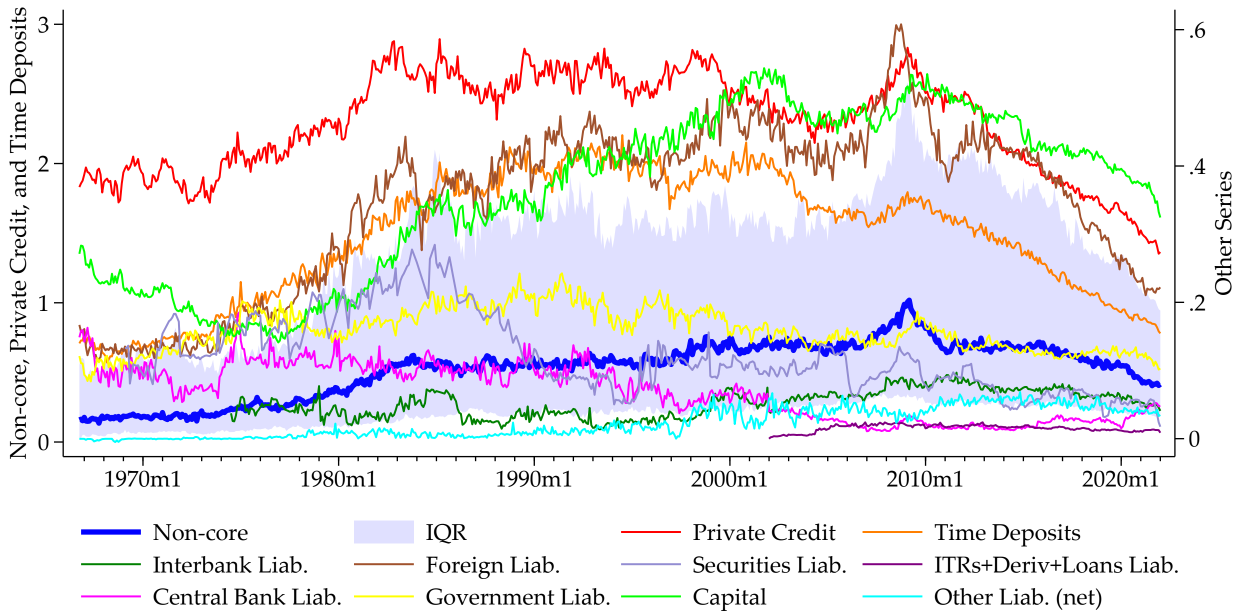
[38] *RCON* refers to domestic data. When domestic data is not available, I use consolidated data, denoted as *RCFD*.

[39] https://fred.stlouisfed.org/series/USACPALTT01IXNBQ.

C Figures and Tables

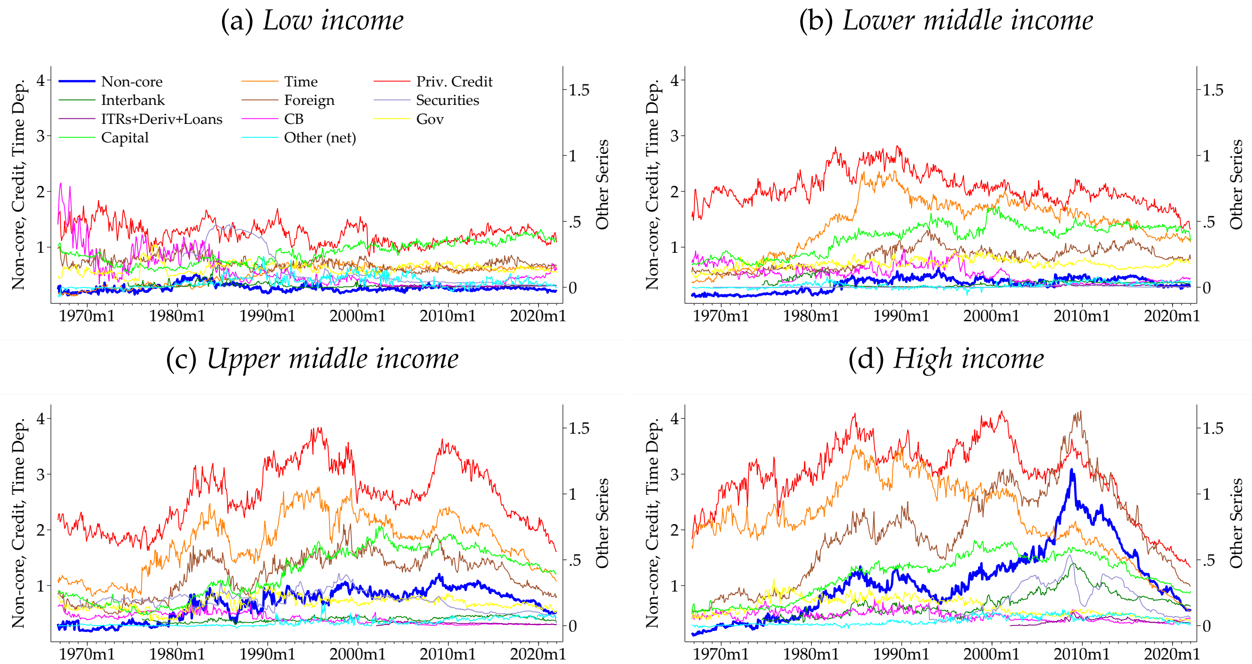
C.1 Appendix Figures

Figure C1: *Balance sheet positions over time.*



Notes: The Figure shows the ratio of non-core funding to demand deposits (blue line), the ratio of private credit to demand deposits (red line), and the ratios of those liability positions listed in Table 1 to demand deposits (other lines) for the median country over time. *ITRs+Deriv+Loans* refers to the sum of the following three liability positions: Insurance Technical Reserves, Derivatives, and Loans. The blue-shaded area shows the interquartile range of the ratio of non-core funding to demand deposits. *Non-core* is defined in Definition 1.

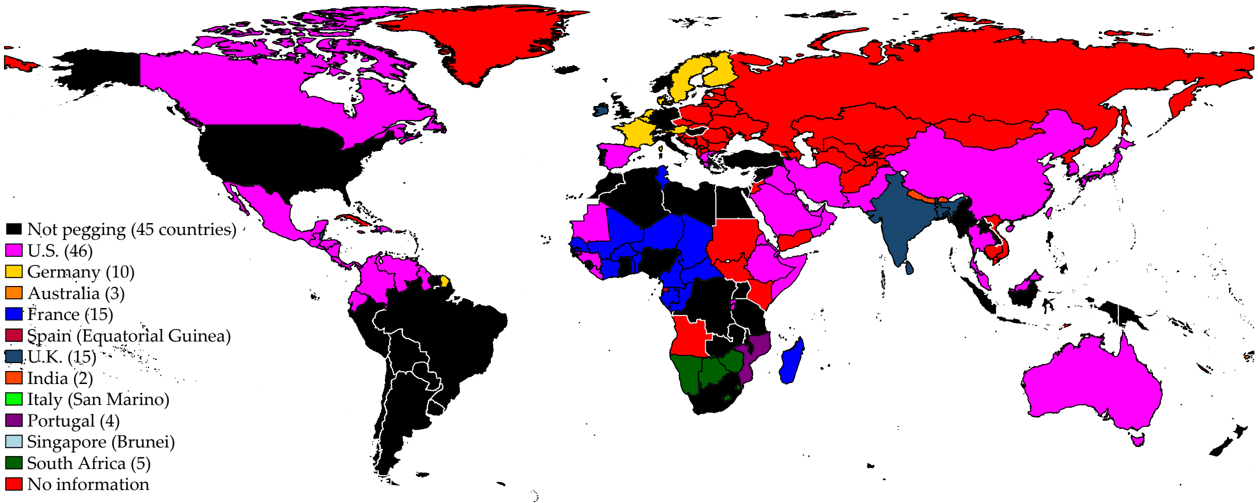
Figure C2: *Funding of the median country over time by income group.*



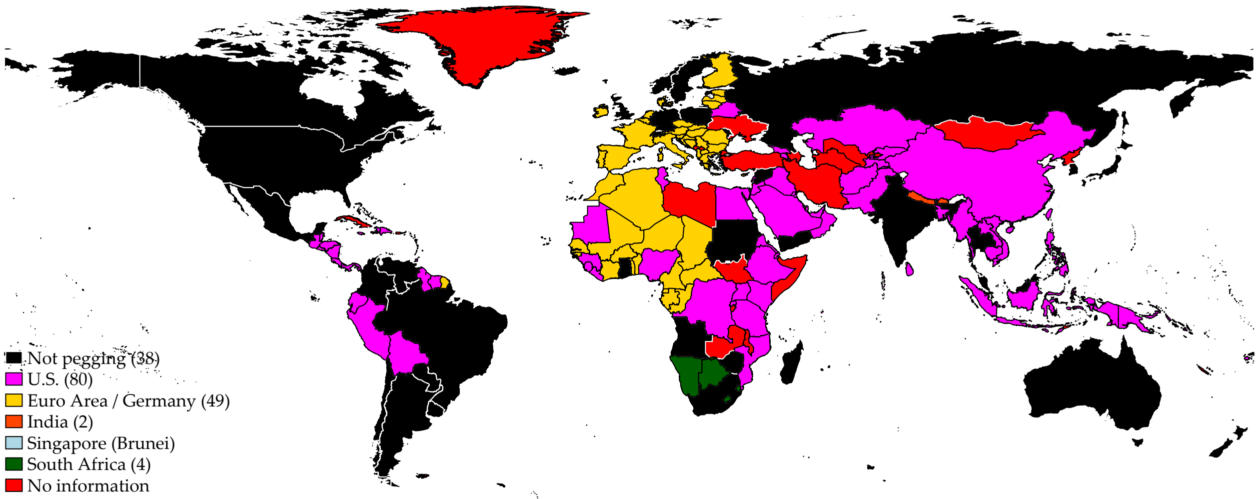
Notes: The Figure shows the ratio of non-core funding to demand deposits (blue line), the ratio of private credit to demand deposits (red line), and the ratios of those liability positions listed in Table 1 to demand deposits (other lines) for the median country over time. *ITRs+Deriv+Loans* refers to the sum of the following three liability positions: Insurance Technical Reserves, Derivatives, and Loans. *Non-core* is defined in Definition 1. Countries are classified according to the World Bank (2023) Income Classification.

Figure C3: *Anchor countries.*

(a) *End-1975*



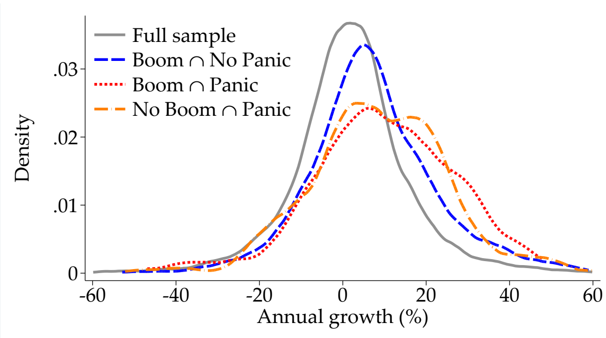
(b) *End-2019*



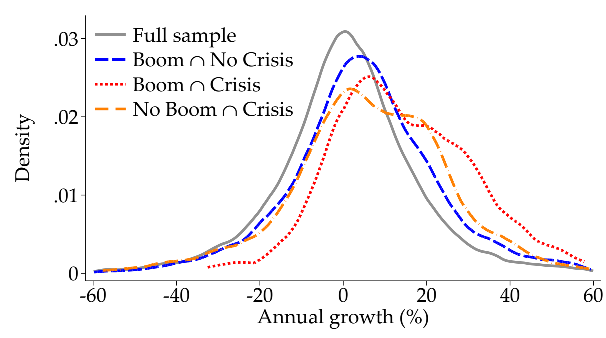
Notes: The legend refers to the anchor countries. Numbers in parentheses denote the number of countries that peg their currency to the respective anchor country.

Figure C4: *Bank funding around banking panics and financial crises: credit booms based on HP filter.*

(a) *Non-core ratio before panics*



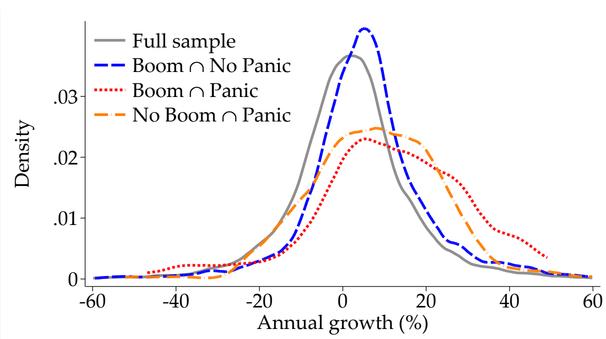
(b) *Non-core ratio before crises*



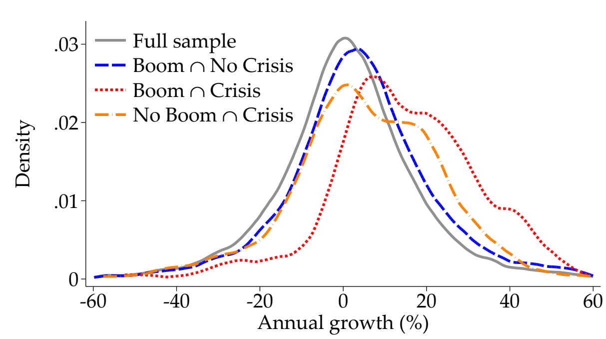
Notes: The same notes as in Figure 3 apply with one exception; credit booms are re-defined. Here, I detrend real private credit based on a two-sided HP filter with a smoothing parameter of 129,600 as proposed by Ravn and Uhlig (2002). I then define an economy as *booming* when detrended real private credit exceeds its country-specific standard deviation.

Figure C5: *Bank funding around banking panics and financial crises: credit booms based on highest quintile.*

Non-core ratio before panics



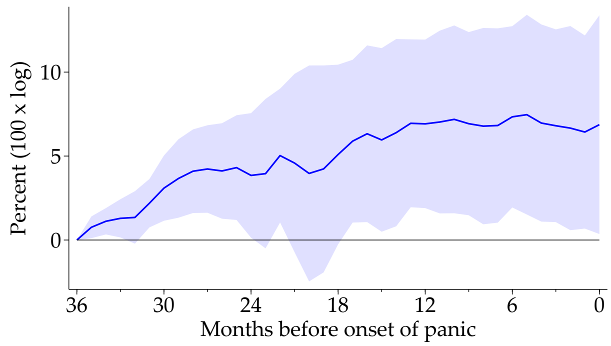
Non-core ratio before crises



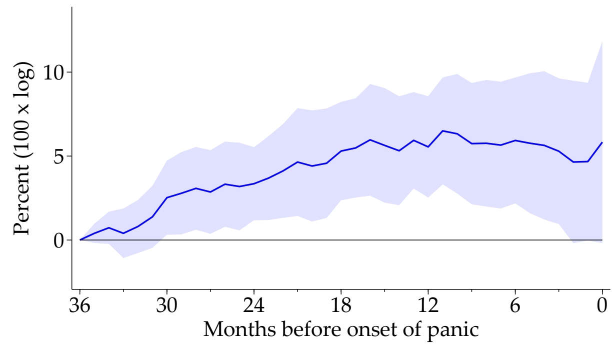
Notes: The same notes as in Figure 3 apply with one exception; here, I define an economy as *booming* when the annual growth rate of real private credit is above the 80^{th} percentile of a country's annual credit growth distribution.

Figure C6: *Pre-panic paths of real private credit and total assets.*

(a) *Real Private Credit*



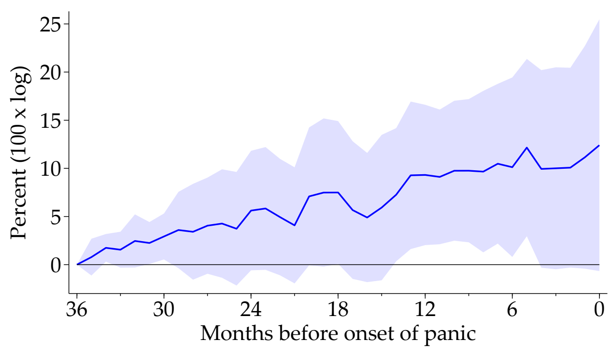
(b) *Real Total Assets*



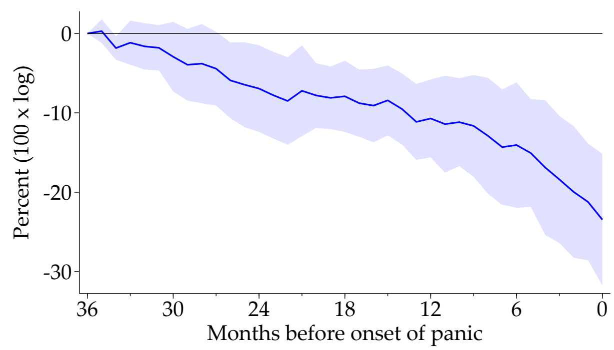
Notes: The same notes as in Figure 4 apply.

Figure C7: *Pre-panic paths of liability positions relative to total assets.*

(a) *Non-core / Total Assets*



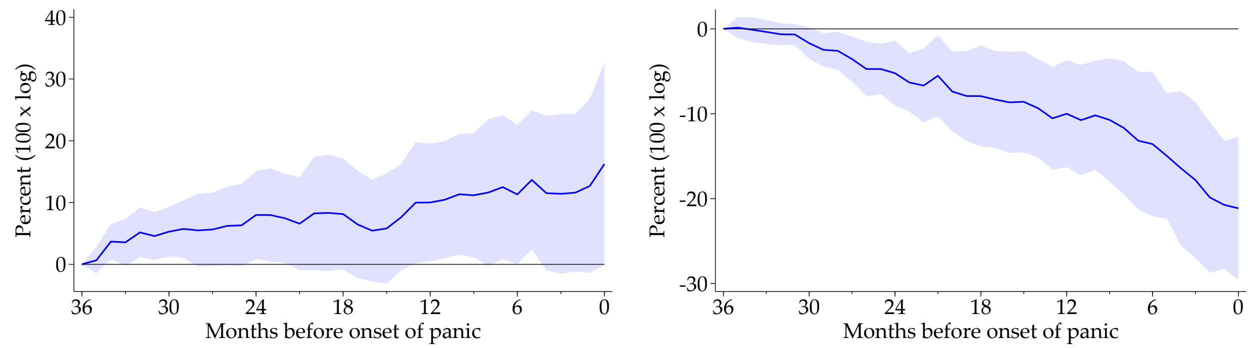
(b) *Demand / Total Assets*



Notes: The same notes as in Figure 4 apply.

Figure C8: *Pre-panic paths of liability positions relative to total private deposits.*

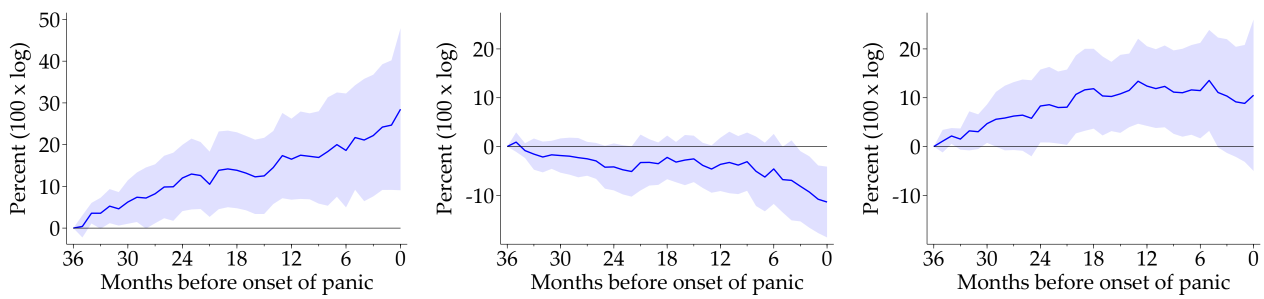
(a) *Non-core / Total Private Deposits* (b) *Demand / Total Private Deposits*



Notes: The same notes as in Figure 4 apply. Private deposits are defined as the sum of demand deposits and time deposits.

Figure C9: *Pre-panic paths of liability positions: including year fixed effects.*

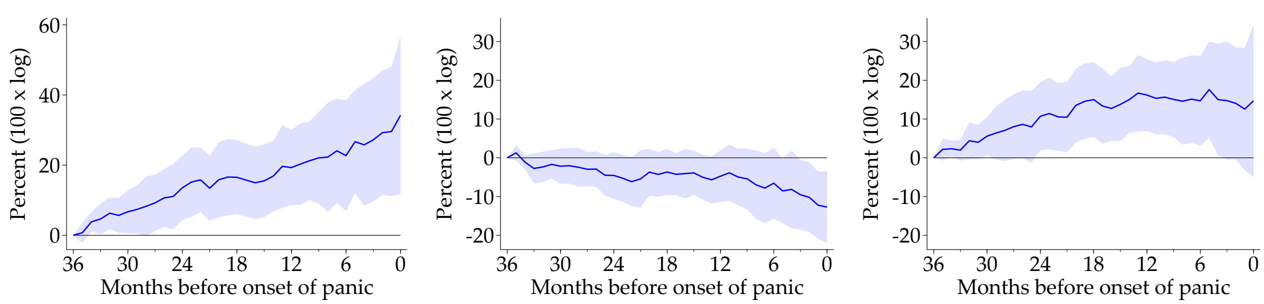
(a) *Non-core/Demand Dep.* (b) *Real Demand Deposits* (c) *Real non-core funding*



Notes: The same notes as in Figure 4 apply with one difference; year fixed effects are added to the linear regression model.

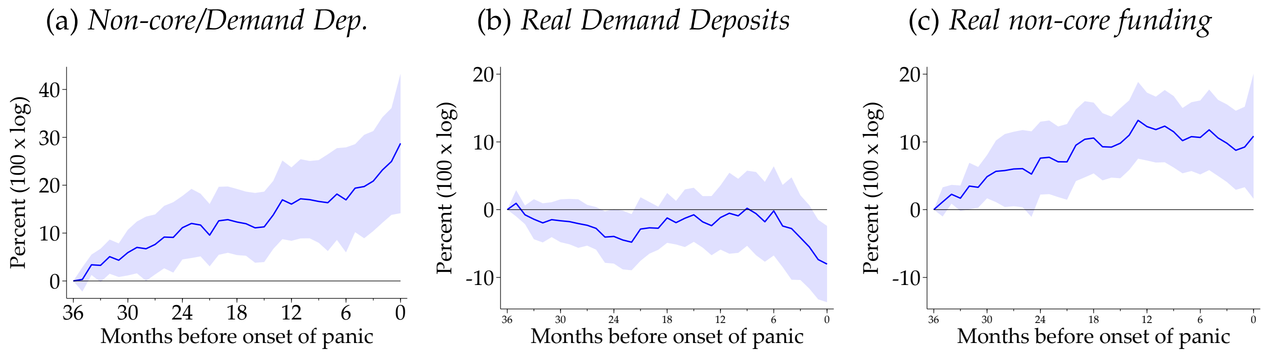
Figure C10: *Pre-panic paths of liability positions: including year $\times$ month fixed effects.*

(a) *Non-core/Demand Dep.* (b) *Real Demand Deposits* (c) *Real non-core funding*



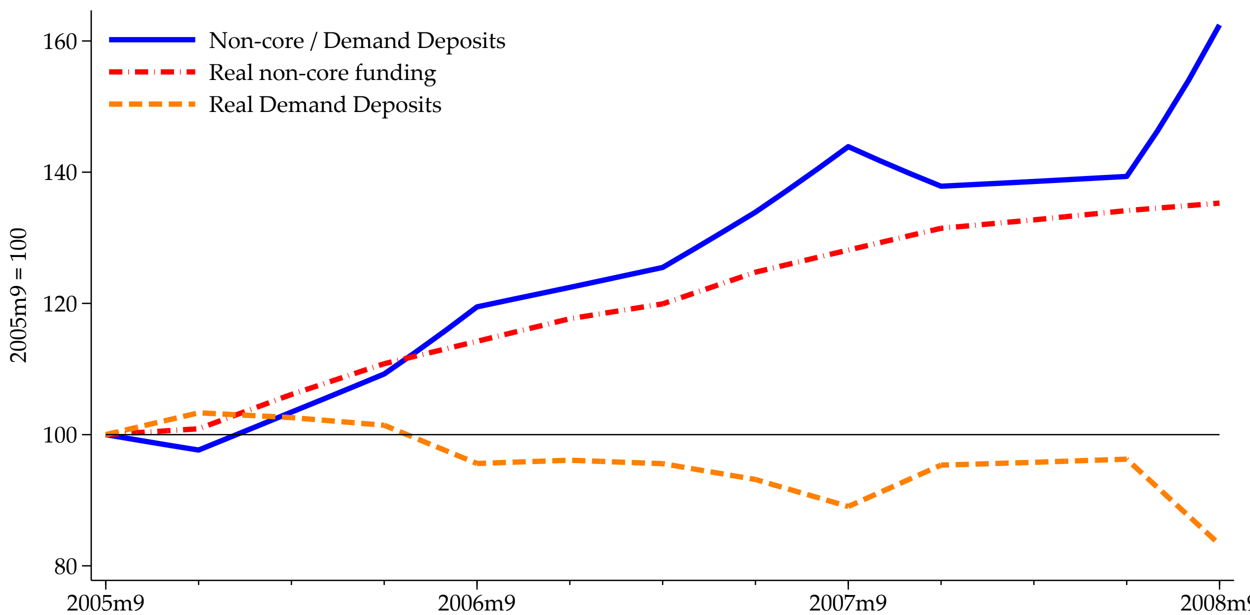
Notes: The same notes as in Figure 4 apply with one difference; year $\times$ month fixed effects are added to the linear regression model.

Figure C11: *Pre-panic paths of liability positions: including country × decade fixed effects.*



Notes: The same notes as in Figure 4 apply with one difference; county fixed effects are replaced with country × decade fixed effects.

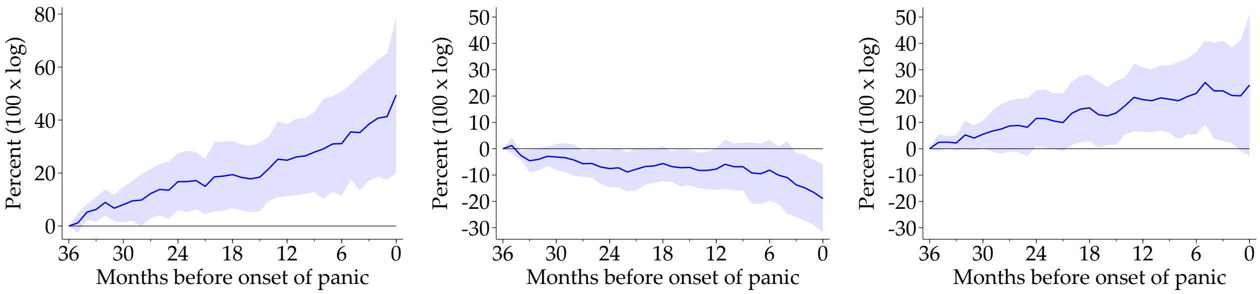
Figure C12: *The path of bank funding in the U.S. before September 2008.*



Notes: Paths of the non-core ratio (blue solid line), real non-core funding (red dashed line), and real demand deposits (orange dash-dotted line) in the U.S. The series are normalized to 100 as of September 2005.

Figure C13: *Pre-panic paths of liability positions: excluding the Global Financial Crisis.*

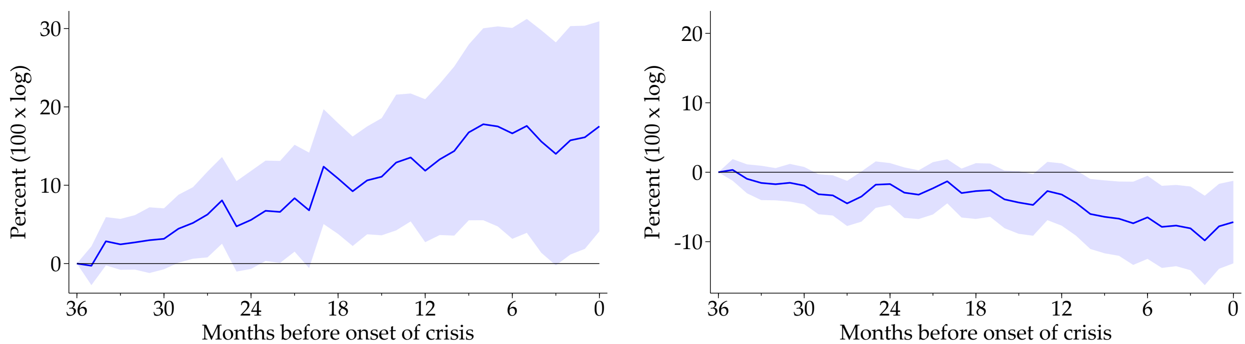
(a) *Non-core/Demand Dep.* (b) *Real Demand Deposits* (c) *Real non-core funding*



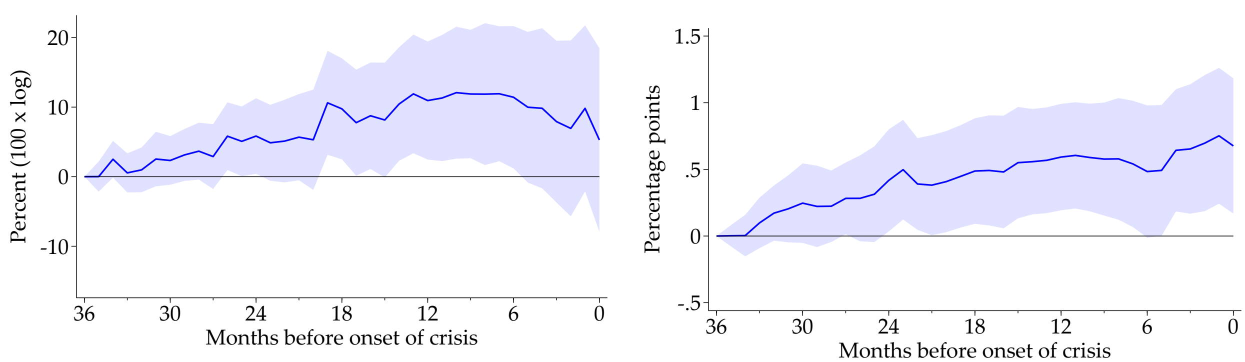
Notes: The same notes as in Figure 4 apply with one difference; the years 2007 and 2008 are excluded from the sample.

Figure C14: *Pre-crisis paths of liability positions.*

(a) *Non-core/Demand Dep.* (b) *Real Demand Deposits*

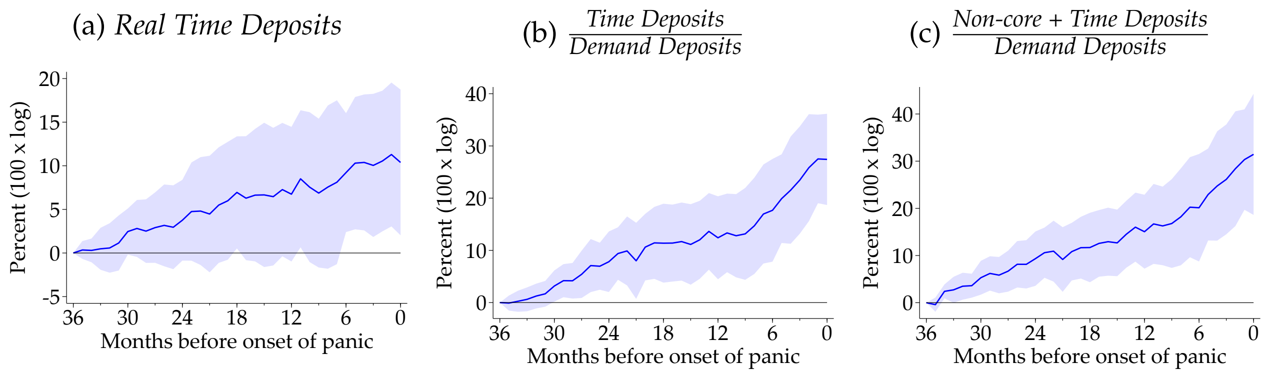


(c) *Real non-core funding* (d) *First-stage residual* $\widehat{\Delta R^{policy}}$



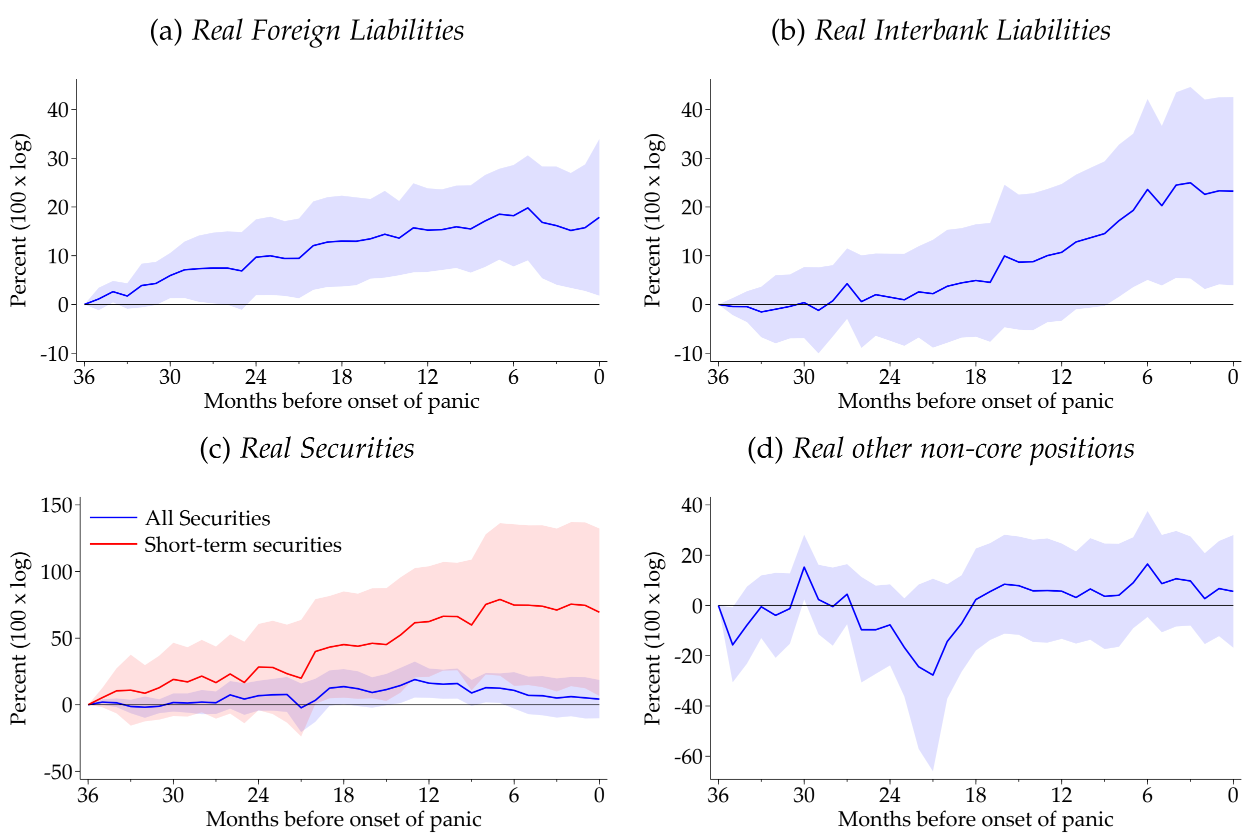
Notes: The same notes as in Figure 4 apply with one modification; here, the Baron, Verner, and Xiong (2021) banking panic indicator is replaced with the Laeven and Valencia (2020) financial crisis indicator.

Figure C15: *Pre-panic paths of time deposits.*



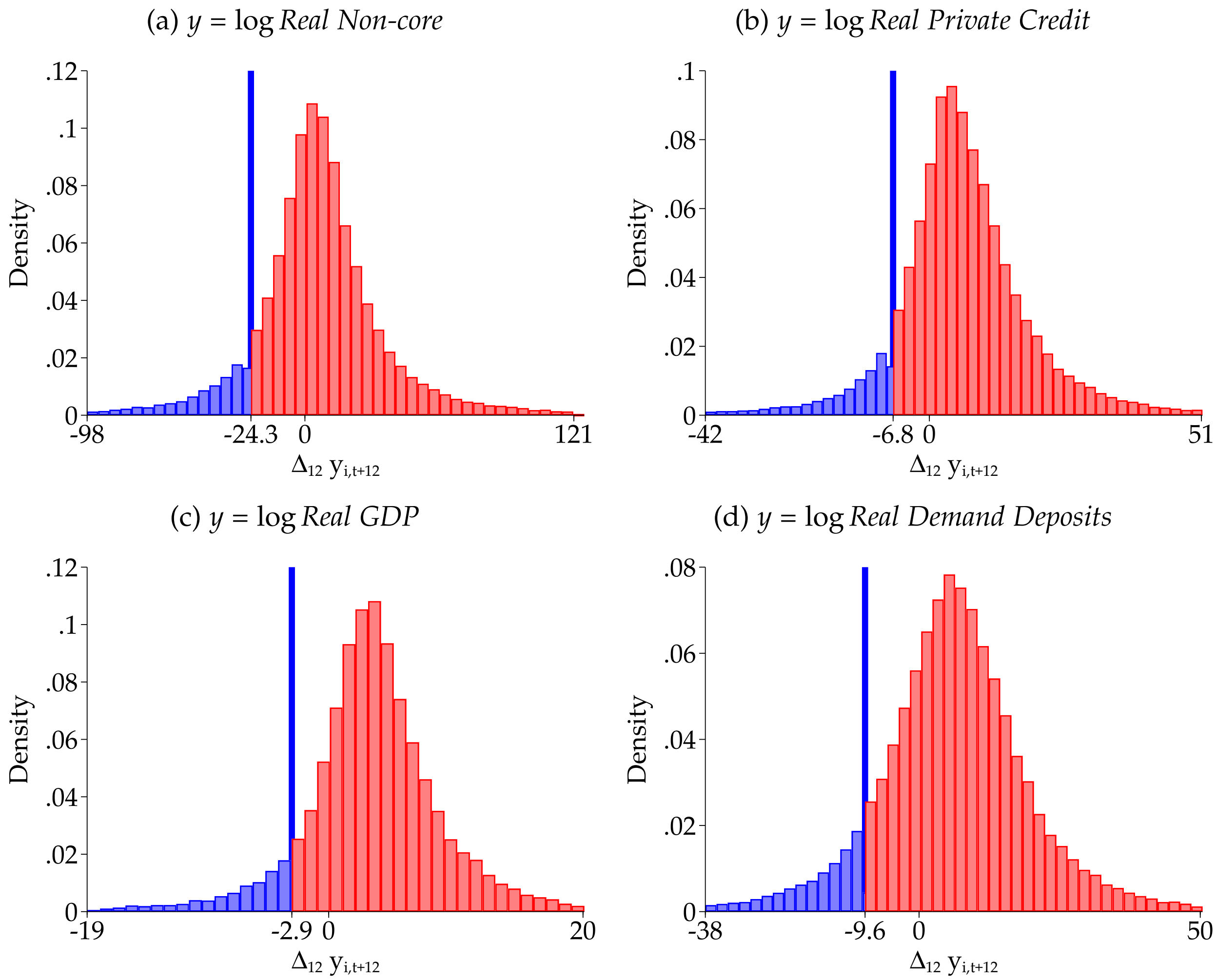
Notes: The same notes as in Figure 4 apply.

Figure C16: *Pre-panic paths of individual non-core positions.*



Notes: The same notes as in Figure 4 apply. Panel (c) exploits that for a subset of the dataset, I can separate long-term securities from short-term securities. Panel (d) refers to the sum of Loan Liabilities, Derivative Liabilities, and Other Liabilities.

Figure C17: *Pooled cross-country-time distributions of* $\Delta_{12} y_{i,t+12}$.



Notes: Pooled cross-country-time distributions of $\Delta_{12} y_{i,t+12}$. y is specified in the panel titles. The vertical blue solid lines indicate the 10^{th} percentile of the distributions.

C.2 Appendix Tables

Table C1: *First stage for the subset of advanced economies.*

Dep. var.: $\Delta R^{policy}_{i,t}$	(1)	(2)	(3)	(4)
$z_{i,t}$	0.463***	0.630***	0.549***	0.448***
	(0.071)	(0.058)	(0.059)	(0.122)
Controls	✗	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	Year	Year × Month
KP weak IV	42.90	119.10	86.45	13.56
Countries	36	36	36	36
Observations	16026	12685	12685	12685

Notes: The same notes as in Table 3 apply with one modification; here, the sample is restricted to advanced economies. The country classification follows IMF (2023c, pp. 119–120). *** $p < 0.01$.

Table C2: *First stage with floaters.*

Dep. var.: $\Delta R^{policy}_{i,t}$	(1)	(2)	(3)	(4)
$z^{peg}_{i,t}$	0.268***	0.397***	0.364***	0.347***
	(0.058)	(0.066)	(0.064)	(0.078)
$z^{float}_{i,t}$	0.126	0.125	0.101	0.097
	(0.114)	(0.127)	(0.128)	(0.126)
Controls	✗	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	Year	Year × Month
KP weak IV	10.75	19.25	17.06	10.08
Countries	157	154	154	154
Observations	46184	36894	36894	36894

Notes: OLS estimates of γ_1 and γ_2 with country-based cluster-robust standard errors of $\Delta R^{policy}_{i,t} = \alpha_i + \alpha_t + \gamma_1 z^{peg}_{i,t} + \gamma_2 z^{float}_{i,t} + \sum_{k=1}^{12} \delta^k \Delta R^{policy}_{i,t-k} + \sum_{k=0}^{12} \boldsymbol{\Gamma}^k \mathbf{X}_{i,t-k} + e_{i,t}$. $z^{peg}_{i,t} = \begin{cases} k_{i,t}\left(\Delta r_{b(i,t),t} - \Delta\hat{r}_{b(i,t),t}\right) & , q_{i,t} = 1 \\ 0 & , q_{i,t} = 0 \end{cases}$ and $z^{float}_{i,t} = \begin{cases} k_{i,t}\left(\Delta r_{b(i,t),t} - \Delta\hat{r}_{b(i,t),t}\right) & , q_{i,t} = 0 \\ 0 & , q_{i,t} = 1 \end{cases}$. $\boldsymbol{X}$ is defined in Section 3.2. In column (1), $\boldsymbol{X}$ and α_t are excluded. In column (2), α_t is excluded. In column (3), α_t refers to year fixed effects. In column (4), α_t refers to year × month fixed effects. *KP weak IV*: Kleibergen-Paap (2006) Wald rk F-statistic. *** $p < 0.01$.

Table C3: *Pass-through of exchange rates.*

Dep. var.: $\Delta \log ER_{i,t+1}$	(1)	(2)	(3)	(4)
$z^{peg}_{i,t}$	0.039	-0.203	-0.001	0.100
	(0.169)	(0.202)	(0.186)	(0.163)
$z^{float}_{i,t}$	0.493***	0.473***	0.597***	0.573***
	(0.134)	(0.151)	(0.149)	(0.130)
Controls	✗	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	Year	Year × Month
KP weak IV	6.83	5.40	8.30	10.23
Countries	157	154	154	154
Observations	46141	36982	36982	36982

Notes: The same notes as in Table C2 apply with one difference; here, the outcome variable is $\Delta \log ER_{i,t+1}$. ER denotes the exchange rate (domestic currency per US Dollar).

Table C4: *The effect of annual policy rate changes on bank funding.*

		Real Quantities	
	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Demand Dep.	Non-core
$\Delta_{12} R^{policy}_{i,t}$	6.814***	-3.190***	4.153**
	(1.954)	(0.901)	(1.881)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	34.99	28.37	34.92
Countries	152	152	152
Observations	28752	30129	29003

Notes: The same notes as in Table 4 apply with the following modifications. Here, the independent variable of interest is $\Delta_{12} R^{policy}_{i,t}$, $\sum_{k=1}^{12} \gamma^h_k \Delta R^{policy}_{i,t-k}$ is excluded from model (2), and the used instrument is $\sum_{k=0}^{11} z_{i,t-k}$. ** $p < 0.05$, *** $p < 0.01$.

Table C5: *The effect of monetary policy on bank funding: controlling for real GDP in the second-stage regression.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	 Non-core
$\Delta R_{i,t}^{policy}$	11.422***	-5.559	9.167***
	(4.075)	(3.922)	(2.931)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	43.20	58.75	43.28
Countries	91	92	92
Observations	13835	14631	14212

Notes: The same notes as in Table 4 apply with one modification; monthly changes in log-transformed real GDP from lag 0 to 12 are included as additional control variables. *** $p < 0.01$.

Table C6: *The effect of monetary policy on bank funding: controlling for real GDP in the second-stage regression and in the base country policy rate prediction.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	 Non-core
$\Delta R_{i,t}^{policy}$	9.472**	-3.658	7.849***
	(3.856)	(3.244)	(2.549)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	38.77	43.20	38.81
Countries	91	92	92
Observations	14181	15010	14546

Notes: The same notes as in Table C5 apply with one modification; monthly changes in log-transformed real GDP from lag 0 to 12 included in the forecasting regression outlined in footnote 9 to estimate residualized base country policy rate changes $\Delta r_{b(i,t),t} - \Delta \hat{r}_{b(i,t),t}$. These revised estimates are then used to re-define the instrument z in equation (1). ** $p < 0.05$, *** $p < 0.01$.

Table C7: *The effect of monetary policy on bank funding: excluding all control variables.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	Non-core
$\Delta R^{policy}_{i,t}$	22.050***	-5.241*	7.908**
	(7.695)	(2.909)	(3.636)
Controls	✗	✗	✗
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	12.64	50.84	45.34
Countries	154	152	152
Observations	34847	34577	32687

Notes: The same notes as in Table 4 apply with one modification; $\sum_{k=0}^{12} \mathbf{\Gamma}_k^h \mathbf{X}_{i,t-k}$ is excluded from model (2). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C8: *The effect of monetary policy on bank funding: including year fixed effects.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	Non-core
$\Delta R^{policy}_{i,t}$	11.670**	-5.717**	5.926
	(5.030)	(2.764)	(4.486)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	Year	Year	Year
KP weak IV	41.49	43.80	40.39
Countries	151	152	152
Observations	31748	33444	32024

Notes: The same notes as in Table 4 apply with one modification; year fixed effects are added to model (2). ** $p < 0.05$.

Table C9: *The effect of monetary policy on bank funding: including year $\times$ month fixed effects.*

		Real Quantities	
	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Demand Dep.	Non-core
$\Delta R_{i,t}^{policy}$	19.416**	-8.335*	8.165
	(8.073)	(4.316)	(6.148)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	Y $\times$ M	Y $\times$ M	Y $\times$ M
KP weak IV	15.26	17.35	15.87
Countries	151	152	152
Observations	31748	33444	32024

Notes: The same notes as in Table 4 apply with one modification; year $\times$ month fixed effects are added to model (2). * $p < 0.1$, ** $p < 0.05$.

Table C10: *The effect of monetary policy on bank funding: including country $\times$ decade fixed effects.*

		Real Quantities	
	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Demand Dep.	Non-core
$\Delta R_{i,t}^{policy}$	11.908***	-4.914*	7.407**
	(3.822)	(2.822)	(3.266)
Controls	✓	✓	✓
Fixed effects	Ctry. $\times$ Dec.	Ctry. $\times$ Dec.	Ctry. $\times$ Dec.
KP weak IV	41.39	47.28	40.54
Countries	152	153	153
Observations	31749	33445	32025

Notes: The same notes as in Table 4 apply with one modification; country fixed effects are replaced by country $\times$ decade fixed effects in model (2). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C11: *The effect of monetary policy on bank funding: core and non-core funding as a share of total assets.*

	$\frac{\text{Non-core}}{\text{Total Assets}}$	$\frac{\text{Demand Deposits}}{\text{Total Assets}}$	$\frac{\text{Time Deposits}}{\text{Total Assets}}$	$\frac{\text{Total Deposits}}{\text{Total Assets}}$
$\Delta R^{policy}_{i,t}$	1.233**	-1.462***	-0.386	-1.735**
	(0.499)	(0.449)	(0.797)	(0.774)
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
KP weak IV	46.00	46.08	41.98	45.30
Countries	152	152	149	152
Observations	31727	32416	31524	32045

Notes: The same notes as in Table 4 apply. Total deposits are the sum of demand and time deposits. ** $p < 0.05$, *** $p < 0.01$.

Table C12: *The effect of monetary policy on bank funding: core and non-core funding as a share of total deposits.*

	$\frac{\text{Demand Deposits}}{\text{Total Deposits}}$	$\frac{\text{Time Deposits}}{\text{Total Deposits}}$	$\frac{\text{Non-core}}{\text{Total Deposits}}$
$\Delta R^{policy}_{i,t}$	-7.761**	2.658**	7.664**
	(3.225)	(1.288)	(3.764)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	45.60	44.46	45.24
Countries	152	149	151
Observations	32837	32248	31572

Notes: The same notes as in Table 4 apply. Total deposits are the sum of demand and time deposits. ** $p < 0.05$.

Table C13: *The effect of monetary policy on bank funding for the subset of advanced economies.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities	
		Demand Dep.	Non-core
$\Delta R^{policy}_{i,t}$	14.333***	-7.902***	9.006***
	(3.125)	(2.924)	(3.001)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	83.98	133.68	89.41
Countries	35	35	36
Observations	10528	11377	10916

Notes: The same notes as in Table 4 apply with one modification; the sample is restricted to advanced economies. The country classification follows IMF (2023c, pp. 119–120). *** $p < 0.01$.

Table C14: *The effect of monetary policy on bank funding for the subset of pegging countries.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities	
		Demand Dep.	Non-core
$\Delta R^{policy}_{i,t}$	13.828***	-6.254**	7.824**
	(4.055)	(2.849)	(3.713)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	43.45	55.28	43.00
Countries	99	100	99
Observations	13070	13775	12972

Notes: The same notes as in Table 4 apply with one modification; the sample is restricted to those countries that have a fixed exchange rate regime. ** $p < 0.05$, *** $p < 0.01$.

Table C15: *The effect of monetary policy on bank funding for the subset of non-euro-area countries.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	Real Quantities Non-core
$\Delta R_{i,t}^{policy}$	15.672***	-10.736**	5.900
	(5.643)	(4.268)	(4.816)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	26.80	28.49	26.09
Countries	148	149	149
Observations	29663	31034	29939

Notes: The same notes as in Table 4 apply with one modification; here, countries are excluded from the date onwards when they joined the Euro Area. ** $p < 0.05$, *** $p < 0.01$.

Table C16: *The effect of contractionary monetary policy on bank funding.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities Demand Dep.	Real Quantities Non-core
$\Delta R_{i,t}^{policy}$	34.442***	-19.031**	18.327*
	(12.849)	(8.019)	(10.423)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	23.47	25.60	22.93
Countries	151	152	152
Observations	31748	33444	32024

Notes: The same notes as in Table 4 apply with one modification; $\Delta R_{i,t}$ is set to 0 whenever $\Delta R_{i,t} < 0$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C17: *The effect of expansionary monetary policy on bank funding.*

	$\frac{\text{Non-core}}{\text{Demand Dep.}}$	Real Quantities	
		Demand Dep.	Non-core
$\Delta R_{i,t}^{policy}$	25.061***	-12.592***	13.334**
	(6.685)	(4.811)	(6.178)
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	23.97	30.35	23.06
Countries	151	152	152
Observations	31748	33444	32024

Notes: The same notes as in Table 4 apply with one modification; $\Delta R_{i,t}$ is set to 0 whenever $\Delta R_{i,t} > 0$. ** $p < 0.05$, *** $p < 0.01$.

Table C18: *The effect of monetary policy on foreign liabilities.*

	Real		Ratio to Demand Deposits	
	All	AEs	All	AEs
$\Delta R_{i,t}^{policy}$	12.386***	6.477**	17.235***	13.900***
	(4.700)	(2.942)	(5.046)	(3.285)
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
KP weak IV	43.76	93.36	48.85	89.55
Countries	151	36	150	35
Observations	32699	10843	31890	10457

Notes: The same notes as in Table 4 apply with one modification; here, the response variable refers to Foreign Liabilities. *AE* refers to advanced economies as classified in IMF (2023c, pp. 119–120). ** $p < 0.05$, *** $p < 0.01$.

Table C19: *The effect of monetary policy on interbank liabilities.*

	Real		Ratio to Demand Deposits	
	All	AEs	All	AEs
$\Delta R^{policy}_{i,t}$	13.837	8.243	13.966	13.247
	(13.049)	(7.874)	(11.928)	(8.129)
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
KP weak IV	30.68	404.84	28.38	399.45
Countries	137	33	137	33
Observations	20778	5398	20400	5322

Notes: The same notes as in Table 4 apply with one modification; here, the response variable refers to Interbank Liabilities. *AE* refers to advanced economies as classified in IMF (2023c, pp. 119–120).

Table C20: *The effect of monetary policy on security liabilities.*

	Real		Ratio to Demand Deposits	
	All	AEs	All	AEs
$\Delta R^{policy}_{i,t}$	12.218	17.586**	19.104**	25.016***
	(7.493)	(6.969)	(7.914)	(6.826)
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
KP weak IV	29.75	67.31	33.44	61.14
Countries	113	32	113	32
Observations	16845	6817	16638	6734

Notes: The same notes as in Table 4 apply with one modification; here, the response variable refers to Security Liabilities. *AE* refers to advanced economies as classified in IMF (2023c, pp. 119–120). ** $p < 0.05$, *** $p < 0.01$.

Table C21: *The effect of monetary policy on other non-core liabilities.*

	Real		Ratio to Demand Deposits	
	All	AEs	All	AEs
$\Delta R_{i,t}^{policy}$	1.487	25.192	10.910	33.599*
	(30.941)	(15.539)	(33.877)	(17.620)
Controls	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
KP weak IV	16.75	158.26	16.92	191.65
Countries	139	34	139	34
Observations	17771	5571	17738	5514

Notes: The same notes as in Table 4 apply with one modification; here, the response variable refers to the sum of Loan Liabilities, Derivative Liabilities, and Other Liabilities. *AE* refers to advanced economies as classified in IMF (2023c, pp. 119–120). * $p < 0.1$.

Table C22: *Predictive power of shifts in banks' funding mix beyond banking panics and financial crises: excluding all control variables.*

(a) Non-core funding and private credit

	$y = \log$ *Real Non-core*		$y = \log$ *Real Private Credit*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-3.445***	1.222***	-0.651**	1.412***
	(0.763)	(0.279)	(0.306)	(0.326)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✗	✗	✗
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
Countries	186	160	186	159
Observations	56892	49825	56274	50539

(b) GDP and demand deposits

	$y = \log$ *Real GDP*		$y = \log$ *Real Demand Deposits*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-0.879***	2.085***	-0.004	0.104
	(0.252)	(0.664)	(0.282)	(0.353)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✗	✗	✗
Country FEs	✓	✓	✓	✓
Time FEs	✗	✗	✗	✗
Countries	103	101	186	174
Observations	18214	18146	56342	54722

Notes: The same notes as in Table 6 apply with one modification; $\mathbf{\Gamma}\,\mathbf{X}_{i,t}$ is excluded from models (3) and (4). ** $p < 0.05$, *** $p < 0.01$.

Table C23: *Predictive power of shifts in banks' funding mix beyond banking panics and financial crises: including year fixed effects.*

(a) Non-core funding and private credit

	$y = \log$ *Real Non-core*		$y = \log$ *Real Private Credit*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36} \left(\log \frac{Non\text{–}core}{Demand} \right)_{i,t}$	-4.232***	1.115***	-0.773***	0.997***
	(0.771)	(0.271)	(0.296)	(0.285)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✓	✗	✓
Country FEs	✓	✓	✓	✓
Time FEs	Year	Year	Year	Year
Countries	186	159	186	159
Observations	56892	48099	56274	50161

(b) GDP and demand deposits

	$y = \log$ *Real GDP*		$y = \log$ *Real Demand Deposits*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36} \left(\log \frac{Non\text{–}core}{Demand} \right)_{i,t}$	-1.043***	1.003*	0.013	0.022
	(0.198)	(0.544)	(0.282)	(0.294)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✓	✗	✓
Country FEs	✓	✓	✓	✓
Time FEs	Year	Year	Year	Year
Countries	103	100	186	172
Observations	18214	16719	56342	53230

Notes: The same notes as in Table 6 apply with one modification; year fixed effects are added to models (3) and (4). * $p < 0.1$, *** $p < 0.01$.

Table C24: *Predictive power of shifts in banks' funding mix beyond banking panics and financial crises: including month fixed effects.*

(a) Non-core funding and private credit

	$y = \log$ *Real Non-core*		$y = \log$ *Real Private Credit*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-4.171***	1.085***	-0.768**	1.022***
	(0.772)	(0.266)	(0.298)	(0.292)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✓	✗	✓
Country FEs	✓	✓	✓	✓
Time FEs	Y × M	Y × M	Y × M	Y × M
Countries	186	159	186	159
Observations	56892	47905	56274	49250

(b) GDP and demand deposits

	$y = \log$ *Real GDP*		$y = \log$ *Real Demand Deposits*	
	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$	$\Delta_{12} y_{i,t+12}$	$\mathbb{1}\{\Delta_{12} y_{i,t+12} < 10^{th} p.\}$
$\Delta_{36}\left(\log \frac{Non\text{–}core}{Demand}\right)_{i,t}$	-1.034***	1.261	0.015	-0.004
	(0.195)	(0.781)	(0.284)	(0.290)
Estimation	OLS	Logit	OLS	Logit
Controls	✗	✓	✗	✓
Country FEs	✓	✓	✓	✓
Time FEs	Y × M	Y × M	Y × M	Y × M
Countries	103	99	186	172
Observations	18214	13405	56342	52366

Notes: The same notes as in Table 6 apply with one modification; year×month fixed effects are added to models (3) and (4). ** $p < 0.05$, *** $p < 0.01$.

Table C25: *Relative frequencies of rising policy rates and rising non-core funding ratios.*

(a) *Relative frequencies conditional on* $Panic_{i,t+1,t+12} = 0$

	$\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} \leq 0$	$\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0$
$\Delta R^{policy}_{i,t-12} < 0$	32.94	21.34
$\Delta R^{policy}_{i,t-12} > 0$	19.54	26.19

(b) *Relative frequencies conditional on* $Panic_{i,t+1,t+12} = 1$

	$\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} \leq 0$	$\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0$
$\Delta R^{policy}_{i,t-12} < 0$	20.44	19.89
$\Delta R^{policy}_{i,t-12} > 0$	17.13	42.54

Table C26: *The effect of monetary-policy-induced changes in bank funding on financial crisis risk.*

Dep. var.: Financial crises	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	12.474***		4.031*
	(3.555)		(2.103)
$\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		0.829**	1.117**
		(0.379)	(0.536)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			27.322***
			(9.328)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	27.59		8.89
Countries	141	141	141
Observations	28926	28926	28926

Notes: The same notes as in Table 7 apply with one modification; here, the dependent variable refers to financial crises. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C27: *The effect of monetary-policy-induced changes in real non-core funding on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	17.082***		7.753
	(6.362)		(4.837)
$\mathbb{1}\{\Delta_{12} \log \textit{Real Non-core}_{i,t} > \textit{median}\}$		0.085	-0.361
		(0.881)	(0.990)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12} \log \textit{Real Non-core}_{i,t} > \textit{median}\}$			24.216**
			(10.485)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	37.31		20.34
Countries	42	42	42
Observations	13703	13703	13703

Notes: The same notes as in Table 7 apply with one modification; $\mathbb{1}\{\Delta_{12}\left(\frac{\textit{Non–core}}{\textit{Demand}}\right)_{i,t} > 0\}$ is replaced with $\mathbb{1}\{\Delta_{12} \log \textit{Real Non-core}_{i,t} > \textit{median}\}$. ** $p < 0.05$, *** $p < 0.01$.

Table C28: *The effect of monetary-policy-induced changes in real demand deposits on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	15.484***		20.425***
	(5.169)		(7.805)
$\mathbb{1}\{\Delta_{12} \log Real\ Demand_{i,t} > median\}$		-2.212**	-1.193
		(0.840)	(0.908)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12} \log Real\ Demand_{i,t} > median\}$			-10.149
			(8.483)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	54.62		28.27
Countries	42	42	42
Observations	14277	14277	14277

Notes: The same notes as in Table 7 apply with one modification; $\mathbb{1}\{\Delta_{12} \left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$ is replaced with $\mathbb{1}\{\Delta_{12} \log Real\ Demand_{i,t} > median\}$. ** $p < 0.05$, *** $p < 0.01$.

Table C29: *The effect of monetary-policy-induced changes in foreign liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	14.996***		6.448*
	(5.106)		(3.595)
$\mathbb{1}\{\Delta_{12}\left(\frac{Foreign}{Demand}\right)_{i,t} > 0\}$		2.116***	1.585**
		(0.633)	(0.694)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Foreign}{Demand}\right)_{i,t} > 0\}$			22.922**
			(9.618)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	55.66		23.32
Countries	41	41	41
Observations	13037	13037	13037

Notes: The same notes as in Table 7 apply. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C30: *The effect of monetary-policy-induced changes in interbank liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	16.720***		-2.636
	(4.250)		(4.118)
$\mathbb{1}\{\Delta_{12}\left(\frac{Interbank}{Demand}\right)_{i,t} > 0\}$		4.273***	3.960**
		(1.317)	(1.608)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Interbank}{Demand}\right)_{i,t} > 0\}$			43.553***
			(10.957)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	37.22		42.06
Countries	38	38	38
Observations	6076	6076	6076

Notes: The same notes as in Table 7 apply. ** $p < 0.05$, *** $p < 0.01$.

Table C31: *The effect of monetary-policy-induced changes in security liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	16.753***		13.859**
	(4.698)		(5.565)
$\mathbb{1}\{\Delta_{12}\left(\frac{Securities}{Demand}\right)_{i,t} > 0\}$		0.881	0.675
		(1.200)	(1.299)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Securities}{Demand}\right)_{i,t} > 0\}$			7.193
			(10.277)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	71.25		29.89
Countries	40	40	40
Observations	9904	9904	9904

Notes: The same notes as in Table 7 apply. ** $p < 0.05$, *** $p < 0.01$.

Table C32: *The effect of monetary-policy-induced changes in short-term security liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	14.011***		4.567
	(4.804)		(5.546)
$\mathbb{1}\{\Delta_{12}\left(\frac{STSecurities}{Demand}\right)_{i,t} > 0\}$		1.940	2.085
		(1.631)	(1.791)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{STSecurities}{Demand}\right)_{i,t} > 0\}$			24.131
			(14.840)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	115.34		29.27
Countries	39	39	39
Observations	7101	7101	7101

Notes: The same notes as in Table 7 apply. *** $p < 0.01$.

Table C33: *The effect of monetary-policy-induced changes in long-term security liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	23.539***		30.134***
	(4.295)		(9.389)
$\mathbb{1}\{\Delta_{12}\left(\frac{LTSecurities}{Demand}\right)_{i,t} > 0\}$		1.253	0.221
		(1.981)	(1.977)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{LTSecurities}{Demand}\right)_{i,t} > 0\}$			-15.635
			(16.812)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	53.79		24.79
Countries	38	38	38
Observations	4616	4616	4616

Notes: The same notes as in Table 7 apply. *** $p < 0.01$.

Table C34: *The effect of monetary-policy-induced changes in derivative liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	20.806***		8.110
	(3.951)		(6.446)
$\mathbb{1}\{\Delta_{12}\left(\frac{Derivatives}{Demand}\right)_{i,t} > 0\}$		4.657*	4.604*
		(2.377)	(2.413)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Derivatives}{Demand}\right)_{i,t} > 0\}$			28.544**
			(13.427)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	147.42		49.47
Countries	37	37	37
Observations	3997	3997	3997

Notes: The same notes as in Table 7 apply. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C35: *The effect of monetary-policy-induced changes in other non-core liability ratios on panic risk.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	15.811***		14.592***
	(5.310)		(5.538)
$\mathbb{1}\{\Delta_{12}\left(\frac{\text{Other non-core}}{\textit{Demand}}\right)_{i,t} > 0\}$		-0.138	-0.380
		(0.934)	(0.905)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{\text{Other non-core}}{\textit{Demand}}\right)_{i,t} > 0\}$			4.838
			(9.676)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	58.10		6.15
Countries	42	42	42
Observations	13788	13788	13788

Notes: The same notes as in Table 7 apply. Here, *Other non-core* refers to the sum of Loan Liabilities and Other Liabilities. *** $p < 0.01$.

Table C36: *The effect of monetary-policy-induced changes in bank funding on panic risk: controlling for year fixed effects.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	15.833***		7.524*
	(4.237)		(4.147)
$\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		0.117	0.137
		(0.617)	(0.796)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			20.327**
			(8.792)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	Year	Year	Year
KP weak IV	41.93		17.83
Countries	41	41	41
Observations	13406	13406	13406

Notes: The same notes as in Table 7 apply with one modification; here, I additionally control for year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C37: *The effect of monetary-policy-induced changes in bank funding on panic risk: controlling for country×decade fixed effects.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	6.614**		1.143
	(2.804)		(3.695)
$\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		1.629**	1.525**
		(0.714)	(0.746)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			12.647*
			(7.503)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Fixed effects	C × D	C × D	C × D
KP weak IV	45.61		23.17
Countries	41	41	41
Observations	13406	13406	13406

Notes: The same notes as in Table 7 apply with one modification; here, I additionally control for country×decade fixed effects. * $p < 0.1$, ** $p < 0.05$.

Table C38: *The effect of monetary-policy-induced changes in bank funding on panic risk: changes in non-core ratios over a two-year period.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-24}$	32.181**		4.579
	(13.940)		(6.543)
$\mathbb{1}\{\Delta_{24}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		2.190**	1.420
		(1.040)	(0.936)
$\Delta R^{policy}_{i,t-24} \times \mathbb{1}\{\Delta_{24}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			62.003***
			(16.840)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	31.48		9.80
Countries	41	41	41
Observations	11769	11769	11769

Notes: The same notes as in Table 7 apply with one modification; here, $\Delta R^{policy}_{i,t-12}$ and $\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$ are replaced with $\Delta R^{policy}_{i,t-24}$ and $\mathbb{1}\{\Delta_{24}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$, respectively. ** $p < 0.05$, *** $p < 0.01$.

Table C39: *The effect of monetary-policy-induced changes in bank funding on panic risk over a two-year horizon.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	45.115***		14.892*
	(14.544)		(7.888)
$\mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$		3.276**	2.641
		(1.414)	(1.743)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Non\text{–}core}{Demand}\right)_{i,t} > 0\}$			71.189***
			(22.582)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	49.59		34.80
Countries	41	41	41
Observations	12934	12934	12934

Notes: The same notes as in Table 7 apply with one modification; here, the binary dependent variable equals 1 if a panic starts between year-month $t+1$ and $t+24$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C40: *The effect of monetary-policy-induced changes in bank funding on panic risk: the ratio between time deposits and demand deposits.*

Dep. var.: Banking panics	(1)	(2)	(3)
$\Delta R^{policy}_{i,t-12}$	15.899***		1.820
	(5.395)		(3.109)
$\mathbb{1}\{\Delta_{12}\left(\frac{Time}{Demand}\right)_{i,t} > 0\}$		2.713***	1.511
		(0.931)	(1.171)
$\Delta R^{policy}_{i,t-12} \times \mathbb{1}\{\Delta_{12}\left(\frac{Time}{Demand}\right)_{i,t} > 0\}$			34.366**
			(17.026)
Estimation	2SLS	OLS	2SLS
Controls	✓	✓	✓
Country FEs	✓	✓	✓
Time FEs	✗	✗	✗
KP weak IV	57.04		10.78
Countries	42	42	42
Observations	14017	14017	14017

Notes: The same notes as in Table 7 apply. ** $p < 0.05$, *** $p < 0.01$.