The Deposit Franchise and the Risk-Taking Channel of Monetary Policy*

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November 2025

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Abstract

We develop a tractable model in which a bank's deposit franchise shapes its risk-taking response to monetary policy. Banks with weaker pass-through to deposit rates (lower deposit betas) see larger profit gains when rates rise and therefore reduce risk-taking more after contractionary shocks. We test this channel using the Federal Reserve's confidential loan-level data, interacting high-frequency monetary policy surprises with pre-determined banks' deposit betas, in regressions saturated with bank and borrower-time fixed effects. We find that low-deposit-beta banks reduce risk-taking significantly more following monetary tightening, confirming that the deposit franchise plays a crucial role in the interaction of monetary policy and financial stability. In a horse race against bank capital-based explanations of risk-taking (e.g., search-for-yield), our deposit-franchise mechanism retains independent explanatory power.

Keywords: Monetary Policy, Deposit Franchise, Banks, Risk, Financial Stability

JEL Codes: E52, E58, G21, G28

*These are our views and not those of the Federal Reserve Board, or the Federal Reserve System. We thank Carlo Altavilla, Mehdi Beyhaghi, Miguel Faria-e-Castro, Marco Grotteria, Rajkamal Iyer, Frederic Malherbe, Gregor Matvos, Nuno Paixão, Jose-Luis Peydro, Farzad Saidi, Andre Silva, Kerem Tuzcuoglu, Matias Vieyra, Kaspar Wuthrich, Paolo Zaffaroni, and seminar and conference participants at the Bank of Canada, the Federal Reserve Board, the Federal Reserve Bank of St. Louis, and the London Juniors Finance Conference for helpful comments and discussions. We thank Filipe de Castro Ribeiro Ferreira for excellent research assistance.

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1 Introduction

Understanding how monetary policy shapes banks' willingness to bear risk is central both to understanding monetary policy transmission and the design of financial stability policy. A large body of work documents a risk-taking channel of monetary policy: when short-term rates fall, banks tend to originate riskier loans, hold riskier portfolios, and loosen lending standards (Maddaloni and Peydró, 2011; Borio and Zhu, 2012; Jiménez et al., 2014; Dell'Ariccia et al., 2017). The risk-taking behaviours are often attributed to search-for-yield motives, where low rates reduce returns on safe assets, prompting banks to seek riskier investments, as well as to risk-shifting or moral hazard incentives stemming from limited liability.

This paper proposes and tests a new mechanism at the core of the business model of modern banks: the deposit franchise. Banks with a deposit franchise pay deposit rates that are below the policy rate and adjust only slowly (low deposit betas), so higher policy rates enlarge future profits from deposit-taking. When interest rates increase, a richer franchise gives bank managers more "skin in the game," as they have more profits to lose if a risk-taking strategy backfires. Consequently, a monetary tightening should make high-franchise banks more risk-averse than otherwise similar low-franchise banks.

We formalise this intuition in a tractable model of bank franchise value to examine how deposit pricing influences the risk-taking channel of monetary policy. In the model, banks have a deposit franchise — they exhibit imperfect pass-through of the policy rate to depositors (i.e., a deposit beta less than one) — and profit from the resulting deposit spreads. Banks with weaker deposit-rate pass-through have a stronger deposit franchise because, in the cross-section, those banks charge larger deposit spreads and earn higher profits from the deposit market, both in terms of higher cash flows and a larger present value. The deposit franchise allows banks to increase deposit spreads and earn more profits when interest rates rise.

The risk choice of banks reflects the trade-off between the additional profits from risk-taking and the potential loss of the deposit franchise and the profits it induces in the event of a bank failure. Following rate hikes, the expected future profits of high-franchise banks rise more than those of low-franchise banks. Consequently, our model predicts that high-franchise (low-beta) banks reduce credit risk more in response to contractionary monetary policy, as their franchise generates greater profits to protect.

In order to test the model's predictions, we utilise the Federal Reserve's confidential, quarterly, loan-level supervisory data (FR Y-14) from 2015 to 2024. This data includes bank-reported probabilities of default (PD) at the borrower level, giving us a direct ex ante measure of credit risk which allows us to study risk-taking as changes in expected default risk—rather than relying on ex post defaults, spreads, or ratings. Our final panel includes close to 5 million loan-quarter observations. Empirically, we first verify the aggregate finding of the risk-taking channel, which indicates that contractionary monetary policy reduces risk-taking overall. Moreover, we show this risk-taking channel is persistent as banks' risk choices are affected for nearly two years after a monetary policy shock, suggesting potentially important implications for financial stability.

We next confirm the key cross-sectional prediction of our model: the risk reduction is more pronounced for banks with a lower deposit beta. To causally test the novel prediction of our theory, we employ a shift–share design that combines time-series monetary policy surprises (the "shift") with cross-sectional variation in banks' deposit betas (the "shares"). The time-series shocks are the high-frequency surprises of Jarociński and Karadi (2020) which isolate unexpected changes in the short-term risk-free rate. For the cross-section, we exploit banks' *pre-determined* deposit betas (the pass-through of policy rates to deposit rates) measured from 1984 to 2014, which capture their deposit franchise (Drechsler et al., 2021).[1] An additional advantage of our empirical strategy is that the FR Y-14 data allows us to include granular borrower-time fixed effects, forcing identification to come from within-quarter comparisons of loans that different banks make to the same firm. Because each firm's credit demand, investment opportunities, and macro exposure are differenced out, any remaining response must arise from the supply side—namely, how the policy surprise re-values each bank's pre-existing deposit franchise.

Our results show that banks with a stronger deposit franchise (lower beta) decrease risk-taking significantly more in response to contractionary monetary policy shocks, precisely as predicted by our model. Our findings are robust to alternative measures of risk-taking, such as loan charge-offs, as well as to alternative measures of bank deposit franchise, such as bank-level deposit HHI (computed as in Drechsler et al., 2017). Moreover, we show that our deposit-franchise mechanism retains independent explanatory power in a horse race against bank capital-based explanations of the risk-taking channel of monetary policy, such as the aforementioned search-for-yield. Finally, we show these heterogeneous risk responses extend to banks' aggregate balance sheets: high-beta banks increase the portfolio share of their riskiest assets following contractionary monetary policy shocks, consistent with our loan-level estimates.

The policy message is two-fold. First, the effectiveness of short-rate changes in containing credit risk depends on the distribution of deposit betas across the banking system;

[1] We use deposit betas estimated from 1984-2014 to ensure the variation in deposit betas is not driven by the shocks in the estimation period.

in eras when franchise strength is concentrated in a few large institutions, the aggregate damping of risk-taking will be uneven. Second, deposit-market competition policy, fintech entry, and rate-advertising regulations can inadvertently reshape monetary-policy transmission by shifting betas. Regulators therefore need to treat deposit-market structure and monetary transmission as jointly determined: measures that erode franchise value may stimulate deposit competition but also weaken the built-in prudential buffer that low-beta banks provide during tightening cycles.

Related Literature. First, we introduce a new channel through which monetary policy transmits to bank risk-taking. Existing theories on the risk-taking channel of monetary policy focus on search-for-yield (Rajan, 2006; Borio and Zhu, 2012) and risk-shifting incentives (De Nicolò et al., 2010; Dell'Ariccia et al., 2014; Bonfim and Soares, 2018; Abbate and Thaler, 2019).[2,3] In this paper, we uncover a deposit-franchise channel within the broader risk-taking channel, where monetary policy influences banks' risk-taking incentives through its interaction with the deposit franchise, complementing existing search-for-yield and risk-shifting models.

Second, our work provides novel empirical contributions to the literature on the risk-taking channel of monetary policy. Existing works in this area typically focus on the transmission of monetary policy to credit risk-taking in general or the heterogeneity across banks with different levels of capitalisation (Altunbas et al., 2010; Maddaloni and Peydró, 2011; Jiménez et al., 2014; Ioannidou et al., 2015; Dell'Ariccia et al., 2017; Delis et al., 2017; Paligorova and Santos, 2017; Peydró et al., 2021; Correa et al., 2022; Li et al., 2024).[4] While we confirm the aggregate pattern where contractionary monetary policy shocks reduce bank risk-taking using US administrative data and rich borrower-time fixed effects, we also establish new cross-sectional patterns consistent with our deposit-franchise theory: banks with stronger deposit franchise (lower deposit betas) reduce credit risk more aggressively following contractionary monetary policy shocks. Importantly, we also trace out the dynamics of both the aggregate and cross-sectional effects using local projections and thus provide an additional insight relative to the existing literature.

Third, we connect the growing literature on the deposit channel of monetary policy (Drechsler et al., 2017, 2021, 2024; Xiao, 2020; Supera, 2021; Wang et al., 2022; Choi and

[2] Adrian and Shin (2010), Borio and Zhu (2012), and Adrian et al. (2019) emphasise that low interest rates can boost risk-taking by increasing bank capital and relaxing bank constraints, which are often introduced to restrict risk-taking under limited liability and potential moral hazard problems.

[3] Bauer et al. (2023) also suggest that low interest rates can increase the risk appetite of banks.

[4] A closely related literature focuses on the impact of low interest rates on bank risk-taking (Heider et al., 2019; Whited et al., 2021).

Rocheteau, 2023; Kho, 2025; Wang, 2025) to credit risk-taking and financial stability outcomes. Earlier works by Hannan and Berger (1991) and Neumark and Sharpe (1992) first empirically documented the imperfect pass-through of policy rates to deposit rates.[5] Recent works by Drechsler et al. (2017, 2021) further show that deposit franchise plays a central role in banks' risk management and the transmission of monetary policy to deposits and lending. Building on their results, we demonstrate that the endogenous relationship between deposit franchise value and interest rates amplifies risk-taking responses when policymakers tighten rates.

Fourth, we contribute to a recently resurgent literature on the interaction between banks' interest rate risk and credit risk. While Hellwig (1994) first pointed out the difficulty in separating interest rate risk and credit risk in banks, recent papers have shown this both quantitatively and empirically (see e.g., Elenev and Liu, 2025; Uppal, 2025). In our framework, banks' deposit franchise directly influences their exposure to interest rate risk, which subsequently determines their response in terms of credit risk taking. As such, our model describes a novel way through which a bank's interest rate risk and credit risk are tightly connected with implications for bank risk management.[6]

Finally, we speak to the long-standing competition–stability debate (Keeley, 1990; Demsetz et al., 1996; Allen and Gale, 2000, 2004; Hellmann et al., 2000; Boyd and De Nicolo, 2005; Beck et al., 2006; Martinez-Miera and Repullo, 2010; Jiménez et al., 2013; Vives, 2016; Berger et al., 2017; Carlson et al., 2022; Li and Song, 2023). In our framework, what matters is not competition per se, but the interaction between deposit franchise and monetary policy, and the resulting dynamics of risk-taking. We build on the existing view that deposit franchise value plays a disciplinary role in restricting excessive risk-taking,[7] and further postulate that the deposit franchise is not only influenced by competition but also interacts with the level of interest rate and, therefore, monetary policy (Drechsler et al., 2017, 2021). Accordingly, we show that deposit franchise plays a crucial role, not only in the overall fragility of the banking system, but importantly, also in the *transmission* of monetary policy to credit risk-taking and financial stability.

[5] See also Driscoll and Judson (2013), Yankov (2024), and d'Avernas et al. (2025) for more recent evidence.

[6] Other papers that consider interactions between interest rate risk and credit risk include Di Tella and Kurlat (2021), Jiang et al. (2024), and Begenau et al. (2025).

[7] Unlike the existing literature, we focus our analysis on banks' profitability in deposit markets, rather than studying competition in general.

2 Theoretical Framework

In this section, we develop a tractable model of bank deposit franchise to illustrate how the deposit franchise interacts with the risk-taking channel of monetary policy. In the model, banks' risk choice reflects the trade-off between the additional profits from risk-taking and the potential loss of deposit franchise in the event of a bank failure. Deposit franchise reduces the sensitivity of depositors' demand to banks' deposit rates, allowing banks to charge higher deposit spreads and earn more profits when interest rates increase. Following rate hikes, the expected future profits of high-franchise banks rise more than those of low-franchise banks. Naturally, high-franchise banks reduce credit risk more following interest rate increases, as they have more at stake to protect.

2.1 Model Setup

Deposit Franchise. Denote the deposit rate offered by bank i as r_i^D. As in Drechsler et al. (2021) and DeMarzo et al. (2024), we assume that the bank has a deposit franchise, which allows it to pay a deposit rate lower than the policy rate,

$$r_i^D = \beta_i^D r.$$

Here, r is the policy rate (e.g., the Fed Funds rate) and $0 < \beta_i^D < 1$ is the deposit beta that determines the sensitivity of bank i's deposit rate with respect to the policy rate. For a given policy rate, the bank pays a lower deposit rate if it has a larger deposit franchise (i.e., β_i^D is lower). Drechsler et al. (2017) micro-found this deposit rate behaviour as the optimal rate-setting strategy for banks with market power over depositors. Recent works by Lu et al. (2024), Cirelli and Olafsson (2025), Egan et al. (2025), and Lu and Wu (2025) show that depositor inactivity and inattention can drive the imperfect deposit rate pass-through and are important sources of banks' deposit franchise.

Bank Risk-Taking. In addition, banks choose the riskiness of their loan portfolio. The interest income on bank i's assets is $(\theta_i + r)$ where r is the policy rate and θ_i is the loan spread earned by issuing riskier loans.

Crucially, risk-taking increases the likelihood of bank failures. The *survival* probability of the bank is given by the function $p(\theta_i)$. As in Allen and Gale (2004) and Boyd and De Nicolo (2005), we impose the following restrictions on $p(\cdot)$,

$$p'(\cdot) < 0, \quad p''(\cdot) \leq 0, \quad p(0) = 1, \quad p(\bar{\theta}) = 0.$$

First, $p(\cdot)$ is decreasing in θ_i, as risk-taking increases the probability of bank failure. Second, $p(\cdot)$ is concave, reflecting a "decreasing return to risk-taking." As the risk premium θ_i rises, the bank must bear greater default risk in exchange for additional risk premia.[8] Third, if a bank invests all of its deposits in safe assets (e.g., Fed Funds), it has zero default risk. Fourth, there exists an upper bound of risk-taking $\bar{\theta}$ such that the bank fails with certainty if $\theta_i \geq \bar{\theta}$.

For tractability, we will assume the following functional form of $p(\cdot)$ for the results proven in Section 2.2.

Assumption 1 *The survival probability is given by* $p(\theta_i) = 1 - \lambda\theta_i^2$.

It is easy to verify that this function satisfies the four requirements on $p(\cdot)$ for positive values of λ. In this case, the risk-taking limit is $\bar{\theta} = \lambda^{-\frac{1}{2}}$.

Banks' Optimization Problem. Bank i chooses risk-taking θ_i to maximise its expected profit, which is the product of the bank's survival probability $p(\theta_i)$ and its profit margin $(\theta_i + r - r_i^D)$,

$$\max_{\theta_i} \; p(\theta_i)(\theta_i + r - r_i^D) \quad \text{s.t.} \quad r_i^D = \beta_i^D r. \tag{1}$$

The bank faces the following key trade-off related to risk-taking: by taking on more risk, it earns a higher risk premium and profit margin, but the probability of default also heightens, in which case it has to forfeit profit $(\theta_i + r - r_i^D)$.

2.2 Model Implications

The first-order condition with respect to risk-taking is

$$-p'(\theta_i)(\theta_i + r - r_i^D) = p(\theta_i). \tag{2}$$

The left-hand side reflects the marginal contribution of risk-taking to the probability of bank default $-p'(\theta_i)$, in which case it forgoes the profit $(\theta_i + r - r_i^D)$. The right-hand side term is the expected marginal profit from risk-taking, which equals one but only materialises if the bank does not fail.

[8]This condition is necessary to ensure that banks do not take on an infinite amount of risk.

How does the deposit franchise interact with the bank's risk-taking decision? Recall that the bank's deposit spread is given by

$$r - r_i^D = (1 - \beta_i^D) r.$$

If the deposit beta β_i^D is low, depositors are less sensitive to the deposit rate offered by the bank. Hence, low-beta banks increase their deposit rates less in response to policy rate hikes. As a result, their deposit spread and expected profit rise, prompting them to curb risk more aggressively than high-beta banks to preserve the higher expected profit.

More formally, we can differentiate the condition (2) to focus on the impact of interest rates on risk-taking, which yields

$$\frac{\partial \theta_i}{\partial r} = -\frac{1 - \beta_i^D}{2 + p(\theta_i)[-p''(\theta_i)][p'(\theta_i)]^{-2}}. \tag{3}$$

Since $p''(\theta_i) \leq 0$, both the numerator and denominator in (3) are positive, which implies $\partial \theta_i / \partial r < 0$. Moreover, the magnitude of $\partial \theta_i / \partial r$ is larger (in absolute terms) when the deposit franchise, $(1 - \beta_i^D)$, is larger. When there is no deposit franchise (i.e., $\beta_i^D = 1$), the impact of interest rates on risk-taking disappears. The core conclusion from this analysis is that the deposit franchise amplifies the impact of interest rate changes on risk-taking.

Finally, the following Proposition summarises the transmission of monetary policy to risk-taking both in the aggregate and the cross-section.[9]

Proposition 1 (The Risk-Taking Channel of Monetary Policy)

(i) *Banks with a positive deposit franchise (i.e.,* $\beta_i^D < 1$*) take on less risk following increases in the policy rate,*

$$\frac{\partial \theta_i}{\partial r} < 0.$$

(ii) *Moreover, low-deposit-beta banks reduce risk more than high-deposit-beta banks following increases in the policy rate, as long as r is below banks' risk-taking limit* $\bar{\theta}$*,*

$$\frac{\partial}{\partial(-\beta_i^D)} \left(\frac{\partial \theta_i}{\partial r} \right) < 0.$$

[9] We relegate the proof to Appendix A.

2.3 Discussions

Relationship with Existing Mechanisms. The classic search-for-yield mechanism suggests that expansionary monetary policy (i.e., rate cuts) reduces banks' asset returns and narrows banks' net interest margins, therefore pushing them toward riskier assets to compensate for lower profitability (e.g., Rajan, 2006; Borio and Zhu, 2012). In our framework, the same rate cut reduces banks' profitability from deposit-taking by compressing deposit spreads, eroding their incentives to protect their deposit franchise, especially for low-beta (high-franchise) banks. The loss of deposit franchise then contributes to banks' incentive to chase risk as they have less to lose in the adverse scenario where credit risk-taking results in a bank failure.

Another strand of models linking interest rates to risk-taking focuses on moral hazard, which emphasises that limited liability induces banks to shift risk to depositors. Monetary policy can either alleviate or exacerbate the risk-shifting incentives by affecting banks' funding costs, leverage, and cash flows, leading to changes in their risk-taking behaviour (e.g., Adrian and Shin, 2010; De Nicolò et al., 2010; Dell'Ariccia et al., 2014; Bonfim and Soares, 2018). In contrast, our analysis focuses on the interaction between the deposit market and the moral hazard problem stemming from limited liability. Our model builds on the intuition that deposit franchise value tempers banks' risk-shifting incentives (Keeley, 1990; Demsetz et al., 1996; Hellmann et al., 2000), and that the deposit franchise consideration is endogenous to monetary policy: when rates rise, banks enjoy increases in deposit spreads and profits, which thereby gives bank managers more "skin in the game" and leads them to curb risk-taking to protect their deposit franchise.

In the cross-section, both existing theories typically point to bank capitalisation as the main driver of risk-taking responses across banks (e.g., Jiménez et al., 2014; Dell'Ariccia et al., 2017), whereas we highlight the key role of the deposit franchise. According to our theory, heterogeneous responses in profits across banks with different deposit franchises to interest rate changes imply that low-deposit-beta banks contract risk more aggressively than their high-deposit-beta peers following a tightening of monetary policy.

Interest Rate Risk Hedging and Credit Risk-Taking. Low-deposit-beta banks see their deposit franchise values rise more following interest rate hikes. Drechsler et al. (2021) show that low-beta banks optimally choose to hold a larger fraction of their assets in long-term securities, which lose value when interest rates rise. As a result, banks can maintain a stable equity value despite fluctuations in interest rates.

How can deposit franchise value influence risk-taking when banks are hedged against interest rates? Importantly, interest rate risk hedging is achieved when banks stay solvent and their deposit franchise is present. In our framework, when credit risk-taking renders a bank insolvent, the deposit franchise value is lost permanently.[10] In normal times, bank equity value depends on the sum of its asset value and franchise value and can be hedged against interest rates. Upon default, while bank securities can be liquidated, the deposit franchise evaporates, generating heavier losses for low-beta banks. Hence, even if the impacts of monetary policy on deposit franchise are hedged in normal times, they become first-order when the possibility of defaults is considered.

To further illustrate this point, consider two banks of the same size. Bank *A* has a stronger deposit franchise (lower deposit beta) while Bank *B* has a weaker deposit franchise (higher deposit beta). In addition to credit risk, banks can also choose the duration of their assets. Bank *A* optimally chooses a higher asset duration than bank *B* to hedge its cash flows (Drechsler et al., 2021). When interest rates increase, Bank *A*'s assets lose more value, which is offset by the higher profits it earns from wider deposit spreads, conditional on its survival. However, when banks fail under higher interest rates, they can no longer capture any deposit spread while still having to bear asset value losses. Following higher interest rates, the asset value Bank *A* can recoup during the default process declines more and is lower than that of Bank *B*, which effectively increases its cost of default.[11] As a result, Bank *A* will also optimally choose to reduce its credit risk more when rates are higher.

Therefore, although we do not explicitly model banks' asset duration choice in our baseline model, we can still capture the key trade-off associated with credit risk-taking: higher credit risk generates higher loan premia and profits for banks, but it also raises the likelihood of bank failure, which can lead to a permanent loss of deposit franchise. Again, reducing credit risk following contractionary monetary policy shocks serves as a means to preserve banks' deposit franchises, and the incentive to do so is stronger for banks with lower deposit betas.

We further note that our arguments on the trade-off around credit risk-taking also apply when banks are unable to fully hedge their interest rate risk (e.g., Di Tella and Kurlat, 2021; Jiang et al., 2024). Regardless of whether the equity value of banks is hedged against interest rates, a significant source of value destruction in the event of default still stems from the loss of the deposit franchise. The prediction of our model remains: banks that experienced larger increases in their deposit profitability after interest rate increases, such as those with lower deposit betas, optimally reduce their credit risk more to protect

[10] This is akin to the bank run scenario studied in Drechsler et al. (2025).

[11] It also weakens the bank's fundamentals and can raise the ex-ante probability of a run (e.g., Drechsler et al., 2025).

their deposit franchise.

The Risk-Adjusted Present Value of the Deposit Franchise. In this paper, we associate a strong deposit franchise with a low deposit beta and high deposit spread, whereas the literature also defines deposit franchise as the risk-adjusted present value of the profits from deposit-taking (e.g., Gomes et al., 2023; DeMarzo et al., 2024; Gupta, 2025). Here, we show that the two definitions are tightly connected and point to the same cross-sectional relationship.

In our framework, imperfect deposit-rate pass-through generates $r - r_i^D$ units of profits per unit of deposit. The expected profit from deposit-taking is simply the bank's survival probability multiplied by its deposit spread, $p(\theta_i)(r - r_i^D)$. To understand the present value of the deposit franchise, we can assume that the static problem (1) is repeated for an infinite number of periods.[12] Suppose that the bank is risk-neutral and discounts the expected profit at the risk-free rate r, the deposit franchise then has a present value of

$$\text{(Deposit Franchise Value)}_i = \frac{p(\theta_i)(r - r_i^D)}{r} = p(\theta_i)(1 - \beta_i^D). \tag{4}$$

Intuitively, $1 - \beta_i^D$ is the present value of the deposit franchise absent any risk (DeMarzo et al., 2024), and the survival probability $p(\theta_i) < 1$ is the "risk adjustment" that increases the bank's effective discount rate and reduces its franchise value.[13]

In equilibrium, low-beta banks take on less risk to preserve their franchise value (i.e., $\partial\theta_i/\partial\beta_i^D > 0$),[14] which leads to higher survival probabilities. Hence, the risk-adjusted deposit franchise value is indeed higher for low-beta banks, confirming our use of the deposit beta as a proxy for the deposit franchise in the cross-section. Further, Proposition 1(i) shows that banks take on less risk when interest rates rise. As a result, the survival probability $p(\theta_i)$ increases with interest rates, and so does the risk-adjusted franchise value of any given bank.

It is worth noting that the present value of the deposit franchise value in (4) might not directly depend on the policy rate r, as argued by DeMarzo et al. (2024). How is it still possible that the bank's risk-taking responses to monetary policy depend on its deposit franchise concerns? Intuitively, we can also write the first-order condition (2) in the

[12] In practice, the deposit franchise has a finite duration, and risk-taking and bank defaults can have intertemporal consequences. We abstract away from these forces in this stylised model as they do not affect the main implications of the model.

[13] Equivalently, (4) is also the franchise value of a bank with no default risk for an investor with a discount rate of $r/p(\theta_i) > r$.

[14] See Appendix A for a proof and Li and Song (2023) for supporting empirical evidence.

present value form,

$$\underbrace{\frac{1}{r}\frac{d[p(\theta_i)\theta_i]}{d\theta_i}}_{\text{PV(marginal gain)}} = \underbrace{-p'(\theta_i)(1-\beta_i^D)}_{\text{PV(marginal cost)}}.$$

As the discount rate r increases, the present value of future risk-taking declines regardless of the deposit franchise strength, incentivising the bank to take on less risk, which supports the classic risk-taking channel (Proposition 1(i)). Further, the marginal cost of risk-taking reflects the increase in the probability of deposit franchise loss and is linked to the marginal contribution of θ_i to (4), namely $-p'(\theta_i)(1-\beta_i^D)$. Importantly, although $-p'(\theta_i)(1-\beta_i^D)$ does not depend on r directly, it is a steeper function of θ_i for low-beta banks as $p'(\theta_i) < 0$. Therefore, while the gains from risk-taking fall for all banks in response to rate hikes, low-beta banks curb risk more aggressively than high-beta banks (Proposition 1(ii)).

3 Data and Descriptive Statistics

We assemble a panel that combines supervisory loan-level data with standard regulatory filings and high-frequency monetary-policy surprises.

3.1 FR Y-14 Supervisory Data

Our primary dataset is derived from the Corporate Loan Schedule H.1, part of the Federal Reserve's *Y-14Q* regulatory collection (hereafter, "Y-14"). The Y-14 data were introduced following the 2007–2009 financial crisis, under the Dodd-Frank Act, to support supervisory stress-testing and macroprudential oversight. They cover large U.S. bank holding companies (BHCs) subject to the Comprehensive Capital Analysis and Review (CCAR) program. The Corporate Schedule H.1 provides detailed, facility-level information on all corporate loan exposures with committed amounts exceeding $1 million. As Bidder et al. (2021) highlight, these loans capture more than two thirds of all commercial and industrial loans extended by BHCs in the US. For banks in our sample, the data are reported quarterly and represent the full population of qualifying loan facilities. The schedule includes granular information on credit terms, borrower characteristics and internal risk ratings.

Importantly, the Y-14 data include banks' internal risk assessments for each borrower. Among the available measures, we focus on the probability of default (PD) following, among others, Faria-e-Castro et al. (2024), which reflects the institution's estimate of the likelihood that a loan will become non-performing over the next year. Specifically, the PD captures the event that the borrower either fails to repay the loan in full or becomes delinquent on scheduled payments. Per reporting guidance, banks are required to assess the PD at the borrower level, rather than at the individual loan level. This standardization allows for comparability across loans extended to the same firm, even when multiple banks are involved.[15] We restrict the sample to 2015:Q1-2024:Q2 where the start of the sample is determined by the fact that the risk assessments that we use in our analysis became consistently available at that time. Moreover, we restrict our empirical analysis to loans with a PD of less than or equal to five percent not to capture outliers.

3.2 Call Reports

We use quarterly Call Reports to complement our loan-level data with bank-level information. The primary purpose of using this data is to estimate bank-level deposit betas. Our approach to calculate the deposit beta is based on Drechsler et al. (2021). Specifically, we run the following regression over the period 1984 to 2014:

$$\Delta \text{DepIntExp}_{it} = \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau}^{D} \Delta \text{FedFunds}_{t-\tau} + \varepsilon_{it} \tag{5}$$

where $\Delta\text{DepIntExp}_{it}$ is the change in bank i's deposit interest expense rate from t to $t+1$, α_i are bank fixed effects, and $\Delta\text{FedFunds}_t$ is the change in the Fed funds rate from t to $t+1$.[16] We thus define the bank-level deposit beta as the sum of the beta coefficients in (5): $\beta_i^D = \sum_{\tau=0}^{3} \beta_{i,\tau}^D$. Finally, we winsorise our betas at the 3 percent level which ensures no deposit beta is greater than one. Given the Y-14 data is at the Bank Holding Company (BHC) level, we use the bank-level deposit beta of the lead commercial bank within the holding company structure which represents the majority of deposits and loans within the BHC.

We merge bank-level income statement and balance sheet data from quarterly call reports with our deposit beta estimates. This data serves a number of purposes. First, we use this data to construct balance tables in order to compare differences between high deposit beta banks and low deposit beta banks, providing support for our identification

[15] See the U.S. implementation of the Basel II Capital Accord for the definition of default (p. 69398) and the definition of probability of default (p. 69403): `https://www.govinfo.gov/content/pkg/FR-2007-12-07/pdf/07-5729.pdf`

[16] The deposit interest expense rate is the total quarterly interest expense on domestic deposits divided by domestic deposits and then annualised (multiplied by four).

strategy. Second, we use this data to support additional robustness exercises. Finally, this data enables us to conduct horse race regressions in order to compare and contrast the predictions of our deposit franchise mechanism with alternative channels identified in the literature that rely on bank capital heterogeneity.

3.3 Monetary Policy Data

The monetary policy data has two components. The first is the central bank policy rate, which in our context is the Fed Funds Rate (FFR), obtained from FRED. The second is a measure of a monetary policy shock. We use the measure of monetary policy shocks from Jarociński and Karadi (2020), which is periodically updated and thus has the advantage of being available from 1990 until September 2024.

We use the shock series from Jarociński and Karadi (2020) as they combine high frequency identification and sign restrictions in order to identify the structural monetary policy shock and purge the information effect. Specifically, they incorporate the 30-minute change in three-month Fed-funds futures around each FOMC statement and the simultaneous S&P 500 move into a sign-restricted VAR: a rate rise accompanied by a stock-price fall (negative co-movement) is tagged as a pure monetary-policy shock, while a rate rise alongside a stock-price rise (positive co-movement) is classified as a central-bank information shock, the sign restrictions enforcing the separation directly in the data. Using this cleaner shock therefore lets us attribute any change in loan-level PDs to the incentive effects of the rate move itself (deposit-franchise valuation, search-for-yield, etc.) rather than to shifting expectations about borrowers' fundamentals—exactly the isolation the risk-taking channel requires.

To ease interpretation, shocks have been normalised such that they represent a one percentage point hike in the FFR on impact.

3.4 Final Panel

After merging all sources and applying the filters above, we obtain approximately 4.9 million loan-quarter observations from 24 US bank holding companies, between 2015 and 2024 covering 208,435 unique corporate borrowers. Each observation is uniquely identified by (bank i, borrower b, loan k, quarter t). In Table 1 below, we report the summary statistics of our merged panel.

Table 1: Summary Statistics

	N	Mean	25^{th}	75^{th}	Std. Dev.
Loan-level variables					
Probability of Default	4.9M	2.26	0.17	1.38	8.83
Probability of Default (< 25%)	4.8M	1.42	0.17	1.28	2.83
Probability of Default (< 5%)	4.5M	0.82	0.15	1.07	0.94
Loan size ($M)	4.9M	8.60	0	5.52	30.64
Interest rate	3.4M	4.11	2.63	5.20	2.88
Collateralized loan	4.9M	0.78	1	1	0.41
Loan maturity (< 20 years)	4.2M	5.43	3.35	6.99	3.18
Bank-level variables					
Tier 1 capital ratio	984	0.13	0.11	0.14	0.03
Equity/assets	984	0.11	0.09	0.12	0.02
Total assets ($M)	984	534,173	151,148	466,138	714,751

Note: This table reports summary statistics for loan-level and bank-level variables in the final merged panel dataset. Columns show the number of observations (N), mean, 25th percentile, 75th percentile, and standard deviation. *Probability of Default* is the loan-level default probability (percentage points). *Probability of Default (< 25%)* and *Probability of Default (< 5%)* repeat the same variable after trimming PDs above 25% and 5%, respectively. *Loan size ($M)* is the outstanding principal balance in millions of U.S. dollars. *Interest rate* is the contractual annual interest rate (percent). *Collateralized loan* is an indicator equal to 1 for loans secured by collateral and 0 otherwise. *Loan maturity (< 20 years)* is the remaining maturity in years (capped at 20 years). *Tier 1 capital ratio* is the bank's Tier 1 capital divided by risk-weighted assets. *Equity/assets* is the bank's book equity divided by total assets. *Total assets ($M)* is total bank assets in millions of U.S. dollars.

4 Empirical Strategy and Results

In this section, we lay out our empirical framework and document the main results. Using an improved loan-level measure of ex ante risk, we first re-establish the aggregate risk-taking channel of monetary policy for the United States: easing shocks are followed by a statistically and economically significant rise in loan-book risk, fully in line with earlier evidence.

Our second—and novel—result confirms the cross-sectional prediction of the model: banks endowed with greater deposit franchise, proxied by lower deposit betas, tighten their risk exposure more when policy rates increase. This finding lends credence to the deposit-franchise mechanism as a distinct strand of monetary policy transmission.

4.1 The Risk-Taking Channel of Monetary Policy

We begin by documenting the risk-taking channel, abstracting from any cross-sectional heterogeneity in deposit franchise. The objective is threefold. First, it provides a benchmark against which our deposit franchise mechanism can be compared. Second, it serves as a validation exercise for our enhanced data and identification strategy. Third, it provides evidence consistent with Proposition 1(i).

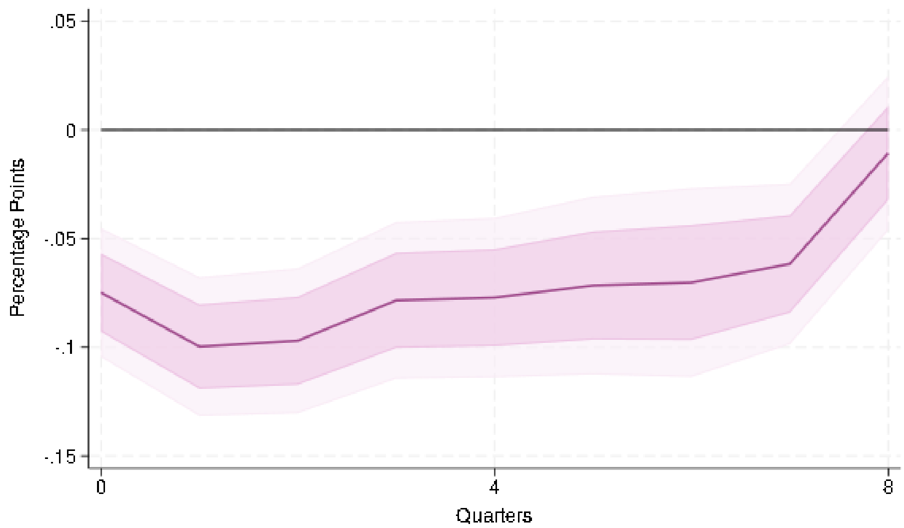
In order to confirm the risk-taking channel and thus Proposition 1(i) in our setup, we estimate the following local projections for horizons $h = 0 \ldots 8$:

$$z_{k,i,t+h} = \alpha_i + \delta_b + \sum_{l=0}^{4} \beta_{h,l} \text{Shock}_{t-l} + \varepsilon_{k,i,t+h} \tag{6}$$

where $z_{k,i,t+h}$ is ex ante risk (PD) for loan k at horizon h, Shock_{t-l} is the monetary policy shock from Jarociński and Karadi (2020) which seek to isolate unexpected changes in the short-term risk-free rate, α_i are bank fixed effects, and δ_b reflect borrower fixed effects. $\{\beta_{h,0}\}_{h=0}^{8}$ traces out the impulse response function and can be interpreted as the response of bank risk-taking at time $t + h$ to a contractionary monetary policy shock at time t. We cluster the standard errors at the bank-by-time level to account for the heterogeneous effects of monetary policy shocks across banks, which is at the heart of our theory.

Figure 1 below confirms Proposition 1(i) and the risk-taking channel of monetary policy in our data: higher rates reduce bank risk-taking. Specifically, we find that a contractionary monetary policy shock that induces a one percentage point hike in the Federal Funds Rate (FFR) causes the PD on bank loans to fall by nearly 0.08 percentage points on impact. Given that the average PD in our sample is around 0.8%, this reflects an economically meaningful decrease in bank risk-taking of around 10%.

Figure 1: Average Risk-Taking Falls After A Contractionary Monetary Policy Shock



Note: This figure plots impulse-responses from local projections (6) over horizons 0–8 quarters, showing the responses of the loan-level probability of default after a +1 pp monetary policy shock. Bank and borrower fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

While Figure 1 does not present new evidence, we innovate relative to the existing evidence on the risk-taking channel of monetary policy in the US in several important ways: (i) loan-level PDs, (ii) borrower fixed effects, and (iii) dynamic impulse-response functions that trace the channel over a full two-year horizon.

Given that the PD is continuous, forward-looking, and updated whenever the lender adjusts tenor, collateral, guarantees, or model overrides, it captures ex ante risk-taking far more precisely than ex post defaults or coarse agency ratings. Dell'Ariccia et al. (2017) also use a measure of ex ante risk-taking by banks in the US to document the risk-taking channel of monetary policy. However, they rely on the now-discontinued Survey of Terms of Business Lending (STBL), where risk is recorded on a five-point scale and borrower identities are unknown. Because our data identify each borrower, we can include borrower fixed effects, purging permanent cross-firm heterogeneity and ensuring that the estimated risk-taking coefficient is not driven by the static mix of firms that receive credit.[17] Table B.1 in Appendix B validates PD as a loan-level measure of ex ante risk-taking in the spirit of Dell'Ariccia et al. (2017): collateralised loans and higher interest rates correlate

[17]When we omit borrower fixed effects, the risk-taking response is larger as the estimate now also reflects the extensive-margin shift in which borrowers obtain loans (Figure B.1).

positively with a higher probability of default while loan size and maturity correlate negatively. Using local projections, we follow the risk-taking channel out to eight quarters. Understanding the first-quarter impact is important, but financial stability concerns are more likely to arise if risk choices persist. Figure 1 shows they do: after a contractionary surprise, banks originate safer loans for almost two years. Symmetrically, an unexpected easing can set in motion a prolonged build-up of risk.

Taken together, these results confirm that our data and identification strategy recover the well-established aggregate risk-taking channel: when monetary policy tightens, banks originate safer loans on average. We next ask whether this aggregate pattern masks the more nuanced, franchise-driven heterogeneity predicted by our model.

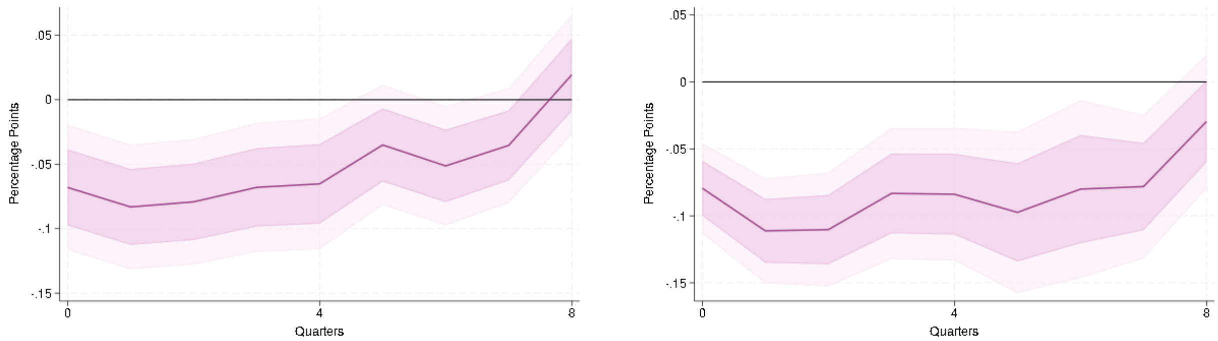
4.2 The Role of the Deposit Franchise

Our theoretical framework in Section 2, specifically Proposition 1(ii), predicts that a monetary policy tightening reduces loan risk more at banks with a greater deposit franchise (i.e., lower deposit betas), because a rate hike expands deposit spreads more for banks with a sticky depositor base. Protecting that franchise gives these low-beta banks an extra incentive to curb risk, whereas high-beta peers—whose deposits re-price more elastically—should adjust far less. In this section, we develop an empirical strategy to test this novel prediction.

We start by dividing the banks in our sample into two equal-sized groups of high- and low-beta banks and then estimating equation (6) for each subsample. Figure 2 presents the results. Given the deposit betas are pre-determined, we interpret Figure 2 as suggesting that there are differences in the way banks with different betas react to the same shock. In particular, and consistent with Proposition 1(ii), low-beta banks are more responsive than high-beta banks. However, differences in credit demand across low- and high-beta banks could confound these findings. Therefore, we next formally test the role of the deposit franchise and control for potential credit demand heterogeneity.

Our formal test of Proposition 1(ii) employs a shift-share-type design that combines time-series monetary policy surprises—the high-frequency shocks of Jarociński and Karadi (2020) (the "shift")—with cross-sectional heterogeneity in banks' deposit betas (the "share"). As before, we estimate each bank's average pass-through of policy rates to deposit rates over 1984–2014; a lower beta indicates a stronger deposit franchise and therefore a larger profit gain when rates rise. Because these betas are measured before our 2015–2024 estimation window, they are pre-determined with respect to the shocks and can be treated as structural primitives that our theoretical model takes as given. The interaction term

Figure 2: Comparison Of Average Risk-Taking Dynamics



(a) High Beta (b) Low Beta

Note: This figure plots impulse-responses from local projections (6) over horizons 0–8 quarters, showing the responses of the loan-level probability of default after a +1 pp monetary policy shock for two subsamples. Panel (a) restricts to high deposit-beta banks; panel (b) restricts to low deposit-beta banks. Bank and borrower fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

$\text{Shock}_t \times \text{DepositBeta}_i$ therefore has a direct structural interpretation: it captures the causal effect of monetary policy, transmitted through deposit-franchise exposure, on loan-level risk-taking. This mapping provides a clean empirical counterpart to Proposition 1(ii).

As mentioned earlier, a key advantage of our empirical strategy is that we leverage the Federal Reserve's loan-level supervisory data. This allows us to include borrower-time fixed effects, forcing identification to come from within-quarter comparisons of loans that different banks make to the same firm. Because each firm's credit demand, investment opportunities, and macroeconomic exposure are differenced out, any remaining response must arise from the supply side—namely, how the policy surprise affects each bank through its pre-existing deposit franchise.

Formally, we introduce the interaction term to the specification in (6), and thus estimate local projections for horizons $h = 0, \dots, 8$:

$$z_{k,i,t+h} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i) + \varepsilon_{k,i,t+h} \tag{7}$$

where $z_{k,i,t+h}$ captures the ex ante risk for loan k at horizon h as measured by the PD, Shock_t is the Jarociński and Karadi (2020) monetary policy shock measure, DepositBeta_i is the pre-determined bank deposit beta estimated from 1984 to 2014, $\delta_{b,t}$ capture borrower-time fixed effects, and α_i represents the bank fixed effect. As before, standard errors are clustered at the bank-by-time level and robust to bank-level clustering.

Figure 3 shows the impulse response function traced out by $\{\lambda_{h,0}\}_{h=0}^{8}$. It shows that banks with a stronger deposit franchise (a lower beta) decrease risk-taking significantly more after a contractionary monetary policy shock, precisely in line with the predictions of our model. The result is persistent, and increasing, across our entire projection horizon of two years. While Figure 3 shows results based on all loans (i.e., both new and existing loans), the results are qualitatively similar when focusing on new loans only (see B Figure B.2).[18]

Moreover, our finding is robust across both trimmed and untrimmed PD samples as seen in Figure 3 Panels A, B, and C. We include these different samples to highlight that our result does not hinge on particular outliers in the loan-risk distribution. Nonetheless, one might still be concerned that PDs themselves are not a perfect measure of risk-taking by banks. Using the same Y-14 data, Beyhaghi et al. (2025) verify that bank-reported PDs predict both loan interest rates and ex post performance, consistent with PDs capturing risk-taking by banks. In Appendix B Table B.1, we show this positive association between interest rates and PDs also exists in our sample.

As further validation, we re-estimate (7) with loan-level charge-offs as the outcome variable instead of loan-level PDs. If PDs accurately capture ex ante risk-taking by banks, then one would expect that the results for charge-offs—which capture ex post loan performance—would be similar to those when using PDs. Figure 4 confirms this: charge-offs rise more for high-beta banks, consistent with these banks reducing risk less than low-beta banks in response to a contractionary monetary policy shock.[19]

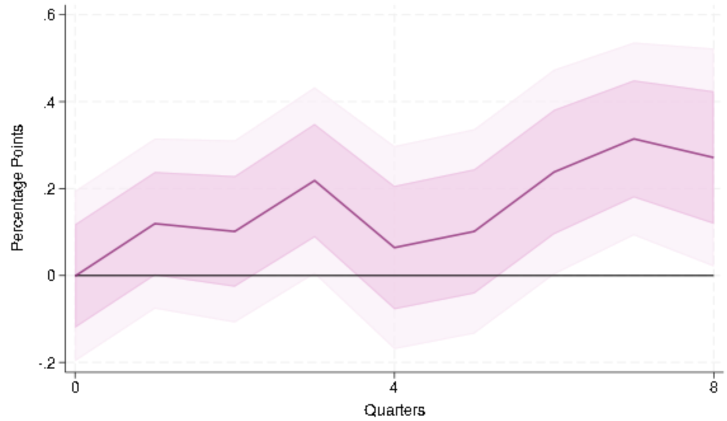
Having established that our main results are robust across different PD samples as well as robust to replacing PDs with loan-level charge-offs, we next assess the validity and interpretation of our deposit franchise measure. Specifically, we address three complementary issues. First, we examine whether our results could be affected by endogeneity in deposit betas and show that pre-determined betas—estimated well before our sample period—are persistent and plausibly exogenous to contemporaneous shocks. Second, we provide direct evidence that these betas capture meaningful variation in franchise strength by showing that they predict deposit profitability in the cross-section. Finally, we verify that our findings are not specific to this measure by constructing and testing an alternative proxy for deposit franchise value based on deposit market concentration (HHI).

[18]Note that while the results for new loans are qualitatively similar, they are noisier due to reductions in the sample size.

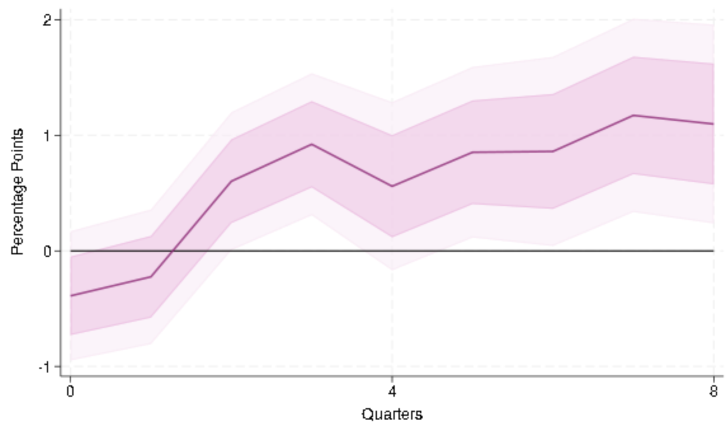
[19]Our result is also robust to different measures of risk, including loan-specific loss given default rates.

Figure 3: Banks With Higher Deposit Franchise (Low Beta) Reduce Risk-Taking More

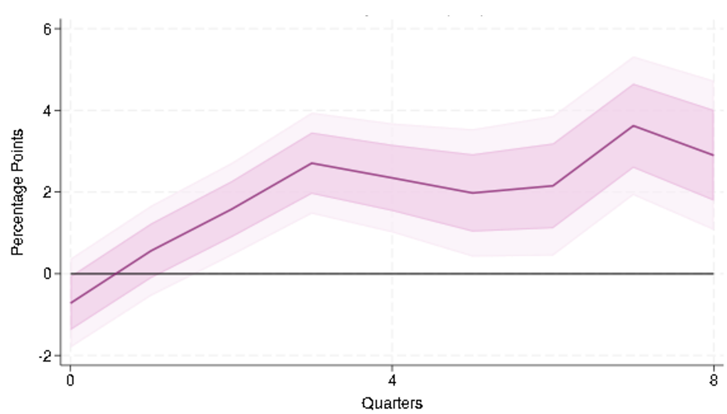
Panel A: PD Trimmed (5%)



Panel B: PD Trimmed (99%)

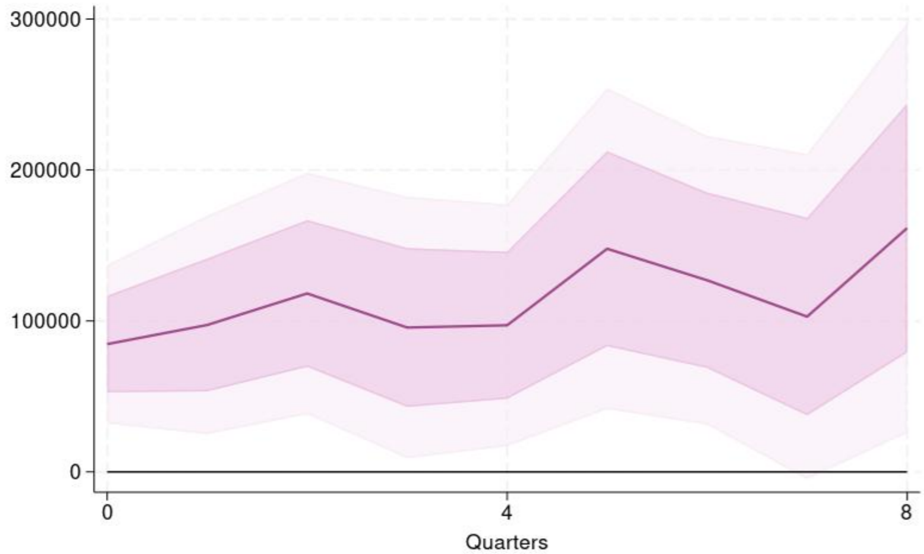


Panel C: PD Untrimmed



Note: This figure plots impulse-responses from local projections (7) over horizons 0–8 quarters, showing the responses of the loan-level probability of default to a +1 pp monetary policy shock interacted with banks' deposit beta. In Panel (a), PDs above 5% are trimmed. In Panel (b), PDs above 99% are trimmed. Panel (c) uses untrimmed PDs. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

Figure 4: Average Risk-Taking Falls After A Contractionary Monetary Policy Shock



Note: This figure plots impulse-responses from local projections (7) over horizons 0–8 quarters, showing the responses of the loan-level charge-offs to a +1 pp monetary policy shock interacted with banks' deposit beta. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

Deposit Beta Endogeneity. In our theoretical framework, we treat each bank's deposit beta as an exogenous parameter rather than a choice variable. This assumption delivers a one–for–one mapping between the model's comparative statics and the empirical shift–share specification. The immediate endogeneity concern in the data that the deposit beta adjusts mechanically to the monetary policy shocks is mitigated by estimating betas on pre-sample data (1984–2014).[20]

A remaining source of endogeneity is the possible correlation between the deposit beta and latent bank attributes that also shape risk-taking. For instance, a bank that expects to tighten lending standards may deliberately keep deposit rates sluggish (e.g., due to expectations of a recession), so a low deposit beta could proxy for forward-looking risk appetite. Indeed, it is possible that low- and high-beta banks are different in many important ways. For example, low-beta banks might be more retail-oriented and thus could differ systematically in portfolio mix, governance, or regulatory scrutiny; if these traits are omitted, the coefficient on $\text{Shock}_t \times \text{DepositBeta}_i$ would absorb their influence and thus our estimates would no longer be unbiased.

We address these issues in two ways. First, as highlighted in Drechsler et al. (2021), de-

[20] Emin et al. (2025) show that the pass-through to deposit rates does vary with the level of interest rates.

posit betas are relatively stable over time, which suggests they reflect slow-moving market power rather than transitory pricing decisions around any single shock. Consistent with this, our pre-determined betas—estimated over 1984–2014—are strongly and statistically significantly associated with the betas estimated using our main sample (a non-overlapping period from 2015 until 2024).[21] Moreover, our shocks are high-frequency surprises that are not systematically predictable at the time they occur.

Second, Table 2 documents that low and high-beta banks are similar across a number of core bank and loan characteristics. Most importantly, these banks are similar in their size, capital ratio, and average PD. The final column reports the normalised difference following Imbens and Wooldridge (2009), where $|\Delta_{IW}| < 0.25$ suggests sufficient comparability and thus reasonable balance.[22] These analyses support our structural interpretation of the coefficient on $\text{Shock}_t \times \text{DepositBeta}_i$ as the causal effect of monetary policy transmitted through the deposit franchise.

Table 2: Balance Across High and Low-Deposit Beta Banks (12 banks each group)

Variable	High beta	Low beta	N (High / Low)	Δ_{IW}
Bank-level variables				
Tier 1 capital ratio	0.133	0.130	492 / 492	0.104
Total assets ($M)	566,238	502,107	492 / 492	0.063
Net income/assets	0.006	0.007	492 / 492	0.090
Deposits/assets	0.781	0.805	492 / 492	0.320
Loan-level variables				
Probability of Default	2.41	2.14	2.15M / 2.71M	0.022
Probability of Default (< 25%)	1.38	1.44	2.11M / 2.69M	0.016
Probability of Default (< 5%)	0.80	0.83	1.98M / 2.53M	0.016
Loan Size ($M)	8.84	8.42	2.15M / 2.71M	0.009
Interest rate	4.06	4.15	1.30M / 2.05M	0.021
Collateralized loan	0.73	0.83	2.15M / 2.71M	0.168
Loan maturity (< 20 years)	5.25	5.58	1.84M / 2.35M	0.075

Note: This table compares observable characteristics between high and low deposit-beta banks. Reported are the group means, the number of observations, and the normalised differences following Imbens and Wooldridge (2009).

[21] Our pre-determined deposit betas are also highly correlated with those of Drechsler et al. (2021), estimated over 1984–2023. The updated deposit betas of Drechsler et al. (2021) are available on Philipp Schnabl's website.

[22] Banks with greater deposit franchise (lower betas) have a higher deposit-to-asset ratio on average, which is natural as they focus more on the deposit business.

Deposit Franchise and Deposit Profitability. A key implication of our mechanism is that banks with stronger deposit franchises—those whose funding costs adjust less to changes in policy rates—should earn greater profits from deposit-taking when interest rates rise. If our pre-period deposit betas indeed capture this underlying franchise strength, they should also predict banks' deposit profitability. In other words, banks with higher deposit betas should experience lower profits from their deposit business following a tightening shock.

To test this prediction, we construct a measure of deposit return on assets (Deposit RoA), defined as the ratio of profits from deposit-taking to total assets,

$$\text{Deposit RoA} \equiv \frac{\text{Profits from Deposits}}{\text{Assets}} = \frac{rD - r^D D}{A}, \tag{8}$$

where r is the policy rate, r^D is the deposit rate, and D is the total amount of deposits. In other words, profits from deposit-taking are defined as the difference between a bank's actual interest expense and the interest expense it would incur if it had to pay the policy rate to depositors.

We then estimate a bank-level regression of Deposit RoA on monetary policy shocks interacted with banks' deposit betas:

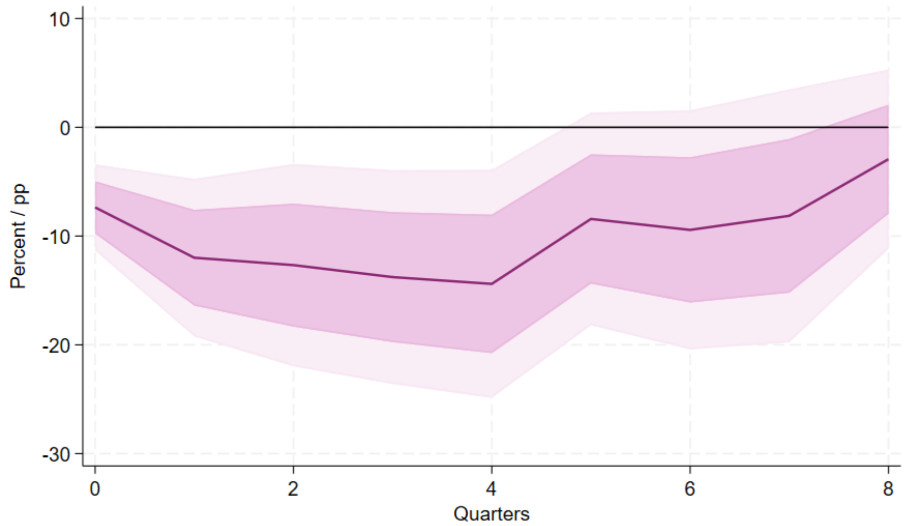
$$\begin{aligned}\text{Deposit RoA}_{i,t+h} =& \alpha_i + \delta_t + \sum_{l=1}^{4} \beta_{h,l} \text{Deposit RoA}_{i,t-l} \\ &+ \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i) + \varepsilon_{i,t+h}\end{aligned} \tag{9}$$

Because this specification is estimated at the bank level rather than the loan level, we cannot include borrower–time fixed effects as we did in earlier specifications. However, it allows us to extend the analysis beyond the supervisory Y-14 data and include all commercial banks, which substantially increases our sample size.[23]

Consistent with our theoretical mechanism, Figure 5 shows that the interaction term is negative: following a contractionary monetary policy shock, banks with lower deposit betas experience larger increases in deposit profitability. This finding confirms that predetermined deposit betas capture meaningful cross-sectional variation in deposit franchise strength.

[23]Note that the larger sample of banks includes a number of outlier deposit betas. We restrict these outlier values to be between zero and one.

Figure 5: Banks With Higher Betas Experience a Larger Fall in Deposit Profitability



Note: This figure plots impulse-responses from local projects (9) over horizons 0–8 quarters, showing the responses of the bank-level deposit RoA to a +1 pp monetary policy shock interacted with banks' deposit beta. Bank fixed effects are controlled. Standard errors are clustered at the bank level. Shaded areas indicate 68% and 90% confidence intervals.

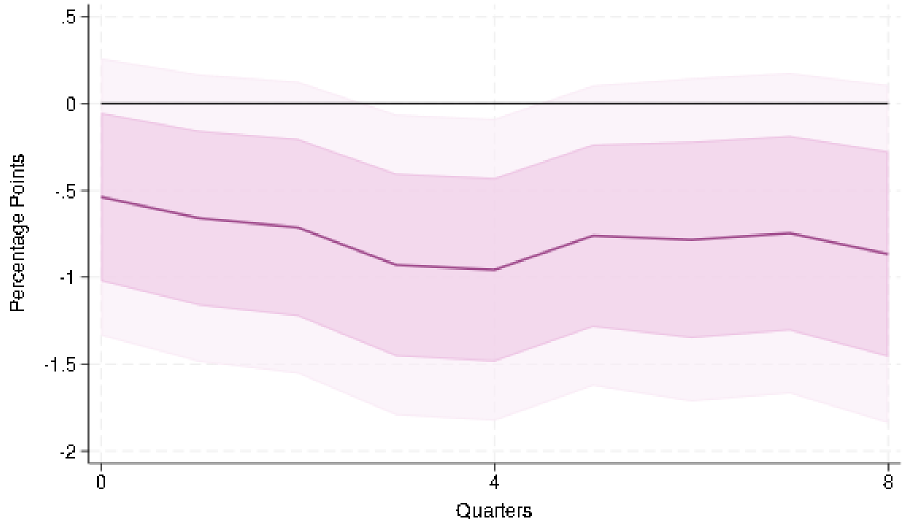
Alternative Measure of Deposit Franchise. Our preferred measure of deposit franchise is the deposit beta, which maps directly to the structural parameter in our model. As a robustness check—and notwithstanding potential limitations—we also use local deposit-share HHI, computed at the bank level as in Drechsler et al. (2017).[24] We re-estimate (7) replacing the bank-level deposit beta with bank-level HHI. Because a higher HHI reflects greater franchise, our mechanism predicts a negative coefficient on the interaction between the monetary policy shock and HHI. Consistent with this, Figure 6 shows a negative coefficient, indicating that banks with higher measured concentration reduce risk-taking more following a contractionary policy shock.

4.3 Horse-Racing

A cut in the policy rate can propagate to bank risk-taking through conceptually distinct balance sheet channels whose identifying dimensions are likewise different. As discussed in Section 2.3, a number of existing channels in the literature, such as the search-for-yield channel and risk-shifting channel, rely on cross-sectional differences in bank capitalisa-

[24]We interpret HHI as a coarse proxy for deposit franchise, because the link between local concentration and actual pricing power can be weakened by a few factors, including uniform pricing and bank business models (Begenau and Stafford, 2023; d'Avernas et al., 2025).

Figure 6: Banks With Higher Deposit Franchise (Higher HHI) Reduce Risk-Taking More



Note: This figure plots impulse-responses over horizons 0–8 quarters, showing the responses of the loan-level probability of default to a +1 pp monetary policy shock interacted with banks' local deposit-share HHI. The specification is identical to (7) except that DepositBeta_i is replaced with the bank's HHI. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

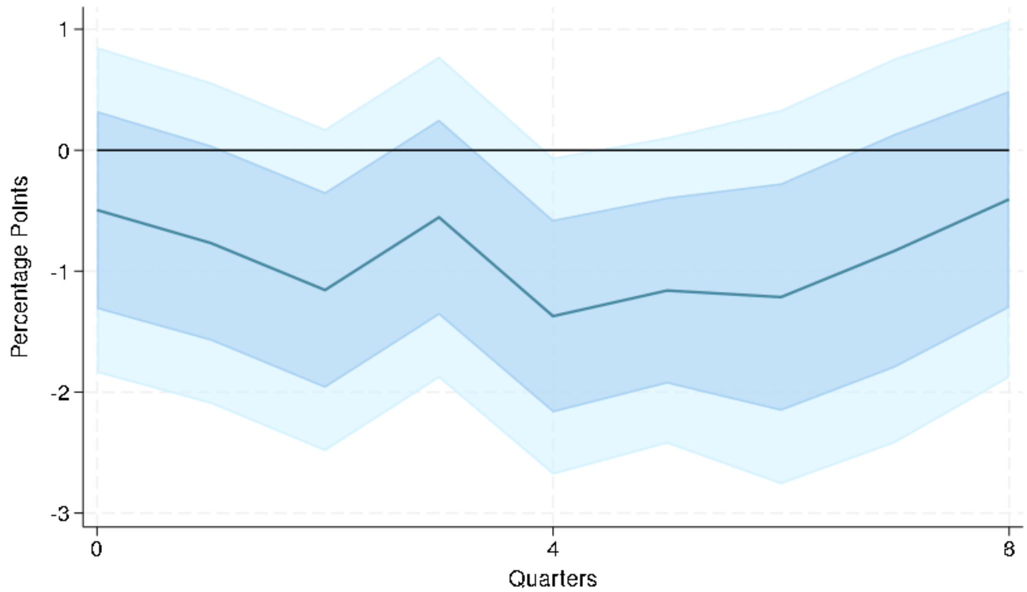
tion to explain risk-taking responses across banks (e.g., Dell'Ariccia et al., 2017). We examine whether capitalisation-based mechanisms hold within our sample. As such, we estimate the following regression:

$$z_{k,i,t+h} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{L} \gamma_{h,l} \cdot (\text{Shock}_{t-l} \times \text{CapitalRatio}_i) + \varepsilon_{k,i,t+h} \tag{10}$$

Consistent with Dell'Ariccia et al. (2017), Figure 7 shows that following a rate hike, banks with higher capital ratios reduce risk-taking more. As before, we innovate relative to the existing literature examining capitalisation-based mechanisms for the risk-taking channel of monetary policy in the US in three ways: (i) loan-level PDs, (ii) borrower-time fixed effects, and (iii) dynamic impulse response functions. While we get similar results, it is worth highlighting that our estimates are noisier, which may highlight the importance of using loan-level PDs and borrower-time fixed effects.

In contrast to capitalisation-based mechanisms, in the deposit franchise channel that we introduce and empirically test, the mechanism operates via monopoly rents: a rate cut compresses deposit spreads, eroding future deposit profits and thereby weakening the disciplinary force that normally restrains banks with sticky deposit bases; these low-beta

Figure 7: Banks With Higher Capital Reduce Risk-Taking More



Note: This figure plots impulse-responses from local projections (10) over horizons 0–8 quarters, showing the responses of the loan-level probability of default to a +1 pp monetary policy shock interacted with banks' tier 1 capital ratio. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

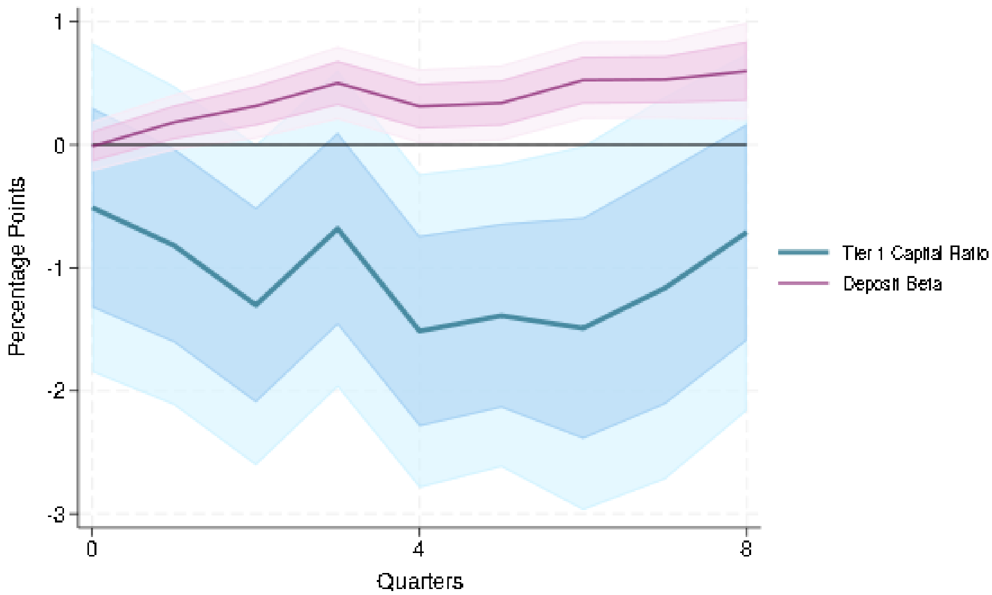
banks, now with less profits to lose, likewise increase risk-taking. Given these existing channels, a natural question arises: once we condition on both sources of heterogeneity (capitalisation and deposit franchise), does one subsume the other or do both coexist? We address this by estimating a loan-level "horse race" that incorporates both bank capital and bank deposit betas in the same saturated design.

Formally, we estimate loan-level local projections that interact the monetary policy shock with (i) the bank's deposit beta and (ii) the bank's capital ratio for horizons $h = 0 \ldots 8$, while saturating borrower-time and bank fixed effects:

$$\begin{aligned} z_{k,i,t+h} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{L} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i) \\ + \sum_{l=0}^{L} \gamma_{h,l} \cdot (\text{Shock}_{t-l} \times \text{CapitalRatio}_i) + \varepsilon_{k,i,t+h} \end{aligned} \tag{11}$$

As can be seen in Figure 8, both the coefficient on (Shock × DepositBeta) and (Shock × CapitalRatio) are statistically significant with the predicted signs (the latter is negative, again consistent with Dell'Ariccia et al., 2017). Taken together, the joint significance and correct signs indicate coexistence rather than subsumption: capital-based (search-for-yield/risk-shifting) and deposit-franchise mechanisms both operate, and our deposit-franchise channel retains explanatory power even conditional on bank capital.

Figure 8: Banks With Higher Franchise Reduce Risk-Taking More



Note: This figure plots impulse-responses from local projections (11) over horizons 0–8 quarters. The purple line shows the responses of the loan-level probability of default to a +1 pp monetary policy shock interacted with banks' deposit beta. The blue line shows the responses of the loan-level probability of default to a +1 pp monetary policy shock interacted with banks' tier 1 capital ratio. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

4.4 Bank-Level Portfolio Adjustments

Our loan-level design isolates supply-driven changes in risk-taking using borrower–time fixed effects, but it does not reveal how banks adjust their overall balance sheet composition in response to monetary policy. As a complementary exercise, we examine whether the deposit-franchise mechanism also appears at the portfolio level. Because bank-level regressions cannot saturate credit demand, we view this analysis as descriptive and supportive rather than causal. Nonetheless, it provides a natural external validation test: do the banks that adjust their marginal loan risk in the way predicted by the model also rebalance their aggregate portfolios in the same direction?

To implement this exercise, we focus specifically on the share of assets assigned a 1250% risk weight in the regulatory capital framework. These exposures represent the riskiest positions banks can hold and therefore provide a clean measure of deliberate portfolio-level risk-taking. Other asset categories are less informative for our purposes. Holdings of safe assets such as cash or Treasuries are strongly influenced by liquidity regulation and interest-rate hedging motives. Intermediate risk-weight buckets (such as 100% or 150%) bundle together diverse assets whose balances often move for reasons unrelated to active risk-taking, including collateral rules or mechanical reclassifications when borrowers deteriorate. By contrast, assets with a 1250% risk weight are treated as effectively "capital-deducted" positions, meaning banks hold them only when they are explicitly willing to bear substantial credit or valuation risk. Focusing on this segment therefore allows us to isolate the cleanest portfolio-risk margin—one that most closely matches the mechanism emphasised in the model and in our loan-level analysis.

Formally, we define the risky asset share of a bank as the ratio of its assets assigned a 1250% risk weight to total assets,

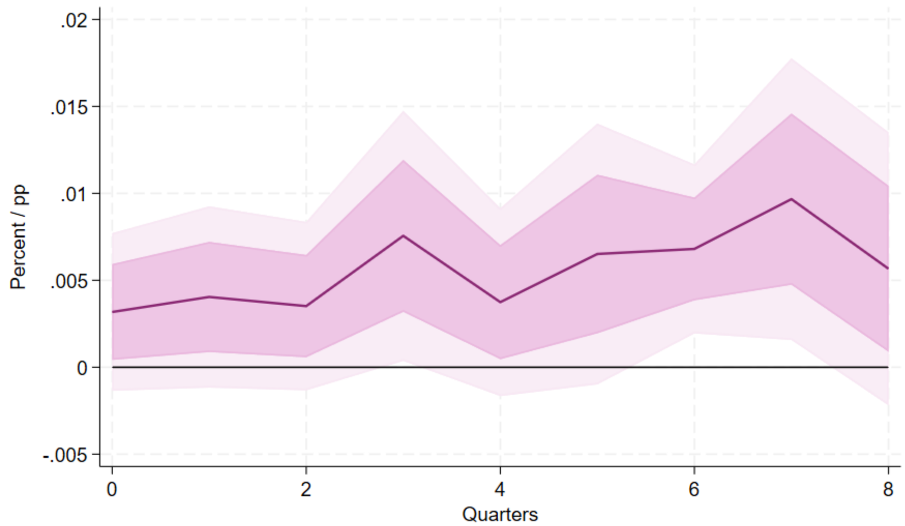
$$\text{Risky Asset Share} \equiv \frac{\text{Assets Assigned 1250\% Risk Weight}}{\text{Assets}}.$$

We then estimate a bank-level regression of the Risky Asset Share on monetary policy shocks interacted with banks' deposit betas:

$$\begin{aligned}\text{Risky Asset Share}_{i,t+h} =& \alpha_i + \delta_t + \sum_{l=1}^{4} \beta_{h,l} \text{Risky Asset Share}_{i,t-l} \\ &+ \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i) + \varepsilon_{i,t+h}\end{aligned} \tag{12}$$

Figure 9 plots the impulse responses from this bank-level specification. Consistent with the deposit-franchise mechanism, banks with a weaker franchise (higher betas) increase their share of 1250%-risk-weighted assets by more than low-beta banks following a contractionary monetary policy shock. The differential response is persistent and closely parallels our findings in the loan-level data. Therefore, the portfolio evidence provides external validation: the deposit franchise is not only a key predictor of how banks adjust risk at the margin, but also of how the risk profile of the banking system evolves in response to monetary policy.

Figure 9: Banks With Higher Betas Increase their Portfolio Share of Risky Assets



Note: This figure plots impulse-responses from local projects (12) over horizons 0–8 quarters, showing the responses of the bank-level risky asset share to a +1 pp monetary policy shock interacted with banks' deposit beta. Bank fixed effects are controlled. Standard errors are clustered at the bank level. Shaded areas indicate 68% and 90% confidence intervals.

5 Conclusion

We show that the deposit franchise constitutes a distinct channel through which monetary policy shapes bank risk-taking. In theory, higher policy rates increase the deposit spreads of low-deposit-beta banks, giving them stronger incentives to protect future profits by curbing risk. Using loan-level supervisory data and high-frequency monetary policy shocks, we confirm this mechanism: contractionary policy reduces risk-taking overall, but especially so for banks with stronger deposit franchises.

These results highlight that the distribution of deposit franchise across banks conditions the effectiveness of monetary policy and carries important financial stability implications. Policies that alter deposit competition and pricing behaviour, whether through regulation, fintech entry, or even advertising rules, can unintentionally reshape how monetary policy transmits to risk-taking. Our findings establish the deposit franchise as a core determinant of risk-taking incentives, and therefore as a key piece in the transmission of monetary policy.

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Appendix A Proof of Proposition 1 and Discussions.

With an exogenous deposit rate pass-through $r_i^D = \beta_i^D r$ and survival probability $p(\theta_i) = 1 - \lambda\theta_i^2$, we can write the expected profit in (1) as

$$\Pi_i(\theta_i; r) = \left(1 - \lambda\theta_i^2\right)\left[(1 - \beta_i^D)r + \theta_i\right], \text{ where } 0 < \beta_i^D < 1, \ \lambda > 0.$$

Maximising Π_i with respect to θ_i yields another expression of the FOC (2),

$$3\lambda\theta_i^2 + 2\lambda(1 - \beta_i^D)r\theta_i - 1 = 0. \tag{13}$$

Differentiating the condition above with respect to r yields

$$\left[6\lambda\theta_i + 2\lambda(1 - \beta_i^D)r\right]\frac{\partial\theta_i}{\partial r} \ + \ 2\lambda(1 - \beta_i^D)\theta_i = 0,$$

which implies that

$$\frac{\partial\theta_i}{\partial r} = -\frac{(1 - \beta_i^D)\theta_i}{3\theta_i + (1 - \beta_i^D)r} < 0.$$

Similarly, one can show that risk-taking increases in β_i^D

$$\frac{\partial\theta_i}{\partial\beta_i^D} = \frac{r\theta_i}{3\theta_i + (1 - \beta_i^D)r} > 0.$$

Note that another expression for $\partial\theta_i/\partial r$ is (3), which under Assumption 1 becomes

$$\frac{\partial\theta_i}{\partial r} = -\frac{2\lambda\theta_i^2(1 - \beta_i^D)}{3\lambda\theta_i^2 + 1} < 0.$$

A set of sufficient conditions for $\frac{\partial\theta_i}{\partial r}$ to be increasing in β_i^D, so that $\frac{\partial^2\theta_i}{\partial r\partial\beta_i^D} > 0$, is that

(1) The denominator $(3\lambda\theta_i^2 + 1)$ is increasing in β_i^D.

(2) The numerator $2\lambda\theta_i^2(1 - \beta_i^D)$ is decreasing in β_i^D.

Note that (1) is already satisfied since $\partial\theta_i/\partial\beta_i^D > 0$, and (2) requires

$$\frac{\partial\theta_i^2(1 - \beta_i^D)}{\partial\beta_i^D} = 2\theta_i(1 - \beta_i^D)\frac{\partial\theta_i}{\partial\beta_i^D} - \theta_i^2 < 0.$$

The condition above holds if

$$
\begin{aligned}
2\theta_i(1-\beta_i^D)\frac{r\theta_i}{3\theta_i+(1-\beta_i^D)r} &< \theta_i^2 \\
\frac{2(1-\beta_i^D)r}{3\theta_i+(1-\beta_i^D)r} &< 1 \\
2(1-\beta_i^D)r &< 3\theta_i+(1-\beta_i^D)r \\
(1-\beta_i^D)\frac{r}{3} &< \theta_i
\end{aligned}
$$

From (13), it is easy to verify that the optimal $\theta_i > r/3 > (1-\beta_i^D)r/3$ when

$$
r < \lambda^{-\frac{1}{2}}\left[\frac{3}{1+2(1-\beta_i^D)}\right]^{\frac{1}{2}},
$$

which is satisfied whenever $r \leq \lambda^{-\frac{1}{2}} = \bar{\theta}$.

Discussion on $r \leq \lambda^{-\frac{1}{2}}$. The bank survival probability function implies

$$
p(\theta_i) = 1 - \lambda\theta_i^2 \quad \Longrightarrow \quad \lambda^{-\frac{1}{2}} = \frac{\theta_i}{\sqrt{1-p(\theta_i)}},
$$

so we can approximate $\lambda^{-\frac{1}{2}}$ with the ratio between the average loan spread and the square root of the average bank failure rate. Between 2015 and 2024, there are on average 3.5 banks failing each year.[25] Given that there are over 4,000 depository institutions insured by the FDIC during this period, the average bank failure rate is at most $3.5/4000 = 0.000875$. The average loan spread in the US is typically above 2%, so a conservative lower bound on $\lambda^{-\frac{1}{2}}$ is $0.02/\sqrt{0.000875} \approx 67.6\%$. Hence, any practically relevant range of policy rates is likely to satisfy the condition $r \leq \lambda^{-\frac{1}{2}}$.

[25] See https://www.fdic.gov/resources/resolutions/bank-failures/in-brief/index.

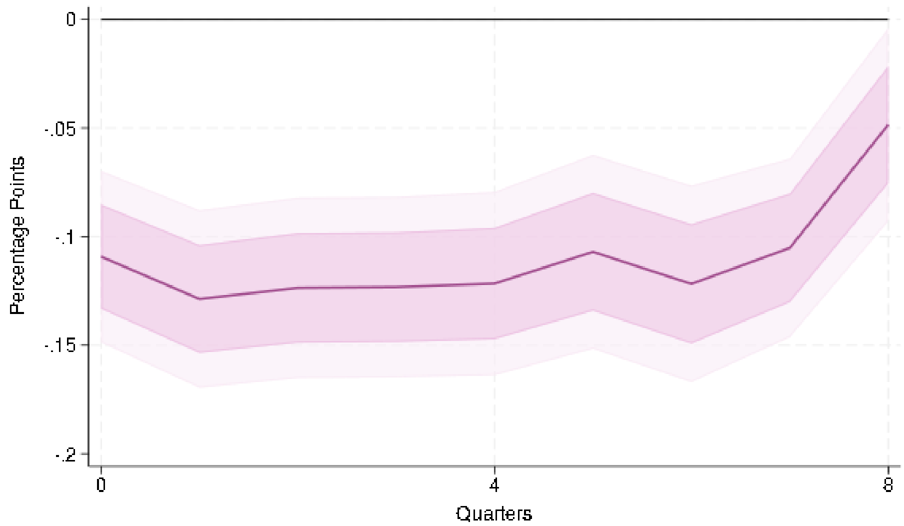
Appendix B Additional Figures and Tables

Table B.1: Determinants of Probability of Default

	(1)	(2)	(3)	(4)
Interest Rate	0.066***	0.066***	0.109***	0.108***
	(0.010)	(0.011)	(0.015)	(0.016)
Loan Size ($M)	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Collateralized Loan	0.354***	0.368***	0.362***	0.377***
	(0.062)	(0.059)	(0.057)	(0.049)
Loan Maturity (Trunc., years)	-0.010*	-0.007	-0.004	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.437***	0.415***	0.220***	0.197***
	(0.071)	(0.066)	(0.072)	(0.064)
Bank FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	2,563,231	2,563,231	2,563,231	2,563,231
R-squared	0.053	0.089	0.078	0.116

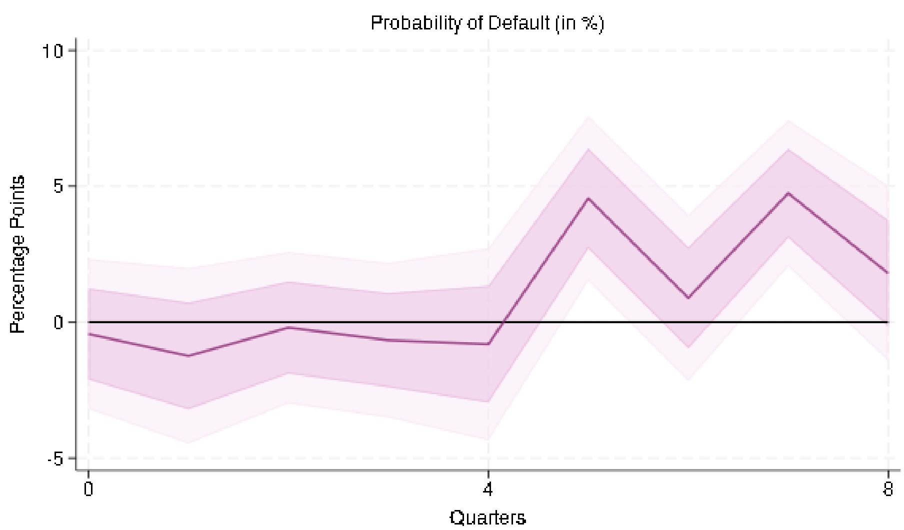
Note: This table reports coefficient estimates from a regression of the loan-level probability of default on loan characteristics. Bank and time fixed effects are controlled. Standard errors, reported in parentheses, are clustered at the bank and time levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure B.1: Average Risk-Taking Falls After A Contractionary Monetary Policy Shock



Note: This figure plots impulse-responses from local projections (6) over horizons 0–8 quarters, showing the responses of the loan-level probability of default after a +1 pp monetary policy shock. Only bank fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

Figure B.2: Banks with Higher Deposit Franchise Reduce Risk-Taking More (New Loans)



Note: This figure plots impulse-responses from local projections (7) over horizons 0–8 quarters, showing the responses of the loan-level probability of default for new loans to a +1 pp monetary policy shock interacted with banks' deposit beta. Bank and borrower-by-time fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.