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

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First Version: July 2025. This Version: July 2026.

Abstract

Why does the same monetary tightening lead some banks to write safer loans than others? We develop a model and identify a novel deposit-franchise mechanism within the risk-taking channel of monetary policy. Sticky deposits generate rents that vanish if the bank fails, giving low-deposit-beta banks more skin in the game. The model predicts that tightening lowers the payoff to risk-taking, so banks with a stronger deposit franchise cut risk more because failure destroys larger rents. We test this prediction using the Federal Reserve's confidential loan-level data, interacting high-frequency monetary policy surprises with predetermined deposit betas in specifications with bank and borrower-time fixed effects. Our findings show that monetary tightening reduces risk-taking, especially at low-beta banks, and the result survives a horse race with bank capital. New-loan originations reveal how banks de-risk: for the same borrower-quarter, low-beta banks originate loans that are more likely to be collateralised and senior.

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, Diana Bonfim, Felix Corell (discussant), Miguel Faria-e-Castro, João Granja, Marco Grotteria, Rajkamal Iyer, Frederic Malherbe, Gregor Matvos, Win Monroe, Jacob Oded (discussant), Nuno Paixão, Jose-Luis Peydro, Rafael Repullo (discussant), Farzad Saidi, Alexi Savov, Andre Silva, Kerem Tuzcuoglu, Matias Vieyra, Lingxuan Wu, Kaspar Wuthrich, Paolo Zaffaroni, and seminar and conference participants at Bank of Canada, Federal Reserve Board, Federal Reserve Bank of St. Louis, Imperial College London, London Juniors Finance Conference, Empirical Financial Intermediation Workshop, Oxford Saïd - VU SBE Macro-Finance Conference, IAAE, FMARC, and PEJ for helpful comments and discussions. We thank Filipe de Castro Ribeiro Ferreira and Jack Keane 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 to 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). Yet the strength of this channel differs across banks, and understanding this heterogeneity is essential for assessing how monetary policy affects financial stability.

Existing explanations focus primarily on banks' asset returns and capital positions. When safe returns are low, banks may search for yield by shifting toward riskier assets. When banks are thinly capitalised, limited liability can strengthen risk-shifting incentives. These mechanisms place bank capital at the centre of the risk-taking channel. This paper proposes and tests a new mechanism at the core of the business model of modern banks: the deposit franchise. Banks with sticky deposit rates pay deposit rates that move less than one-for-one with the policy rate. Monetary policy therefore changes not only the return to bearing credit risk, but also the rents banks have at stake if credit risk-taking goes wrong.

Our central hypothesis is that the deposit franchise gives banks a second form of skin in the game. A bank that takes more credit risk earns a higher loan spread, but it also raises the probability that it fails and loses the rents generated by its deposit franchise. For banks with low deposit betas, these rents are larger because deposit rates adjust sluggishly to policy rates. Their skin in the game is therefore not only their capital, but also the stream of deposit-franchise rents that survives only if the bank remains a going concern. Monetary policy changes this trade-off. When rates rise, risk-taking becomes less attractive relative to the cost of losing the franchise. Because low-beta banks have more franchise rents to lose in failure, they should reduce credit risk more than otherwise similar high-beta banks.

We formalise this idea in a tractable model of bank risk-taking. The model has three key ingredients. First, banks can take more credit risk to earn higher loan spreads. Second, risk-taking increases the probability of failure. Third, banks earn deposit-franchise rents only while they survive. The bank's optimal risk choice therefore balances a marginal benefit against a marginal cost. The marginal benefit is the extra loan income generated by taking more risk. The marginal cost is the increased probability of failure multiplied by the deposit rents the bank loses if it fails.

This simple trade-off delivers the paper's main predictions. A monetary tightening reduces risk-taking because it lowers the relative payoff from bearing additional credit risk. The effect is stronger for banks with lower deposit betas because these banks have a larger deposit franchise at stake. Put differently, low-beta banks face a steeper marginal cost of risk-taking: a risk-taking strategy that ends in failure destroys more value for them than for high-beta banks. The mechanism is therefore closely related to the classic idea that franchise value disciplines bank risk-taking, but it adds a monetary-policy dimension: the strength of this discipline varies with interest rates and with the stickiness of a bank's deposit base.[1]

We test these predictions using the Federal Reserve's confidential, quarterly, loan-level supervisory data (FR Y-14) from 2015 to 2026. The data contain approximately 4.3 million loan-quarter observations from 29 U.S. bank holding companies and 208,435 corporate borrowers. A key advantage of the data is that they provide banks' internal assessments of credit risk, including probabilities of default (PD), loss given default (LGD), and exposure at default (EAD), together with contractual features such as collateral and seniority. This allows us to measure ex ante credit risk and expected losses directly, rather than inferring risk-taking from realised defaults, loan spreads, or coarse ratings. The data also allow us to study the contractual form of credit, which is central for understanding how banks reduce risk.

Our empirical design combines high-frequency monetary policy surprises from Jarociński and Karadi (2020) with cross-sectional variation in banks' deposit franchises. The monetary policy shocks isolate unexpected changes in short-term rates and purge central-bank information effects. For the cross-section, we estimate banks' deposit betas over 1984–2014 following Drechsler et al. (2021). These betas are predetermined relative to our loan-level sample and capture persistent differences in deposit-rate pass-through.[2] Moreover, balance tests suggest minimal differences across low- and high-beta banks across a number of important dimensions such as average risk and leverage. Finally, our main specifications include bank fixed effects and borrower-by-time fixed effects. Identification therefore comes from comparing loans to the same borrower in the same quarter made by banks with different deposit franchises. Because borrower demand, investment opportunities, and time-varying borrower fundamentals are absorbed, the estimates aim

[1] This argument does not necessarily require the present value of the deposit franchise to mechanically rise with the policy rate. We show that the risk-taking trade-off still depends on the deposit franchise when fixed-beta deposit spreads are discounted at the policy rate, as in DeMarzo et al. (2024). Rate hikes reduce the present value of marginal gains from risk-taking, while low-beta banks face a larger marginal cost because failure destroys a larger deposit franchise.

[2] We directly show that our bank-level predetermined betas strongly predict deposit betas in our estimation sample.

to isolate differential supply-side responses to monetary policy shocks.

We begin by documenting the aggregate risk-taking channel in our data. A contractionary monetary policy shock lowers loan-level PDs and the response persists for two years. Thus, monetary policy affects not only the immediate pricing of credit but also the dynamic accumulation of credit risk on bank balance sheets. Symmetrically, unexpected monetary easing can generate a persistent build-up of credit risk.

We then test the central prediction of our proposed deposit-franchise mechanism. Consistent with our model prediction, after a contractionary monetary policy shock, banks with lower deposit betas reduce risk-taking significantly more than banks with higher deposit betas. The reduction in risk-taking occurs both in terms of ex ante probability of default and expected loss. The magnitudes are economically large, suggesting that deposit-franchise heterogeneity is quantitatively important for the transmission of monetary policy to credit risk. We further show that our result is largely robust to using ex post loan performance: delinquency and charge-offs deteriorate more for high-beta banks after contractionary shocks.

The deposit-franchise mechanism we identify is distinct from capital-based explanations of the risk-taking channel. Existing theories often emphasise search-for-yield or risk-shifting incentives, with bank capital as the key cross-sectional state variable. We therefore estimate a horse race that interacts monetary policy shocks with both predetermined deposit betas and bank capital ratios. The deposit-beta interaction remains positive, statistically significant, persistent, and economically larger. The capital interaction has the sign predicted by Dell'Ariccia et al. (2017): higher-capital banks reduce risk more after a contractionary shock. Thus, capitalisation and deposit-franchise strength coexist as distinct sources of heterogeneity in the risk-taking channel of monetary policy.

The richness of the Y-14 data allows us to go further and ask *how* banks reduce risk. This is central to the contribution of the paper. Borrower-by-time fixed effects identify differential supply responses by comparing banks lending to the same borrower in the same quarter. But such specifications do not by themselves reveal the margin through which banks change risk. Banks could adjust by changing screening, loan size, collateral, seniority, or other terms of credit. To shed light on this margin, we restrict attention to newly originated loans, where banks actively choose both the borrower exposure and the contractual form of credit after the monetary policy shock.

In the new-loan sample, the deposit-franchise effect is stronger. Banks with stronger deposit franchises originate loans with lower PDs and lower expected losses. We interpret this as evidence that our deposit franchise mechanism operates not only through the gradual evolution of existing balance sheets, but also through active screening and loan design at origination. More importantly, banks reduce risk through contract design. New loans made by low-beta banks are more likely to be collateralised and senior. These results are especially useful for interpreting the borrower-time fixed effects in the main specifications. Because those fixed effects hold constant investment opportunities and time-varying borrower fundamentals, the risk-taking response cannot be attributed simply to low-beta banks lending to safer firms after monetary tightening. The origination results show more: for a given borrower seeking credit in a given quarter, banks with stronger deposit franchises write loans that are better protected in default. The estimates remain stable when we replace bank fixed effects with borrower-by-bank fixed effects, absorbing persistent relationships between a given borrower and lender.

Taken together, the evidence shows that the deposit franchise shapes both the amount and the form of bank risk-taking after monetary policy shocks. The full loan-portfolio results show that low-beta banks reduce risk more after monetary tightening. The new-loan results show how they do so: they originate loans with lower risk and greater contractual protection through collateral and seniority. The policy implication is not that deposit market power is unambiguously desirable. Sticky deposits can reflect depositor inattention, limited search, switching costs, or weak competition. But our results show that deposit-market structure has financial-stability consequences beyond depositor pass-through and bank funding costs. By changing the rents banks have at stake, deposit competition also changes how monetary policy transmits to credit risk. Policies that affect deposit pass-through, including fintech entry, deposit-rate transparency, and competition policy, can therefore reshape the risk-taking channel of monetary policy. A more competitive deposit market may improve depositor welfare and pass-through, but it may also weaken the deposit-franchise-value discipline that otherwise restrains risk-taking at banks with strong deposit franchises. Policymakers therefore need to treat deposit-market structure and monetary-policy transmission as jointly relevant for evaluating financial stability.

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).[3,4] In this paper, we document a deposit-franchise channel within the broader risk-taking channel, where monetary policy influences banks' risk-taking incent-

[3] 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.

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

ives 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., 2026).[5] 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 franchises (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. Moreover, we push beyond the standard fixed-effect design by showing how risk changes within borrower. Among new originations, low-beta banks write loans with lower expected losses and greater protection in default through collateral and seniority. This contribution is distinct from showing that risk falls: it identifies the contractual margins through which banks implement the risk reduction.

Third, we connect the growing literature on the deposit channel of monetary policy and bank deposit franchise (Drechsler et al., 2017, 2021, 2024, 2026; Xiao, 2020; Supera, 2021; Wang et al., 2022; Choi and Rocheteau, 2023; DeMarzo et al., 2024; d'Avernas et al., 2025; Kho, 2025; Lu and Wu, 2025; Wang, 2025; Usenko, 2026) 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.[6] Recent work by Drechsler et al. (2017) further shows that deposit franchise plays a key role in the transmission of monetary policy to deposits and lending. Building on the existing literature, we demonstrate that banks' deposit franchise value also significantly impacts their risk-taking responses when policymakers tighten rates.

Within the deposit channel literature, more recent work by Gutiérrez et al. (2026) is closely related but studies a different object. Their paper can be viewed as an important extension of the deposit channel of Drechsler et al. (2017): using Spanish credit-register

[5] A closely related literature focuses on the impact of low interest rates on bank risk-taking (Heider et al., 2019; Whited et al., 2021; Bittner et al., 2022).

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

data for SMEs during the 2022–2024 ECB tightening cycle, they show that banks more exposed to concentrated deposit markets contract lending more, especially to firms with higher ex ante default risk. In other words, the main finding is about heterogeneity in credit supply across firms with different risk profiles. The new-loan analysis in Gutiérrez et al. (2026) in turn examines quantities, prices, and realised returns *within* risk bins; the null effect on one-year default suggests that this evidence speaks primarily to pricing and realised returns, rather than loan-level risk choices at origination.

In contrast, our paper studies the risk-taking channel of monetary policy directly using predetermined deposit betas, high-frequency monetary-policy surprises, and confidential U.S. loan-level data. We use borrower-time fixed effects, so identification comes from differences across banks lending to the same borrower in the same quarter. Moreover, instead of firm-level credit growth, we directly study loan-level measures of ex ante risk and contractual protection, particularly for new originations, which is central to the risk-taking channel literature (Jiménez et al., 2014; Dell'Ariccia et al., 2017; Bonfim and Soares, 2018). Specifically, we use ex ante loan-level PD and expected loss as measures of risk-taking, validate them with multiple ex post outcomes, and show that low-beta banks reduce risk at origination through greater contractual protection, including collateral and seniority.

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.[7]

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; Gan, 2004; 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, and further postulate that the deposit franchise also shapes the incentives to change risk-

[7]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).

taking in response to monetary policy. 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 the terms and risk of newly originated loans.

2 Theoretical Framework

In this section, we develop a tractable model of bank deposit franchise value to illustrate how the deposit franchise interacts with the risk-taking channel of monetary policy. In the model, banks choose credit risk by trading off the additional profits from risk-taking against the potential loss of the deposit franchise rents in the event of failure. The deposit franchise reduces the sensitivity of depositors' demand to banks' deposit rates, allowing banks to earn higher deposit spreads and more profits when interest rates increase. Following rate hikes, the expected future profits of high-deposit-franchise banks rise more than those of low-deposit-franchise banks. Consequently, high-deposit-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) provides a microfoundation for 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 faces zero default risk. Fourth, there exists an upper bound on 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' Optimisation 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 increases, 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

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

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

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.

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*

[9] We relegate the proof to Appendix A.

increases in the policy rate, as long as r is below banks' risk-taking limit $\bar{\theta}$*,*

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

2.3 Discussions

Relationship with Existing Risk-Taking Channel 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-deposit-franchise) banks. The loss of the 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: limited liability induces banks to take excessive risk because part of the downside is borne by creditors, depositors, or the deposit insurance system. Monetary policy can either alleviate or exacerbate these risk-shifting incentives by affecting banks' funding costs, leverage, and cash flows, thereby changing 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). Specifically, we show that the risk-taking response to monetary policy depends on the deposit franchise that banks have at stake. When policy rates rise, the present value of the marginal payoff from additional credit risk-taking falls. At the same time, taking more risk raises the probability of failure and therefore the probability of losing the bank's deposit franchise. Because low-beta banks have larger deposit franchises to preserve, they have more "skin in the game," which leads them to reduce credit risk more aggressively following monetary tightening.

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. Since low-beta banks have larger deposit franchises at stake, they have stronger incentives to protect those rents when monetary policy tightens. Our model therefore predicts that low-depositbeta banks contract credit risk more aggressively than their high-beta peers following contractionary monetary policy shocks.

Interest Rate Risk Hedging and Credit Risk-Taking. Drechsler et al. (2021) show that low-beta banks 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 stable cash flows and equity value despite fluctuations in interest rates.

How can deposit franchise value influence risk-taking if 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 both its asset value and franchise value. 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 bank equity 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 increases in 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 the deposit franchise. Again, reducing credit risk following contractionary monetary policy shocks serves as a

[10] This is akin to the bank run scenario studied in Drechsler et al. (2026).

[11] It also weakens the bank's fundamentals and can raise the ex ante probability of a run (e.g., Drechsler et al., 2026).

means to preserve the bank's deposit franchise, 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 do not fully hedge their interest rate risk (e.g., Di Tella and Kurlat, 2021; Jiang et al., 2024; DeMarzo 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 their deposit franchise.

The 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 typically defines deposit franchise value as the present value of the profits from deposit-taking (e.g., Gomes et al., 2023; DeMarzo et al., 2024). 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, conditional on the bank's survival. To understand the present value of the deposit franchise, we can assume that the static risk-taking 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. As in DeMarzo et al. (2024), the deposit franchise then has a present value of

$$\text{DFV}_i = \frac{r - r_i^D}{r} = 1 - \beta_i^D. \tag{4}$$

Further, risk-taking can result in distress where the bank loses its deposit franchise. The expected deposit franchise value (EDFV) is simply $(1 - \beta_i^D)$ multiplied by the bank's survival probability,

$$\text{EDFV}_i = p(\theta_i) \cdot \text{DFV}_i = p(\theta_i)(1 - \beta_i^D). \tag{5}$$

Thus, the survival probability $p(\theta_i) < 1$ is the "risk adjustment" that increases the bank's

[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. Nonetheless, we include a dynamic extension of this model in Appendix D and show that our core predictions remain.

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, $p(\theta_i)(1-\beta_i^D)$, 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.

It is worth noting that the present value of the deposit franchise in (5) 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 concerns regarding the deposit franchise? Intuitively, we can also write the first-order condition (2) in the present value form as

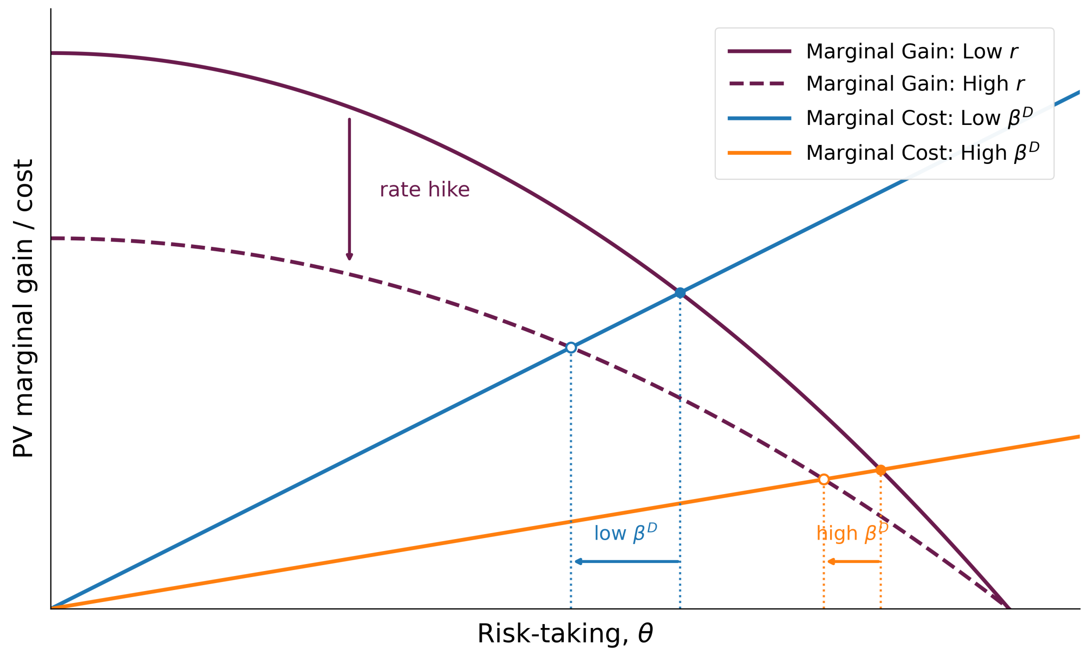
$$\underbrace{\frac{1}{r}\frac{d[p(\theta_i)\theta_i]}{d\theta_i}}_{\text{PV(marginal gain)}} = \underbrace{-p'(\theta_i)(1-\beta_i^D)}_{\text{PV(marginal cost)}}. \tag{6}$$

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)). Furthermore, the marginal cost of risk-taking reflects the increase in the probability of deposit franchise loss, which is directly linked to the marginal contribution of θ_i to (5). Importantly, although $-p'(\theta_i)(1-\beta_i^D)$ does not depend on r directly, it is larger for low-beta banks because they lose more deposit-franchise rents in failure (i.e., 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)). Figure 1 illustrates these dynamics.

[13]Equivalently, (5) 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.

Figure 1: The Risk-Taking Channel for Low- and High-deposit-beta Banks



Note: This figure provides a graphical representation of the risk-taking first-order condition (6). The purple downward-sloping lines represent the present-value marginal gain from risk-taking at low and high policy rates. The upward-sloping blue and orange lines correspond to the marginal cost of risk-taking for banks with low and high β^D, respectively.

2.4 Model Extensions

Endogenous Deposit Beta. Our baseline model treats each bank's deposit beta as a predetermined characteristic. Internet Appendix C shows that the key predictions are preserved when the bank jointly chooses its deposit beta and risk-taking. In that extension, the bank faces deposit demand $D_i(\beta_i) = \bar{D}_i \beta_i^{\eta_i}$ and trades off a lower beta, which widens the deposit spread and raises the deposit franchise value lost in default, against a higher beta, which attracts a larger deposit base. The beta choice therefore interacts with risk-taking choice because beta changes the profits the bank has at stake when higher credit risk increases the probability of failure. Under the maintained assumption that η_i is small enough for the optimal beta to be less than one, policy-rate hikes reduce credit risk-taking, and banks with lower equilibrium betas reduce risk more after a tightening. The primitive source of heterogeneity is depositor rate insensitivity (e.g., due to depositor inattention as in Lu and Wu, 2025), while the observed deposit beta remains an equilibrium proxy for deposit-franchise strength.

Dynamic Formulation & Deposit Rents as a Survival Buffer. Internet Appendix D considers another extension in which the model is cast in a discrete-time dynamic environment and current deposit rents can raise the bank's survival probability by absorbing losses. A rate hike then affects risk-taking through three forces: higher deposit rents raise the value at stake in default, higher current rents strengthen the survival buffer, and policy-rate discounting directly lowers continuation value. Internet Appendix D shows that the baseline predictions are preserved when the deposit franchise, the survival-buffer effect, and the curvature of survival probability with respect to risk are sufficiently strong.

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.[15] We construct a measure of expected loss in thousands

[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-2007-1

of dollars as the product of PD, loss given default (LGD), and exposure at default (EAD), which provides a dollar-denominated risk measure. The Y-14 data also include loan performance outcomes: cumulative chargeoff amounts and days past due, which we use to validate our ex-ante risk measures. We restrict the sample to 2015:Q1-2026:Q1, 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. Our main analyses use untrimmed PDs, and we report trimmed specifications only where explicitly noted.

3.2 Call Reports

We use quarterly Call Reports to complement our loan-level data with bank-level balance sheet and income statement information. Specifically, we rely on the time-consistent Call Report data made available by Correia et al. (2026). 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). Therefore, we run the following regression over the period 1984 to 2014:

$$\Delta \text{DepIntExp}_{it} = \alpha_i + \sum_{\tau=0}^{3} \beta^D_{i,\tau} \Delta \text{FedFunds}_{t-\tau} + \varepsilon_{it} \tag{7}$$

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 (7): $\text{DepositBeta}^{pre}_i = \sum_{\tau=0}^{3} \beta^D_{i,\tau}$, where the superscript *pre* reflects the fact that these deposit betas are predetermined relative to our estimation sample. This measure serves as the empirical counterpart to β^D_i in our model. Finally, we winsorise our betas at the 1 percent level to minimise the impact of outliers.[17] 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

2-07/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).

[17]Our analysis is robust to larger winsorisation thresholds and to using the raw, unwinsorised betas.

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 March 2026.

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 Federal Open Market Committee (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 4.3 million loan-quarter observations from 29 US bank holding companies, between 2015 and 2026 covering 183,308 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	25th	75th	Std. Dev.
Bank-level variables					
Deposit Beta	1,547	0.515	0.431	0.565	0.222
Deposits / Liabilities	1,547	0.8966	0.8671	0.9392	0.0588
Tier 1 Capital Ratio	1,547	0.1333	0.1125	0.1413	0.0353
Leverage Ratio	1,547	0.0921	0.0819	0.1012	0.0172
Return on Assets	1,217	0.0025	0.0020	0.0032	0.0021
C&I Loans / Loans	1,547	0.2516	0.1784	0.3112	0.1139
Average Risk Weight	1,547	0.6947	0.6001	0.7989	0.1721
C&I Charge Offs / C&I Loans	1,528	0.0010	0.0003	0.0013	0.0012
Total Assets ($M)	1,547	4.3e+05	1.1e+05	3.6e+05	6.6e+05
Loan-level variables					
Probability of Default (%)	4.3M	2.66	0.28	1.75	9.29
Loan size ($M)	4.3M	8.78	0.40	6.77	27.44
Interest Rate (%)	4.1M	4.24	2.61	6.00	2.77
Collateralised loan	4.3M	0.84	1.00	1.00	0.37
Senior loan	4.3M	0.83	1.00	1.00	0.38
Loan maturity (< 20 years)	4.1M	5.58	3.28	7.01	3.31

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). *Loan size ($M)* is the outstanding principal balance in millions of U.S. dollars. *Interest rate* is the contractual annual interest rate (percent). *Collateralised loan* is an indicator equal to 1 for loans secured by collateral and 0 otherwise. *Senior loan* is an indicator equal to 1 for credit facilities which are classified as first-lien senior. *Loan maturity (< 20 years)* is the remaining maturity in years (capped at 20 years). *Tier 1 capital ratio* is the bank's Tier 1 capital divided by risk-weighted assets. *Total assets ($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: contractionary shocks are followed by a statistically and economically significant decline in loan-level risk-taking, fully in line with earlier evidence.

Our second—and novel—result confirms the cross-sectional prediction of the model:

banks endowed with greater deposit franchises, 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 and highlights the importance of the structure of the deposit market for understanding the interaction between monetary policy and financial stability.

4.1 The Risk-Taking Channel of Monetary Policy

We begin by documenting the risk-taking channel of monetary policy, 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).

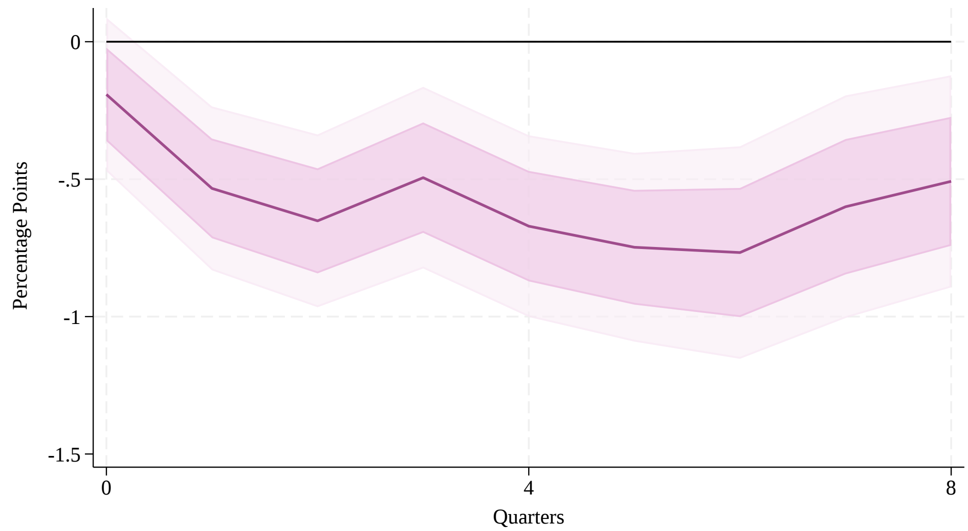
In order to confirm the risk-taking channel and thus Proposition 1(i) in our setup, we estimate the following local projections for horizons $h = 0 \dots 8$:

$$z_{k,b,i,t+h} = \alpha_i + \sum_{l=0}^{4} \beta_{h,l} \text{Shock}_{t-l} + \varepsilon_{k,b,i,t+h} \tag{8}$$

where $z_{k,b,i,t+h}$ is ex ante risk as measured by probability of default (PD) at horizon h for loan k made by bank i to borrower b, Shock_{t-l} is the monetary policy shock from Jarociński and Karadi (2020) which seeks to isolate unexpected changes in the short-term risk-free rate, and α_i are bank 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.

Figure 2 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 about 0.2 percentage points on impact. The effect becomes larger over time: over the following two years, loan-level PDs are at least 0.5 percentage points lower, with the response reaching around 0.75 percentage points at its peak. Given that the average PD over our sample is around 3 percent, the peak response corresponds to a roughly 25 percent decline in ex ante credit risk, representing an economically meaningful reduction in loan-level risk-taking.

Figure 2: Average Risk-Taking Falls After A Contractionary Monetary Policy Shock



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

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. 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 2 shows they do: after a contractionary surprise, banks reduce risk-taking at the loan level 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, loan-level risk-taking falls on average. We next ask whether this aggregate pattern masks the more nuanced, deposit-franchise-driven heterogeneity predicted by our model.

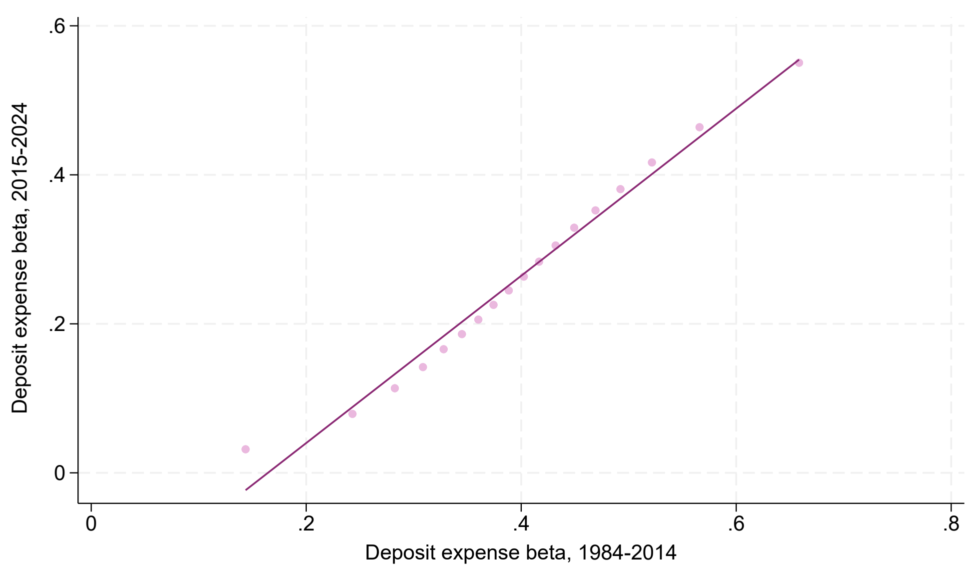
4.2 The Role of the Deposit Franchise

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.

Our formal test of Proposition 1(ii) combines time-series monetary policy surprises—the high-frequency shocks of Jarociński and Karadi (2020)—with cross-sectional heterogeneity in banks' deposit betas. 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 2015–2026 estimation window, they are predetermined with respect to the shocks and can be thought of as structural primitives that our model takes as given.

Figure 3 shows that bank-level betas are highly persistent, as betas estimated over 1984-2014 strongly predict betas estimated over 2015-2024. The interaction term $\text{Shock}_t \times \text{DepositBeta}_i^{pre}$ 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 direct empirical counterpart to Proposition 1(ii).

Figure 3: Predetermined and In-sample Deposit Betas



Note: This scatter plot shows the predetermined deposit betas (1984-2014, x-axis) and the in-sample deposit betas (2015-2024, y-axis) for the universe of commercial banks.

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 is most likely a supply side response—namely, how the policy surprise affects each bank through its pre-existing deposit franchise.

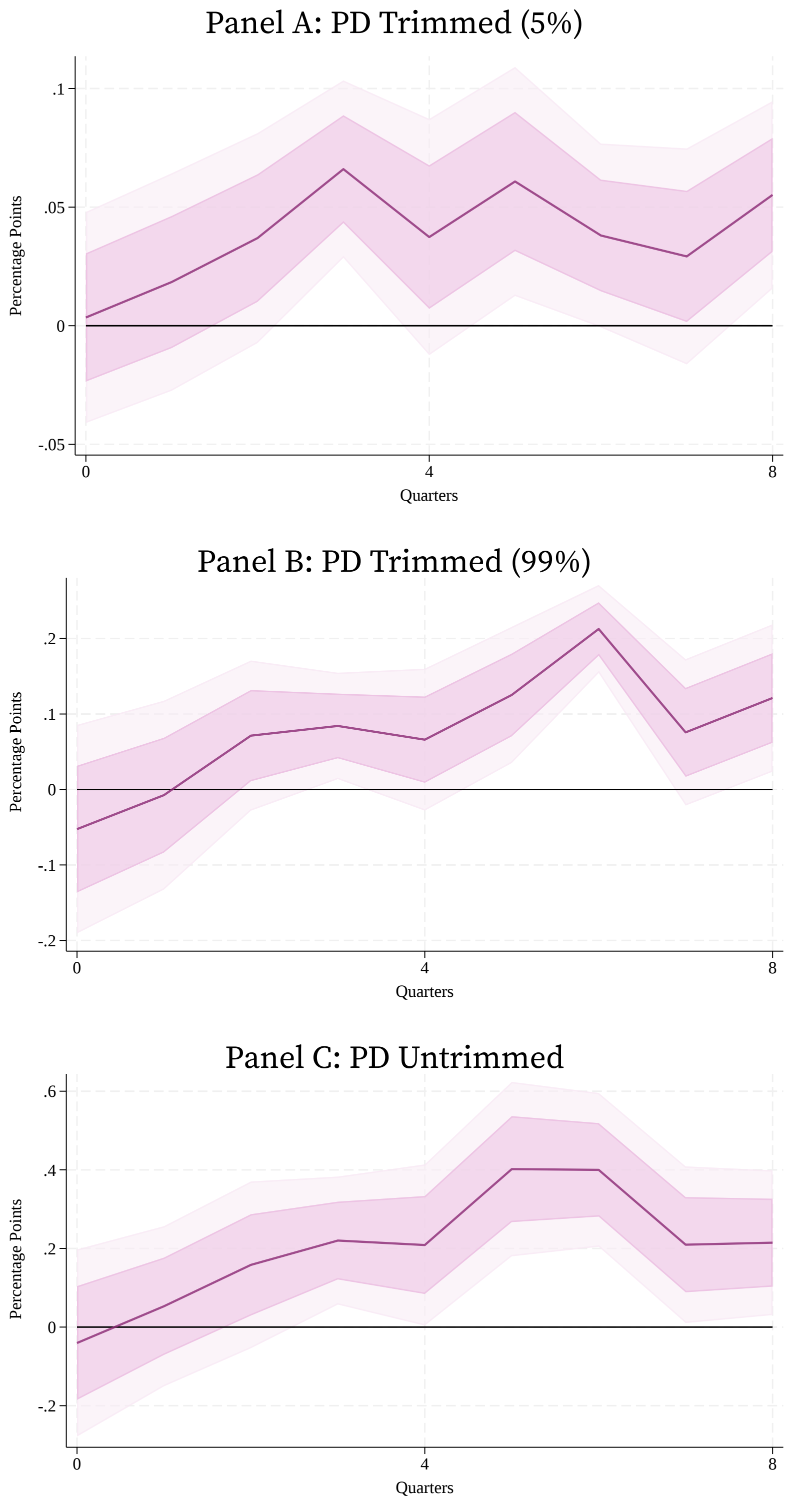
Formally, we introduce the interaction term to the specification in (8), and thus estimate local projections for horizons $h = 0, \ldots, 8$:

$$z_{k,b,i,t+h} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i^{pre}) + \varepsilon_{k,b,i,t+h} \tag{9}$$

where $z_{k,b,i,t+h}$ captures the ex ante risk at horizon h, measured by PD, for loan k made by bank i to borrower b, Shock_t is the Jarociński and Karadi (2020) monetary policy shock measure, $\text{DepositBeta}_i^{pre}$ is the standardised predetermined 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.

Figure 4 shows the impulse response function traced out by $\{\lambda_{h,0}\}_{h=0}^{8}$. The estimates show 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 differential response turns positive after one quarter and remains persistently positive over our projection horizon of two years. In Panel C, which uses untrimmed PDs, the magnitudes are economically meaningful. The figure implies that, for banks with a one-standard-deviation higher deposit beta, loan-level PD is about 0.2 percentage points higher over the third to fourth quarters following a monetary policy shock that raises the policy rate by one percentage point. The difference peaks at roughly 0.4 percentage points after five to six quarters and remains around 0.2 percentage points at the two-year horizon. Therefore, the cross-sectional difference between low- and high-deposit-franchise banks is a sizeable fraction of the aggregate risk-taking response in Figure 2, suggesting that deposit-franchise heterogeneity is quantitatively important for the loan-level adjustment to monetary tightening.

Figure 4: Banks With Higher Deposit Franchise (Low Beta) Reduce Risk-Taking More



Note: This figure plots impulse-responses from local projections (9) 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. Deposit betas are standardised. 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.

Moreover, our finding is robust across both trimmed and untrimmed PD samples as seen in Figure 4 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. In particular, Panel A documents an especially significant trimming by focusing only on loans with a PD of less than 5%, but still finds the same pattern that low-beta banks reduce risk-taking more than high-beta banks.

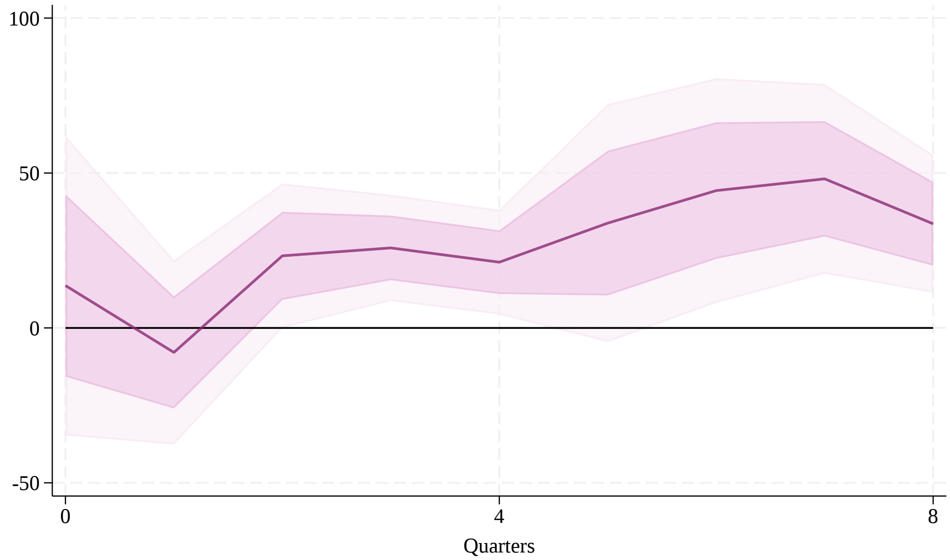
We next examine whether the deposit-franchise channel also appears in a broader measure of ex ante credit exposure: loan-level expected loss. While PD isolates the margin of likelihood of default, a bank's risk-taking decision is ultimately also disciplined by the expected dollar loss on the loan, which depends on the amount exposed and the severity of loss conditional on default. This distinction is important because a reduction in PD need not imply a reduction in overall credit risk if banks simultaneously shift toward loans with higher loss-given-default or larger exposures. For loan k extended by bank i to borrower b in quarter t, we define expected loss as

$$EL_{k,b,i,t} \equiv PD_{k,b,i,t} \times LGD_{k,b,i,t} \times EAD_{k,b,i,t},$$

where LGD is loss given default and EAD is exposure at default. All three components are bank-reported, loan-level, ex ante measures available in the Y-14 data. This measure aggregates the likelihood, severity, and scale of credit losses into a single economically meaningful object, allowing us to test whether the heterogeneous response documented for PDs translates into expected losses on banks' loan books.

Figure 5 re-estimates specification (9) using $EL_{k,b,i,t}$ as the outcome variable. The impulse responses are positive across most horizons, implying that after a contractionary monetary policy shock, expected losses fall less for high-deposit-beta banks than for low-deposit-beta banks. Importantly, the expected-loss dynamics are qualitatively similar to the PD dynamics documented above, indicating that the PD response is not offset by changes in loss severity or exposure at default. Since a positive coefficient means that higher-beta banks have relatively higher expected losses after tightening, the estimates imply that banks with stronger deposit franchises reduce expected credit losses more aggressively. This pattern is consistent with the mechanism that larger deposit franchises strengthen incentives to preserve future rents by curbing risk-taking.

Figure 5: Banks With Higher Deposit Franchise (Low Beta) Reduce Expected Losses More



Note: This figure plots impulse-responses from local projections (9) over horizons 0–8 quarters, showing the responses of the loan-level expected loss to a +1 pp monetary policy shock interacted with banks' deposit beta. Deposit betas are standardised. 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.

A natural concern is that PDs and expected losses are internal bank risk assessments. Although these measures are central to supervisory stress testing and are designed to capture ex ante credit risk, they are ultimately produced by banks' own models. If the response in Figure 4 and Figure 5 reflected changes in internal risk classification rather than genuine changes in credit risk-taking, the interpretation of our results would be weaker. We therefore validate the Y-14 risk measures against realised loan outcomes that are less directly subject to internal-model discretion.[18]

Table 2 shows that the risk measures from Y-14 have strong predictive content for subsequent loan performance.[19] Loans assigned higher PDs and with higher expected losses subsequently experience greater delinquency as measured by the number of days past due and also greater charge-offs. This relationship remains after absorbing bank fixed effects and borrower-time fixed effects, and after controlling for observable loan terms. The table is not intended to identify the deposit-franchise mechanism directly. Rather, it addresses the measurement concern: the bank-reported ex ante risk measures used in our main analysis contain meaningful information about realised credit outcomes.

[18] Using the same Y-14 data, Beyhaghi et al. (2026) also verify that bank-reported PDs predict both loan interest rates and ex post performance.

[19] While Table 2 reports predictive-validation regressions using loan performance measured eight quarters ahead, Online Appendix B Table B.1 shows that the same relationship holds at the 4-quarter horizon.

Table 2: Ex Post Loan Performance and Ex Ante Bank Risk Measures

	Past Due (days)				Charge-offs ($000s)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Probability of Default (%)	0.042***	0.047***			3.342***	3.586**		
	(0.014)	(0.014)			(1.289)	(1.401)		
Expected Loss			0.177***	0.156***			36.813***	39.303***
			(0.060)	(0.060)			(9.810)	(10.670)
Loan-Level Controls		✓		✓		✓		✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	739,013	702,943	719,543	683,963	735,658	699,856	716,213	680,897
R^2	0.699	0.705	0.697	0.704	0.532	0.542	0.537	0.544

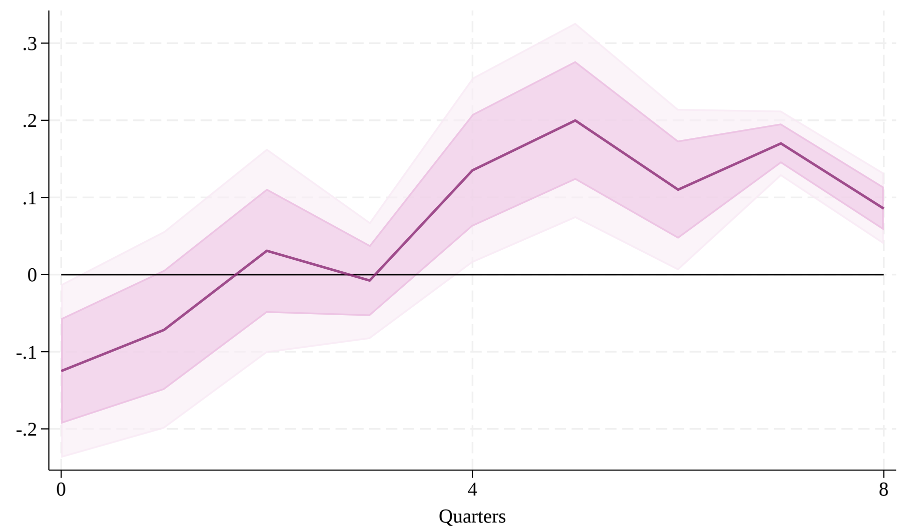
Note: This table reports coefficient estimates from loan-level regressions at horizon $h = 8$. The dependent variables are the number of days past due in columns (1)–(4), and net charge-offs, measured in thousands of dollars, in columns (5)–(8). The main independent variables are the loan-level probability of default (PD) in columns (1)–(2) and (5)–(6), and expected loss (EL) in columns (3)–(4) and (7)–(8). Expected loss is defined as $PD \times LGD \times EAD$, where EAD is measured in millions of dollars. Even-numbered columns include loan-level controls: the interest rate, an indicator for whether the loan is collateralised, and an indicator for whether the loan is senior. All columns include bank fixed effects and borrower-by-time fixed effects. Standard errors are clustered at the bank-by-time level and reported in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The predictive evidence in Table 2 validates the risk measures in levels. We next ask a stricter question: whether the same deposit-franchise pattern appears when the dependent variable is no longer a bank-reported ex ante risk measure. This is a demanding test because it requires realised loan outcomes, which are not subject to internal-model discretion, to move in the same way as PDs and expected losses in response to high-frequency monetary policy shocks interacted with predetermined deposit betas, while retaining the same bank and borrower-time fixed effects.

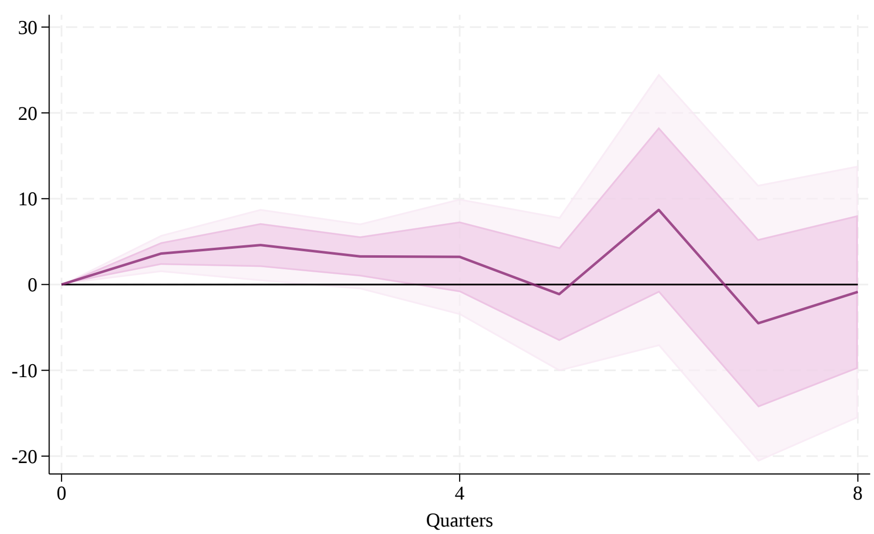
To evaluate this question, we re-estimate (9) with the two measures of *ex post* loan performance: loan delinquency (i.e., the number of days the loan is past due) and loan charge-offs. We do not view these realised outcomes as our primary measures of risk-taking, since they materialise with lags, are noisier measures of banks' ex ante risk choices, and can depend on post-origination shocks and loss-realisation timing. However, if PDs and expected losses capture meaningful variation in banks' ex ante credit risk-taking, then realised loan performance should display a qualitatively similar cross-sectional pattern. Figure 6 supports this interpretation. In both cases, loan performance deteriorates more for high-deposit-beta banks after a contractionary monetary policy shock, consistent with these banks reducing credit risk less than low-deposit-beta banks.[20]

Figure 6: High-Deposit-Franchise (Low-Beta) Banks Have Better Loan Performance

(a) Loan Delinquency



(b) Loan Charge-Offs



Note: This figure plots impulse-responses from local projections (9) over horizons 0–8 quarters, showing the responses of the loan-level delinquency (top) and charge-offs (bottom) to a +1 pp monetary policy shock interacted with banks' deposit beta. Deposit betas are standardised. 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.

[20] The charge-off responses are noisier at longer horizons, which is unsurprising given that charge-offs are realised loss events that occur with variable timing after deterioration in loan quality.

Having established that our main results are robust across different PD samples as well as robust to replacing PDs and expected losses with loan-level measures of ex post performance, we next assess the validity and interpretation of our deposit franchise measure. Specifically, we address two complementary issues. First, we examine whether our results could be affected by endogeneity in deposit betas and show that predetermined 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.

Deposit Beta Endogeneity. In our baseline theoretical framework, we treat each bank's deposit beta as an exogenous parameter rather than a choice variable, though this is relaxed in Internet Appendix C. This allows the model to generate comparative statics in deposit betas that map directly to our empirical interaction. The most immediate empirical concern is that measured deposit betas could adjust mechanically to the monetary policy shocks in our estimation sample. We mitigate this concern by estimating deposit betas using only pre-sample data from 1984 to 2014.

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 $\text{Shock}_t \times \text{DepositBeta}_i^{pre}$ 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), deposit betas are relatively stable over time, which suggests they reflect slow-moving market power rather than transitory pricing decisions around any single shock. On the other hand, Emin et al. (2025) show that pass-through to deposit rates varies with the level of interest rates. However, this does not threaten our specification: we use the pre-sample beta to rank banks by their relative deposit-rate sensitivity, not to impose a constant pass-through across rate environments. The relevant requirement is therefore that pre-sample betas predict banks' relative in-sample betas. Indeed, our predetermined 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 2026), as shown in Figure 3. Moreover, our shocks are high-frequency surprises that are not systematically predictable at the time they occur.

Second, Table 3 documents that low and high-beta banks are similar across a number of core bank and loan characteristics. Most importantly, these banks are similar across all the loan-level variables, including average PD. Moreover, they are also sufficiently similar across a number of bank-level variables such as size, capital ratio, leverage, and return on assets. The final column reports the normalised difference following Imbens and Wooldridge (2009), where $|\Delta_{IW}| < 0.25$ suggests sufficient comparability and thus reasonable balance.[21] These analyses support our structural interpretation of the coefficient on $\text{Shock}_t \times \text{DepositBeta}_i^{pre}$ as the causal effect of monetary policy transmitted through the deposit franchise.

Table 3: Balance Across High and Low-Deposit Beta Banks

Variable	High beta	Low beta	N (High / Low)	Δ_{IW}
Bank-level variables				
Deposit Beta	0.645	0.404	709 / 838	0.889
Deposits / Liabilities	0.8840	0.9073	709 / 838	0.287
Tier 1 Capital Ratio	0.1346	0.1321	709 / 838	0.051
Leverage Ratio	0.0928	0.0916	709 / 838	0.050
Return on Assets	0.0027	0.0024	559 / 658	0.080
C&I Charge Offs / C&I Loans	0.0009	0.0011	709 / 819	0.140
Average Risk Weight	0.6827	0.7049	709 / 838	0.090
Total Assets ($M)	5.5e+05	3.4e+05	709 / 838	0.224
Loan-level variables				
Probability of Default (%)	2.80	2.50	2.17M / 2.11M	0.023
Loan Size ($M)	9.03	8.53	2.17M / 2.11M	0.013
Interest rate (%)	4.29	4.18	2.08M / 2.01M	0.027
Collateralised loan	0.83	0.84	2.17M / 2.11M	0.008
Senior loan	0.83	0.83	2.17M / 2.11M	0.010
Loan maturity (< 20 years)	5.48	5.68	2.09M / 1.99M	0.043

Note: This table compares observable bank-level and loan-level characteristics between high- and low-deposit-beta banks (14 banks in the high-beta group and 15 banks in the low-beta group). Columns report the group means, the number of observations in the high- and low-beta groups, and the normalised differences Δ_{IW} following Imbens and Wooldridge (2009).

[21] Banks with greater deposit franchise strength (lower betas) have a higher deposit-to-liabilities 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 deposit 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,

$$\text{Deposit RoA} \equiv \frac{\text{Profits from Deposits}}{\text{Assets}} = \frac{rD - r^D D}{A}, \tag{10}$$

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 counterfactual interest expense the bank would incur if it paid the policy rate on deposits, minus its actual deposit interest expense.

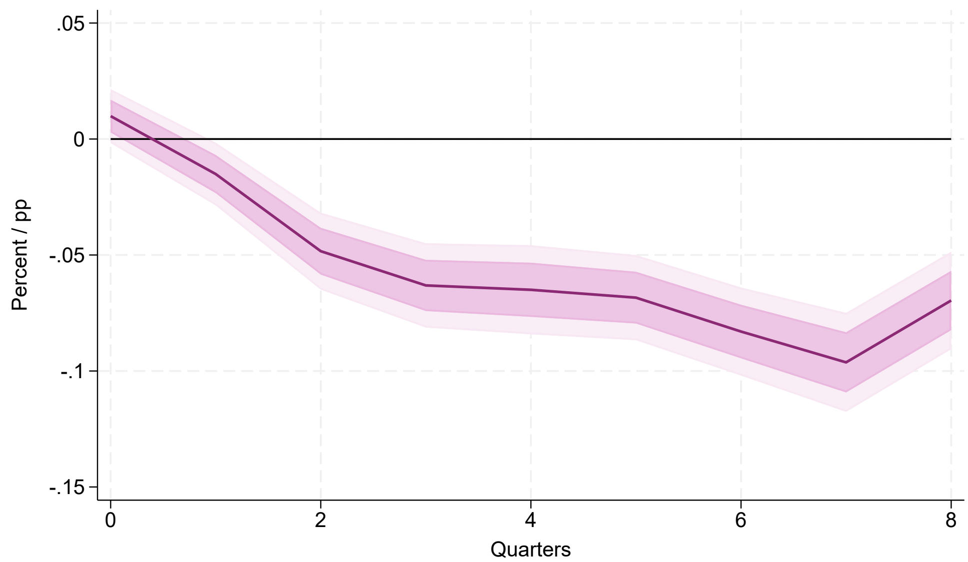
We then estimate a bank-level regression of Deposit RoA on monetary policy shocks interacted with banks' predetermined deposit betas:

$$\text{Deposit RoA}_{i,t+h} = \alpha_i + \delta_t + \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i^{pre}) + \varepsilon_{i,t+h} \tag{11}$$

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.

Consistent with our theoretical mechanism, Figure 7 shows that the interaction term is negative: following a contractionary monetary policy shock, banks with lower deposit betas experience larger increases in deposit profitability. The figure implies that, for banks with a one-standard-deviation higher deposit beta, deposit profitability declines by more than 0.05 percentage points over the first four quarters following a monetary policy shock that raises the policy rate by one percentage point. The implied decline reaches roughly 0.1 percentage points after seven quarters, before partially reversing by the end of the projection horizon. Given that average deposit profitability over our sample period is around 0.7 percent, Figure 7 confirms that predetermined deposit betas capture economically meaningful cross-sectional variation in deposit franchise strength.

Figure 7: Banks With Higher Betas Experience a Larger Fall in Deposit Profitability



Note: This figure plots impulse-responses from local projections (11) 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. Deposit betas are standardised. Bank fixed effects are controlled. Standard errors are clustered at the bank-by-time level. Shaded areas indicate 68% and 90% confidence intervals.

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 capitalisation to explain risk-taking responses across banks (e.g., Dell'Ariccia et al., 2017).

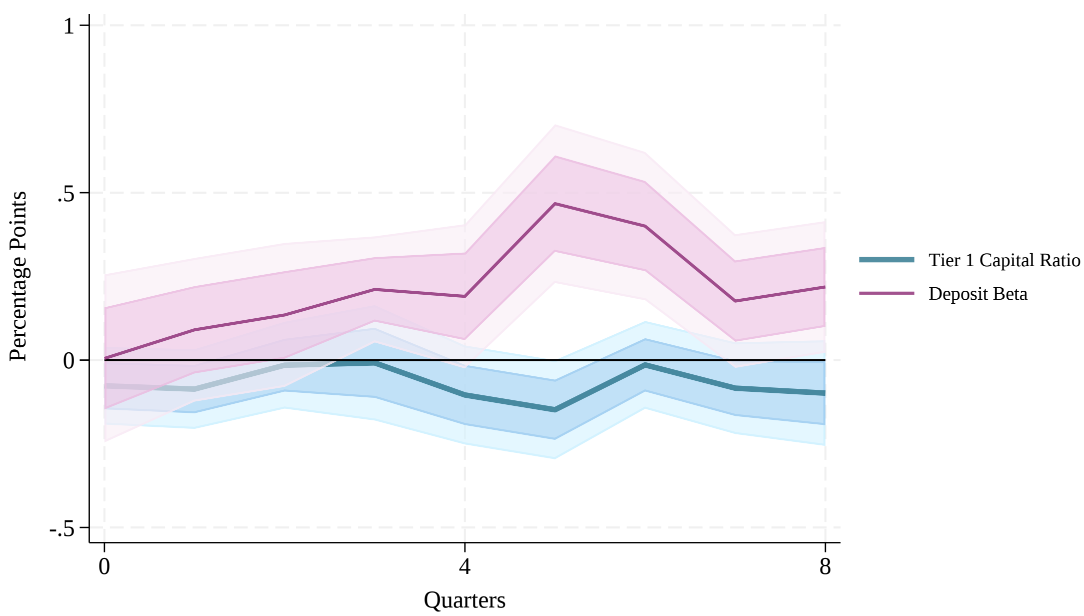
In contrast to capitalisation-based mechanisms, in the deposit franchise channel that we introduce and empirically test, the mechanism operates via monopoly rents: a rate cut compresses deposit spreads, eroding future deposit profits and thereby weakening the disciplinary force that normally restrains banks with sticky deposit bases; these low-beta banks, now with less profit 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 predetermined deposit beta and (ii) the bank's lagged capital ratio for horizons $h = 0 \ldots 8$, while saturating borrower-time and bank fixed effects:

$$z_{k,b,i,t+h} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{4} \lambda_{h,l} \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i^{pre}) + \sum_{l=0}^{4} \gamma_{h,l} \cdot (\text{Shock}_{t-l} \times \text{CapitalRatio}_{i,t-l-1}) + \varepsilon_{k,b,i,t+h} \quad (12)$$

As shown in Figure 8, the coefficient on $(\text{Shock} \times \text{DepositBeta}^{pre})$ remains positive, statistically significant, and persistent after controlling for the interaction between monetary policy shocks and bank capital. Since both deposit beta and the Tier 1 capital ratio are standardised, the magnitudes are directly comparable as responses to a one-standard-deviation difference in each bank characteristic. The deposit-beta interaction is economically larger: a one-standard-deviation higher deposit beta, corresponding to a weaker deposit franchise, is associated with substantially higher loan-level PDs after monetary tightening. The coefficient on $(\text{Shock} \times \text{CapitalRatio})$ is negative, which is consistent with Dell'Ariccia et al. (2017): higher-capital banks reduce risk more following a contractionary shock, or equivalently increase risk more following an easing.

Figure 8: Deposit Franchise and Bank Capital Mechanisms Co-Exist



Note: This figure plots impulse-responses from local projections (12) 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. Deposit betas and capital ratios are standardised. 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.

Taken together, the results indicate that the deposit-franchise channel is not subsumed by bank capital. Rather, capitalisation and deposit-franchise strength capture distinct dimensions of bank heterogeneity, with the deposit franchise emerging as the more quantitatively important predictor of risk-taking responses in our setting.

4.4 New Loans

The preceding analysis uses the full stock of banks' loan portfolios. This is the natural object for measuring the aggregate risk exposure of bank balance sheets, but it can combine several margins of adjustment: banks may originate new credit, renew or amend existing facilities, or shut down risky credit facilities. To sharpen the mechanism, we next restrict attention to new loan originations. This exercise provides a more direct test of the risk-taking channel because each new loan reflects an active risk-taking decision made after the monetary policy shock. In this setting, banks choose not only whether to lend to a borrower but also the contractual form of the credit.

We estimate cumulative versions of our baseline specification, focusing on loans newly originated in the 8 quarters following the monetary policy shock and using the same source of cross-sectional variation in deposit-franchise exposure. We estimate

$$z^{\text{new}}_{k,b,i,t+8} = \alpha_i + \delta_{b,t} + \sum_{l=0}^{4} \lambda_l \cdot (\text{Shock}_{t-l} \times \text{DepositBeta}_i^{pre}) + \varepsilon_{k,b,i,t+8}, \tag{13}$$

where $z^{\text{new}}_{k,b,i,t+8}$ is the outcome variable at $t+8$ for all new loan originations by bank i to borrower b between quarters t and $t+8$, and $\text{DepositBeta}_i^{pre}$ is the standardised predetermined bank deposit beta. The outcome variables are the probability of default, expected loss, and two contractual features that determine a loan's riskiness: whether the loan is collateralised and whether it is senior (first-lien secured). The specifications continue to include borrower-by-time fixed effects, so identification comes from comparing loans to the same borrower in the same quarter across banks with different deposit betas. In the even-numbered columns, we further replace bank fixed effects with borrower-by-bank fixed effects to absorb persistent relationships between a given borrower and lender. This helps alleviate the concern that the findings might be driven by bank specialisation (e.g., Paravisini et al., 2023; Blickle et al., 2026).[22]

[22] As an additional check, in Online Appendix B Table B.2 we estimate the same specification using loan-purpose categories as outcomes and find no differential response by deposit beta. This further addresses the specialisation concern: if low- and high-beta banks systematically served the same borrower for different types of credit, borrower-time fixed effects could still leave residual variation in within-borrower credit demand.

Table 4 reports estimates of (13). The coefficient on Shock × DepositBeta is positive and statistically significant in columns (1) and (2). Since a higher deposit beta indicates a weaker deposit franchise, high-beta banks originate loans with relatively higher PDs than low-beta banks after a contractionary monetary policy shock. Equivalently, banks with stronger deposit franchises reduce the risk of newly originated loans more aggressively. The result holds after including borrower-by-bank fixed effects, indicating that it is not driven by stable matching between particular banks and borrowers. The pattern of expected losses shown in columns (3) and (4) also aligns with the main results: monetary tightening induces banks with stronger deposit franchises to reduce credit risk more.

The magnitudes are economically meaningful. Because deposit betas are standardised in the regressions, the coefficients are interpreted for a one-standard-deviation increase in the deposit beta. A monetary policy shock that raises the policy rate by one percentage point differentially raises the average PD among new originations over the cumulative window by 0.357 percentage points and raises expected loss by nearly eighty thousand dollars in the specifications without borrower-bank fixed effects. The comparison with the full-portfolio estimates in Figure 4 Panel C and Figure 5 is also informative. The response among new loan originations is larger than the corresponding response in the full stock of loans at the same horizon. This suggests that the active origination margin is quantitatively important for the portfolio-level adjustment documented earlier. Because the full-stock estimates combine newly originated loans with legacy facilities whose risk characteristics may adjust only slowly, they likely attenuate the risk adjustment that occurs when banks make new lending decisions. We therefore interpret the new-loan results as evidence that the deposit-franchise channel operates not only through the gradual evolution of existing balance sheets, but also through active screening and loan design at origination.

We next consider the contract-design margins. The coefficients in columns (5) and (7) imply that new loans are 1.5 percentage points less likely to be collateralised and 1.4 percentage points less likely to be senior for a one-standard-deviation increase in the deposit beta. Therefore, the new-loan sample allows us to identify a concrete margin through which this risk reduction occurs. Given that columns (5) through (8) show that the interaction coefficient is negative for both collateralisation and seniority, banks with stronger deposit franchises respond to higher rates by shifting new lending toward credit facilities with greater contractual protection. These estimates remain stable when borrower-by-bank fixed effects are included, so the result is not explained by some bank-borrower pairs being more likely to use collateral or senior loans.

Table 4: Risk-Taking Responses in New Loans

	PD		Expected Loss		Collateral		Seniority	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock × Deposit beta	0.357***	0.295***	79.955***	55.017***	-0.015*	-0.011**	-0.014*	-0.012**
	(0.135)	(0.102)	(24.929)	(19.653)	(0.008)	(0.005)	(0.008)	(0.005)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓		✓		✓		✓	
Borrower × Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Borrower × Bank FE		✓		✓		✓		✓
Observations	1,244,377	1,239,755	1,210,539	1,205,970	1,244,377	1,239,755	1,244,377	1,239,755
R^2	0.855	0.907	0.363	0.461	0.806	0.903	0.797	0.889

Note: This table reports coefficient estimates from cumulative new-loan regressions through horizon $h = 8$. The sample is restricted to newly originated loans. The dependent variables are the loan-level probability of default (PD) in columns (1)–(2), expected loss in columns (3)–(4), an indicator for whether the loan is collateralised in columns (5)–(6), and an indicator for whether the loan is senior in columns (7)–(8). Expected loss is measured in thousands of dollars and defined as $PD \times LGD \times EAD$. The reported coefficient is on the interaction between the monetary policy shock and the bank's predetermined deposit beta, estimated over 1984–2014. Deposit betas are standardised. Columns (1), (3), (5), and (7) include bank fixed effects and borrower-by-time fixed effects. Columns (2), (4), (6), and (8) also include borrower-by-bank fixed effects. All columns include four lags of the interaction term as controls. Standard errors are clustered at the bank-by-time level and reported in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

This evidence helps interpret the borrower-time fixed effects in the main specifications. Because those fixed effects hold constant investment opportunities and time-varying borrower fundamentals, the risk-taking response cannot be attributed simply to low-beta banks lending to safer firms after monetary tightening. Instead, the new-loan results show that banks adjust the terms of credit within borrowers. For a given firm seeking credit in a given quarter, banks with stronger deposit franchises are more likely to originate loans that are better protected in default, which implies lower risk.

Taken together, the new-loan evidence underpins the main result with an origination-level mechanism. The full loan-portfolio analysis shows that banks with stronger deposit franchises reduce risk more after monetary tightening. The origination analysis shows how they do so: they write new loans with lower PDs and expected losses by tilting the contractual structure of lending toward collateralised and senior claims. This pattern is difficult to reconcile with a demand-side explanation because the comparison is made within the same borrower-quarter and, in the most saturated specifications, within the same borrower-bank relationship. It is instead consistent with the deposit-franchise channel operating through a supply-side reduction in loan-level risk-taking.

5 Conclusion

This paper identifies a deposit-franchise channel through which monetary policy shapes bank risk-taking. In standard accounts of the risk-taking channel, monetary policy affects banks primarily through asset-side returns or capital-based incentives. We show the importance of the deposit franchise. Banks with sticky deposit rates earn rents from paying deposit rates below the policy rate. These rents survive only if the bank remains a going concern. The deposit franchise therefore gives banks skin in the game: risk-taking raises loan income, but it also increases the probability that the bank loses the rents generated by its deposit base.

Our model formalises this trade-off and delivers two predictions. First, contractionary monetary policy reduces bank risk-taking. Second, the reduction is stronger for banks with lower deposit betas, because these banks have larger deposit-franchise rents at stake. The mechanism is closely related to the classic idea that franchise value disciplines bank risk-taking, but it adds a monetary-policy dimension: the strength of this discipline varies with interest rates and with the stickiness of banks' deposit bases.

We test these predictions using confidential FR Y–14 loan-level supervisory data, high-frequency monetary policy shocks, and predetermined deposit betas. The results support the deposit-franchise channel. Contractionary monetary policy shocks reduce loan-level probabilities of default and expected losses, and these reductions are significantly stronger for banks with lower deposit betas. Moreover, the channel is not subsumed by capital-based explanations. In a horse race with bank capital, the deposit-beta interaction remains statistically significant and economically important.

The loan-level data also allow us to show how banks reduce risk. In the full loan portfolio, lower risk could reflect many margins, including changes in existing exposures, amendments, exits, or new originations. Focusing on newly originated loans reveals an active origination-level response: banks with stronger deposit franchises originate loans with lower probabilities of default and lower expected losses. They also write loans with greater contractual protection: new loans made by low-beta banks are more likely to be collateralised and senior. These results remain stable after absorbing borrower-by-bank relationships, indicating that the findings are not driven simply by persistent matching between particular borrowers and lenders. The deposit franchise therefore shapes not only the amount of credit risk banks bear, but also the contractual form through which banks manage that risk.

The findings have broader implications for monetary policy, competition policy, and financial-stability regulation. Deposit-market structure affects more than the pass-through of policy rates to depositors and lending quantities; it also changes the rents banks have at stake when choosing credit risk. Policies that increase deposit competition, improve rate transparency, or facilitate fintech entry may benefit depositors and strengthen monetary pass-through, but they may also reduce the franchise-value discipline that restrains risk-taking at banks with sticky deposit bases. This trade-off does not imply that deposit market power is desirable, but it does imply that deposit competition and monetary-policy transmission should be studied jointly. Future research should examine how changes in deposit-market structure alter the allocation of credit risk across banks, how this interacts with bank capital and interest-rate risk, and whether the contractual adjustments we document have real effects on firm investment and financial stability.

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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),

$$3\lambda\theta_i^2 + 2\lambda(1 - \beta_i^D)r\theta_i - 1 = 0. \tag{14}$$

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 (14), 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, an average of 3.5 banks failed each year.[23] 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 $r \leq \lambda^{-\frac{1}{2}}$.

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

Internet Appendices for "The Deposit Franchise and the Risk-Taking Channel of Monetary Policy"

Ricardo Duque Gabriel, Ziang Li, and Ali Uppal

Appendix B Additional Figures and Tables

Table B.1: Ex Post Loan Performance and Ex Ante Bank Risk Measures

	Past Due (days)				Charge-offs ($000s)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Probability of Default (%)	0.083***	0.081***			3.688***	4.018***		
	(0.012)	(0.012)			(0.904)	(0.966)		
Expected Loss			0.280***	0.258***			41.621***	43.804***
			(0.071)	(0.074)			(8.857)	(9.488)
Loan-Level Controls		✓		✓		✓		✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,326,392	1,263,726	1,288,466	1,226,963	1,319,599	1,257,595	1,281,721	1,220,879
R^2	0.650	0.659	0.652	0.660	0.543	0.554	0.544	0.547

Note: This table reports coefficient estimates from loan-level regressions at horizon $h = 4$. The dependent variables are the number of days past due in columns (1)–(4), and net charge-offs, measured in thousands of dollars, in columns (5)–(8). The main independent variables are the loan-level probability of default (PD) in columns (1)–(2) and (5)–(6), and expected loss (EL) in columns (3)–(4) and (7)–(8). Expected loss is defined as $PD \times LGD \times EAD$, where EAD is measured in millions of dollars. Even-numbered columns include loan-level controls: the interest rate, an indicator for whether the loan is collateralised, and an indicator for whether the loan is senior. All columns include bank fixed effects and borrower-by-time fixed effects. Standard errors are clustered at the bank-by-time level and reported in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.2: Risky Loan-Purpose Responses in New Loans

	Risky Purpose	
	(1)	(2)
Shock × Deposit beta	-0.002	-0.001
	(0.006)	(0.003)
Bank FE	✓	
Borrower × Time FE	✓	✓
Borrower × Bank FE		✓
Observations	1,244,361	1,239,741
R^2	0.587	0.725

Note: This table reports coefficient estimates from cumulative new-loan regressions through horizon $h = 8$. The sample is restricted to newly originated loans. The dependent variable is an indicator equal to one if the loan purpose is classified as risky. Risky purposes include investment, expansion, mergers and acquisitions, refinancing or restructuring, real estate, payout or capital-structure transactions, project finance, bridge finance, risky production exposure, and the residual other-purpose category. The omitted lower-risk reference group includes liquidity, working capital, back-up facilities, guarantees, secured asset finance, structured or collateralised finance, and capital-call or subscription lending. The reported coefficient is on the interaction between the monetary policy shock and the bank's predetermined deposit beta. Deposit betas are standardised. Standard errors are clustered at the bank-by-time level and reported in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix C Endogenous Deposit Beta

This appendix extends the baseline model by allowing the bank to choose both its credit risk-taking and its deposit-rate pass-through. The baseline model treats the deposit beta as a predetermined bank characteristic. Here, the primitive source of heterogeneity is depositor rate sensitivity, and the observed deposit beta is an equilibrium outcome.

C.1 Setup

Bank i chooses risk-taking $\theta_i \in [0, \bar{\theta}]$ and a deposit beta $\beta_i \in [0, 1]$. The policy rate is $r > 0$, the bank pays deposit rate $r_i^D = \beta_i r$, and the per-unit margin funded by deposits is

$$M_i(\theta_i, \beta_i; r) \equiv \theta_i + r(1 - \beta_i).$$

The bank survives with probability

$$p(\theta_i) = 1 - \lambda\theta_i^2, \qquad \lambda > 0,$$

so the risk-taking limit is $\bar{\theta} = \lambda^{-1/2}$. The bank faces reduced-form deposit demand

$$D_i(\beta_i) = \bar{D}_i \beta_i^{\eta_i}, \qquad \bar{D}_i > 0, \qquad \eta_i > 0,$$

where η_i captures depositor rate sensitivity. A lower η_i corresponds to a stickier deposit base and therefore a stronger deposit franchise. The bank solves

$$\max_{\theta_i \in [0,\bar{\theta}],\, \beta_i \in [0,1]} \Pi_i(\theta_i, \beta_i; r) = (1 - \lambda\theta_i^2)\,[\theta_i + r(1 - \beta_i)]\,\bar{D}_i \beta_i^{\eta_i}. \tag{C.1}$$

Because $\bar{D}_i$ enters multiplicatively, it does not affect the optimal choices.

Assumption C.1 *Depositor rate sensitivity η_i is small enough that the solution to the bank's first-order conditions satisfies $\beta_i^*(r, \eta_i) < 1$.*

Assumption C.1 lets us focus on the economically relevant interior case in which the bank has a positive deposit franchise.

C.2 First-Order Conditions

For a general increasing deposit demand function $D_i(\beta_i)$, the bank's objective can be written as

$$\Pi_i(\theta_i, \beta_i; r) = p(\theta_i)M_i(\theta_i, \beta_i; r)D_i(\beta_i).$$

At an interior optimum, the risk-taking first-order condition is

$$-p'(\theta_i)M_i(\theta_i, \beta_i; r) = p(\theta_i), \tag{C.2}$$

which is the same marginal trade-off as in the baseline model: more risk raises the loan spread but also raises the probability that the bank loses its profit margin. The deposit-pricing first-order condition is

$$M_i(\theta_i, \beta_i; r)D_i'(\beta_i) = rD_i(\beta_i), \tag{C.3}$$

or, equivalently,

$$\frac{D_i'(\beta_i)}{D_i(\beta_i)} = \frac{r}{M_i(\theta_i, \beta_i; r)}.$$

This condition captures the standard pricing trade-off: a higher beta attracts more deposits but compresses the deposit spread.

Under $D_i(\beta_i) = \bar{D}_i\beta_i^{\eta_i}$, equation (C.3) becomes

$$\frac{\eta_i}{\beta_i}\left[\theta_i + r(1-\beta_i)\right] = r,$$

so an interior beta satisfies

$$\beta_i^* = \frac{\eta_i(\theta_i^* + r)}{r(1+\eta_i)}. \tag{C.4}$$

With quadratic survival probability, equation (C.2) becomes

$$3\lambda(\theta_i^*)^2 + 2\lambda r(1-\beta_i^*)\theta_i^* - 1 = 0.$$

C.3 Solution

When the bank chooses an interior beta, equation (C.4) implies

$$r(1-\beta_i^*) = \frac{r-\eta_i\theta_i^*}{1+\eta_i}, \qquad M_i(\theta_i^*, \beta_i^*; r) = \frac{\theta_i^* + r}{1+\eta_i}.$$

Substituting this expression into the risk-taking first-order condition yields a single quadratic equation in θ_i^*:

$$(3+\eta_i)\lambda(\theta_i^*)^2 + 2\lambda r\theta_i^* - (1+\eta_i) = 0. \tag{C.5}$$

The positive root is

$$\theta_i(r,\eta_i) = \frac{-r + \sqrt{r^2 + \frac{(3+\eta_i)(1+\eta_i)}{\lambda}}}{3+\eta_i}. \tag{C.6}$$

The associated beta is

$$\beta_i(r,\eta_i) = \frac{\eta_i\left[\theta_i(r,\eta_i) + r\right]}{r(1+\eta_i)}. \tag{C.7}$$

Under Assumption C.1, this is the relevant equilibrium.

The solution above is the unique maximum under Assumption C.1. On the interior domain $0 < \theta_i < \bar{\theta}$ and $0 < \beta_i < 1$, the log objective is

$$\ell_i(\theta_i, \beta_i) = \log(1-\lambda\theta_i^2) + \log\left[\theta_i + r(1-\beta_i)\right] + \eta_i \log\beta_i + \log\bar{D}_i.$$

The first term is strictly concave in θ_i, the second term is concave because it is the log of a positive affine function, and the third term is strictly concave in β_i. Hence the log objective is concave on the relevant domain, and the first-order conditions are sufficient for a unique maximum.

C.4 Comparative Statics

Define $A_i \equiv (3+\eta_i)\theta_i^* + r > 0$. Differentiating (C.5) with respect to r gives

$$\frac{\partial\theta_i^*}{\partial r} = -\frac{\theta_i^*}{(3+\eta_i)\theta_i^* + r} < 0. \tag{C.8}$$

Thus, conditional on an interior positive deposit franchise, a higher policy rate reduces bank risk-taking.

Differentiating (C.5) with respect to η_i gives

$$\frac{\partial \theta_i^*}{\partial \eta_i} = \frac{1 - \lambda(\theta_i^*)^2}{2\lambda A_i} > 0, \tag{C.9}$$

because $\theta_i^* < \bar{\theta}$ in the interior. More elastic deposit demand weakens the deposit franchise and leads the bank to choose more risk. The equilibrium beta satisfies

$$\frac{\partial \beta_i^*}{\partial \eta_i} = \frac{\theta_i^* + r}{r(1+\eta_i)^2} + \frac{\eta_i}{r(1+\eta_i)} \frac{\partial \theta_i^*}{\partial \eta_i} > 0. \tag{C.10}$$

Hence, in the interior region, ranking banks by η_i is equivalent to ranking them by their equilibrium deposit betas. Lower-beta banks are banks with more inelastic deposit demand.

The equilibrium beta can also be written as

$$\beta_i^* = \frac{\eta_i}{1+\eta_i}\left(1 + \frac{\theta_i^*}{r}\right).$$

Since $\partial \theta_i^* / \partial r < 0$, it follows that $\partial \beta_i^* / \partial r < 0$. This does not imply that deposit rates fall after a rate hike. The equilibrium deposit rate is

$$r_{D,i}^* = \beta_i^* r = \frac{\eta_i(\theta_i^* + r)}{1+\eta_i},$$

and

$$\frac{dr_{D,i}^*}{dr} = \frac{\eta_i}{1+\eta_i}\left(1 + \frac{\partial \theta_i^*}{\partial r}\right) > 0.$$

The deposit rate rises with the policy rate, but less than one-for-one. The deposit spread

$$s_i^* \equiv r - r_{D,i}^* = \frac{r - \eta_i \theta_i^*}{1+\eta_i}$$

therefore increases with the policy rate in the interior region.

The original cross-sectional prediction is that lower-beta banks reduce risk-taking more after a rate hike. In the joint-choice model, this prediction is most naturally stated first in terms of the primitive η_i and then mapped into the equilibrium beta using (C.10). Differentiating (C.8) with respect to η_i gives

$$\frac{\partial}{\partial \eta_i}\left(\frac{\partial \theta_i^*}{\partial r}\right) = \frac{(\theta_i^*)^2 - r\frac{\partial \theta_i^*}{\partial \eta_i}}{A_i^2}.$$

Using (C.9), this derivative is positive if and only if

$$(1+\eta_i)(3+\eta_i)(\theta_i^*)^2 + \eta_i r \theta_i^* > r^2. \tag{C.11}$$

A simple sufficient condition is $r < \sqrt{3}\,\theta_i^*$. A uniform sufficient condition stated only in terms of the risk-taking limit is

$$r < 0.681\,\bar{\theta}.$$

Under this condition,

$$\frac{\partial}{\partial \eta_i}\left(\frac{\partial \theta_i^*}{\partial r}\right) > 0.$$

Because $\partial \beta_i^* / \partial \eta_i > 0$, this is equivalent to

$$\frac{\partial}{\partial \beta_i^*}\left(\frac{\partial \theta_i^*}{\partial r}\right) > 0 \qquad \Longleftrightarrow \qquad \frac{\partial}{\partial (-\beta_i^*)}\left(\frac{\partial \theta_i^*}{\partial r}\right) < 0.$$

Thus, as in the baseline model, lower-beta banks reduce risk more after a contractionary monetary policy shock.

Proposition C.1 (Joint Choice of Risk-Taking and Deposit Beta) *Suppose bank i solves (C.1), with $\lambda > 0$, $\bar{D}_i > 0$, $\eta_i > 0$, $r > 0$, and $\bar{\theta} = \lambda^{-1/2}$. Under Assumption C.1, the unique optimum is interior in β_i, with θ_i^* and β_i^* given by (C.6) and (C.7). A higher policy rate reduces risk-taking, more elastic deposit demand raises both the equilibrium beta and risk-taking, and condition (C.11) implies that lower-beta banks reduce risk-taking more after a rate hike.*

This extension preserves the main predictions of Proposition 1 under the weak assumption that the equilibrium $\beta_i^D < 1$. It also clarifies the interpretation of deposit betas in the empirical analysis: the observed beta can be an equilibrium object, but it remains an informative ranking of deposit-franchise strength when it is driven by persistent differences in depositor rate sensitivity and measured before the period of the monetary-policy shocks.

Appendix D Dynamic Model

The baseline model assumes that the deposit franchise affects risk-taking through the continuation value that is lost in default. This appendix considers a discrete-time recursive version in which the full continuation value of the bank, rather than only the deposit-franchise value, is at stake. Current deposit rents also raise the bank's survival probability, capturing the idea that deposit cash flows can absorb losses and mechanically improve survival. To make the extension conservative, the policy rate also discounts continuation payoffs.

Deposit Rents and Survival Probability. Let banks differ in their deposit beta β_i^D, and define deposit-franchise strength as

$$x_i \equiv 1 - \beta_i^D.$$

As in the baseline model, the deposit rate is $r_i^D = \beta_i^D r$. Normalise the deposit base to one. Current deposit rents are

$$\mathcal{M}_i(r, x_i) = r - r_i^D = x_i r.$$

Hence $\mathcal{M}_{i,r} = x_i$, so current rents rise more after a rate hike for lower-beta banks.

The bank chooses loan risk θ_i. The one-period survival probability is $p_i(\theta_i, \mathcal{M}_i)$. We assume the following local survival function:

$$p_i(\theta_i, \mathcal{M}_i) = \bar{p}_i - \theta_i - \frac{\kappa_i}{2}\theta_i^2 + b_i\mathcal{M}_i, \qquad 0 < \bar{p}_i < 1, \quad \kappa_i > 0, \quad b_i \geq 0.$$

On the relevant local domain, parameters are such that $0 < p_i < 1$, and

$$p_{i,\theta} = -(1 + \kappa_i\theta_i) < 0, \qquad p_{i,\theta\theta} = -\kappa_i < 0, \qquad p_{i,\mathcal{M}} = b_i \geq 0.$$

The first inequality says that more credit risk lowers the survival probability. The second-derivative condition gives curvature in the survival technology. The third inequality states that current deposit rents weakly raise the survival probability.

Dynamic Bank Problem. The bank discounts continuation payoffs at the policy rate r. The current payoff from risky lending is θ_i. While alive, the bank earns the current payoff $\theta_i + \mathcal{M}_i(r, x_i)$. If the bank survives, it keeps continuation value; if it fails, continuation value is lost. Let $V_i(r, x_i)$ be bank i's next-period value function conditional on survival.

The Bellman equation is

$$V_i(r, x_i) = \max_{\theta_i} \left\{ \theta_i + \mathcal{M}_i(r, x_i) + \frac{1}{1+r} p_i(\theta_i, \mathcal{M}_i(r, x_i)) V_i(r, x_i) \right\}. \tag{D.1}$$

For any given θ_i, the Bellman equation implies

$$V_i(r, x_i) = \frac{\theta_i + \mathcal{M}_i(r, x_i)}{1 - \frac{1}{1+r} p_i(\theta_i, \mathcal{M}_i(r, x_i))} = \frac{(1+r)(\theta_i + \mathcal{M}_i(r, x_i))}{1 + r - p_i(\theta_i, \mathcal{M}_i(r, x_i))}. \tag{D.2}$$

At an interior optimum, the first-order condition is

$$1 + \frac{1}{1+r} p_{i,\theta}(\theta_i, \mathcal{M}_i(r, x_i)) V_i(r, x_i) = 0. \tag{D.3}$$

Using $p_{i,\theta} = -(1 + \kappa_i \theta_i)$, this can be written as

$$V_i(r, x_i) = \frac{1+r}{1 + \kappa_i \theta_i}. \tag{D.4}$$

For a positive continuation value, the second-order condition is

$$\frac{1}{1+r} p_{i,\theta\theta} V_i = -\frac{\kappa_i V_i}{1+r} < 0.$$

Risk-Taking Response to Rate Hikes. Let $\theta_i^*(r, x_i)$ denote the optimal risk-taking choice. Combining the Bellman equation and the first-order condition gives a simple expression for θ_i^*. From (D.2) and (D.4),

$$\frac{1+r}{1 + \kappa_i \theta_i^*} = \frac{(1+r)(\theta_i^* + x_i r)}{1 + r - p_i(\theta_i^*, x_i r)}.$$

Therefore,

$$1 + r - p_i(\theta_i^*, x_i r) = (1 + \kappa_i \theta_i^*)(\theta_i^* + x_i r). \tag{D.5}$$

Substituting

$$p_i(\theta_i^*, x_i r) = \bar{p}_i - \theta_i^* - \frac{\kappa_i}{2} (\theta_i^*)^2 + b_i x_i r$$

into (D.5), and simplifying, gives

$$\frac{\kappa_i}{2} (\theta_i^*)^2 + \kappa_i x_i r \theta_i^* = 1 - \bar{p}_i + r[1 - x_i(1 + b_i)]. \tag{D.6}$$

Differentiating (D.6) with respect to r yields

$$\kappa_i(\theta_i^* + x_i r)\frac{\partial \theta_i^*}{\partial r} + \kappa_i x_i \theta_i^* = 1 - x_i(1 + b_i).$$

Hence

$$\frac{\partial \theta_i^*}{\partial r} = \frac{1 - x_i(1 + b_i + \kappa_i \theta_i^*)}{\kappa_i(\theta_i^* + x_i r)}. \tag{D.7}$$

Since the denominator is positive at an interior optimum with $r \geq 0$, risk-taking falls after a rate hike if and only if

$$x_i(1 + b_i + \kappa_i \theta_i^*) > 1. \tag{D.8}$$

Condition (D.8) has a direct interpretation. A higher policy rate discounts continuation value, which lowers what the bank loses in default and pushes toward more risk-taking. At the same time, a higher policy rate raises current deposit rents by more for banks with larger x_i. These rents raise the value at stake and improve survival through the term $b_i \mathcal{M}_i$. Risk-taking falls when these deposit-rent and survival-buffer effects dominate the direct discounting effect.

Deposit-Franchise Strength. The condition in (D.8) can be expressed in terms of the bank's primitive parameters. Let

$$C_i \equiv 1 - \bar{p}_i, \qquad A_i \equiv 1 - x_i(1 + b_i).$$

Then (D.6) can be written as

$$\frac{\kappa_i}{2}(\theta_i^*)^2 + \kappa_i x_i r \theta_i^* = C_i + r A_i. \tag{D.9}$$

If $A_i \leq 0$, then $x_i(1 + b_i) \geq 1$, so (D.8) holds for any interior positive θ_i^*. If $A_i > 0$, condition (D.8) is equivalent to

$$\theta_i^* > \frac{A_i}{\kappa_i x_i}. \tag{D.10}$$

The left-hand side of (D.9) is increasing in θ_i^* over the relevant interior domain. Therefore, (D.10) holds if and only if the right-hand side of (D.9) is larger than the left-hand side evaluated at $\theta_i^* = A_i/(\kappa_i x_i)$:

$$C_i + r A_i > \frac{A_i^2}{2\kappa_i x_i^2} + r A_i.$$

The rA_i terms cancel, leaving

$$C_i > \frac{A_i^2}{2\kappa_i x_i^2}.$$

Substituting back for A_i and C_i, this condition is equivalent to

$$x_i\left(1 + b_i + \sqrt{2\kappa_i(1-\bar{p}_i)}\right) > 1. \tag{D.11}$$

Thus, banks with sufficiently strong deposit-franchise exposure, a sufficiently strong survival-buffer effect, or sufficiently strong curvature in survival with respect to risk reduce risk-taking after a rate hike.

Equivalently, since $x_i = 1 - \beta_i^D$, condition (D.11) can be written as an upper bound on the deposit beta:

$$\beta_i^D < 1 - \frac{1}{1 + b_i + \sqrt{2\kappa_i(1-\bar{p}_i)}}. \tag{D.12}$$

Banks with sufficiently low deposit betas therefore reduce risk-taking after monetary tightening in this dynamic setting, even though the policy rate also discounts continuation value.

Cross-Section. We next show when the cross-sectional ranking is preserved. Holding $\bar{p}_i$, κ_i, and b_i fixed, define

$$B_i \equiv x_i(1 + b_i + \kappa_i\theta_i^*) - 1, \qquad S_i \equiv \theta_i^* + x_i r.$$

Using (D.7),

$$\frac{\partial\theta_i^*}{\partial r} = -\frac{B_i}{\kappa_i S_i}. \tag{D.13}$$

The bank reduces risk after a rate hike exactly when $B_i > 0$.

Differentiating (D.6) with respect to x_i gives

$$\frac{\partial\theta_i^*}{\partial x_i} = -\frac{r(1 + b_i + \kappa_i\theta_i^*)}{\kappa_i(\theta_i^* + x_i r)} \le 0, \tag{D.14}$$

with strict inequality when $r > 0$. A stronger deposit franchise therefore weakly lowers the level of risk-taking.

Moreover,

$$\frac{\partial B_i}{\partial x_i} = \frac{(1 + b_i + \kappa_i\theta_i^*)\theta_i^*}{\theta_i^* + x_i r} > 0, \tag{D.15}$$

and

$$\frac{\partial S_i}{\partial x_i} = \frac{r(\kappa_i x_i r - (1 + b_i))}{\kappa_i(\theta_i^* + x_i r)}. \tag{D.16}$$

Therefore, if

$$\kappa_i x_i r \leq 1 + b_i, \tag{D.17}$$

then $\partial S_i / \partial x_i \leq 0$. Combining (D.13)–(D.17), for banks satisfying $B_i > 0$,

$$\frac{\partial}{\partial x_i}\left(\frac{\partial \theta_i^*}{\partial r}\right) = -\frac{\frac{\partial B_i}{\partial x_i} S_i - B_i \frac{\partial S_i}{\partial x_i}}{\kappa_i S_i^2} < 0. \tag{D.18}$$

Since $x_i = 1 - \beta_i^D$, this means that lower-beta banks have a more negative risk-taking response to a rate hike. Condition (D.17) ensures that the policy rate is not so high, relative to the survival-buffer term and the curvature of survival, that the cross-sectional ranking is overturned.

Proposition D.1 (Dynamic Risk-Taking Response to Rate Hikes) *Suppose bank i solves the recursive problem* (D.1)*, with* $\mathcal{M}_i(r, x_i) = x_i r$*,* $x_i = 1 - \beta_i^D$*,* $r \geq 0$*, and an interior optimum in the local domain where* $0 < p_i < 1$*. If bank i has a sufficiently strong deposit franchise, equivalently if*

$$\beta_i^D < 1 - \frac{1}{1 + b_i + \sqrt{2\kappa_i(1 - \bar{p}_i)}},$$

then a marginal increase in the policy rate reduces optimal risk-taking:

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

Moreover, if the regularity condition

$$\kappa_i x_i r \leq 1 + b_i$$

also holds, then the risk-taking response is stronger for banks with lower deposit betas. That is, holding $\bar{p}_i$*,* κ_i*, and* b_i *fixed, among banks with sufficiently strong deposit franchises, lower-*β_i^D *banks reduce risk-taking more after monetary tightening.*