

Monetary Policy Uncertainty and Bank Credit Allocation*

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Abstract

We analyze how monetary policy uncertainty (MPU) affects bank credit allocation. First, we develop a theoretical model in which MPU consumes banks' risk-bearing capacity. Higher MPU therefore curbs risky lending, most strongly at less capitalized banks. Second, we test this prediction across U.S. credit markets using FOMC-announcement changes in option-implied rate uncertainty, controlling for the monetary policy stance. In syndicated lending, a one standard deviation increase in MPU widens the gap between high- and low-capital banks in lending to riskier relative to safer borrowers by 1.65 percent. Small business and mortgage originations show similar patterns, consistent with this mechanism.

Keywords: Monetary policy, uncertainty, bank capital, credit allocation

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1 Introduction

In this paper we ask how monetary policy uncertainty (MPU) changes the allocation of bank credit across borrowers of different risk. This is important since central banks increasingly shape not only the level of interest rates but also uncertainty about their future path. Yet, while decades of research document how the monetary policy *stance* affects bank lending and risk taking, much less is known about the effects of MPU.¹

In principle, MPU can change credit composition through both borrower demand and bank supply. On the demand side, higher rate uncertainty raises the option value of waiting, so firms delay investment and borrowing (Bloom, 2009; Husted et al., 2020), and it raises expected debt-service costs for leveraged borrowers close to distress. On the supply side, uncertainty about the policy path is a risk-management problem for banks. Because banks carry duration, repricing, and funding mismatches, higher MPU increases the risk of positions already on their balance sheets, even before any credit losses are realized.

We isolate this credit supply channel and show that MPU reallocates bank credit across borrower risk. We first formalize the mechanism in a tractable model in the spirit of Froot and Stein (1998), in which bank equity supports a finite risk-bearing capacity that can be read as a regulatory capital requirement or an internal value-at-risk limit.² MPU enters as background risk through the bank’s residual interest rate exposure. When the risk limit binds, existing rate exposure and new loans compete for the same risk budget, so a rise in MPU acts like a temporary tightening of the capital constraint that is most acute at thinly capitalized banks. Higher MPU uses up capacity and raises the shadow cost of new lending, disproportionately penalizing risky loans, which consume more capacity per unit of expected surplus. The model therefore delivers a cross-partial prediction: when MPU rises, less capitalized banks reduce lending to riskier borrowers by more, relative to safer borrowers, than well-capitalized banks do, and they raise the rates on those loans by more; when MPU falls, the pattern reverses.

We test this prediction in four U.S. datasets that cover the main segments of private credit: DealScan for syndicated corporate loans, Community Reinvestment Act (CRA) disclosures for small business lending, and Home Mortgage Disclosure Act (HMDA) and CoreLogic records for residential mortgages. Taking the model to these data raises three empirical challenges. The first is to separate credit supply from credit demand, which we address with fixed effects tailored to each market. In DealScan, we compare banks lending to the same firm in the same quarter, using borrower-company-quarter fixed effects to absorb time-varying firm demand (Khwaja

¹For the literature on the monetary policy stance and risk taking, see, for example, Maddaloni and Peydró (2011), Altunbas et al. (2014), Jiménez et al. (2014), Ioannidou et al. (2015), and Dell’Ariccia et al. (2017) for empirical evidence. For discussions of the mechanisms, see Rajan (2006), Adrian and Shin (2010, 2014), Borio and Zhu (2012), Dell’Ariccia et al. (2014), and Martínez-Miera and Repullo (2017).

²Appendix B.2 also derives the risk limit from a target probability of remaining above a continuation threshold, which ties its tightness to franchise value.

and Mian, 2008; Jiménez et al., 2014), and in tighter specifications we compare lenders within the same loan facility. In CRA and HMDA, we compare banks lending in the same county and year, with county-year, bank-year, and bank-county fixed effects that absorb local demand, each lender’s national conditions, and persistent local relationships. Finally, the monthly CoreLogic county data record both average loan sizes and initial interest rates, so we can check whether quantities and prices move in opposite directions, as a contraction in credit supply implies.

The second challenge is to separate MPU from surprises in the expected policy path and from other news released at policy announcements. Following Bauer et al. (2022), we measure MPU with announcement-day changes in market-implied short-rate uncertainty (SRU) at Federal Open Market Committee (FOMC) meetings, which limits the influence of news arriving at other times. FOMC announcements can shift both the expected path of policy rates and beliefs about the economic outlook (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020), and policy surprises are partly predictable from earlier economic data (Bauer and Swanson, 2023a). We therefore control for the orthogonalized stance surprise of Bauer and Swanson (2023b), with its full set of interactions, in every specification. The triple-difference structure further relaxes the identifying assumption. MPU need not be orthogonal to all announcement news; conditional on the stance surprise, the controls, and the fixed effects, it needs only to be uncorrelated with omitted news that changes how bank capital shapes lending across borrower risk.

The third challenge is that bank capital is not randomly assigned, so our capital interactions could proxy for other balance sheet characteristics that shape monetary transmission (Jiménez et al., 2012, 2014; Drechsler et al., 2021). To isolate risk-bearing capacity, we estimate a control ladder on a fixed sample. In DealScan, CRA, and HMDA, bank size, liquidity, profitability, asset quality, deposit mix, wholesale funding, loan portfolio composition, and repricing and maturity gaps each enter with their own full set of interactions with MPU, the stance surprise, and borrower risk. The repricing and maturity gaps also allow residual rate exposure, which the model holds fixed, to differ across banks.

We begin with syndicated corporate loans in DealScan, where we can compare lenders to the same borrower. Measuring firm risk by weak operating cash flow relative to current liabilities before each shock (and, in robustness checks, by higher debt-to-equity ratios), we find that when MPU rises, less capitalized banks cut lending to riskier firms more than well-capitalized banks lending to the same borrower. Quantitatively, a one standard deviation increase in MPU widens the lending gap between banks at the 75th and 25th percentiles of capital, for a firm at the 75th relative to the 25th percentile of risk, by 1.65 percent ($p = 0.020$). Within-facility comparisons, which use facility and bank-quarter fixed effects to compare how syndicate members divide the same loan, point in the same direction, with a differential of 2.12 percent ($p = 0.091$; Appendix Tables A8 to A10).

Because syndicated loans are concentrated among large banks and large firms and record only positive allocations, we next turn to CRA small business originations. The CRA panel covers a much broader set of banks and local markets and includes the extensive margin by retaining zero originations within each bank’s county deposit footprint. Measuring local risk by lagged operating distress among small employers, our Poisson pseudo-maximum likelihood (PPML) estimates mirror the DealScan findings: when MPU rises, less capitalized banks cut lending more in distressed local markets. For the same capital and risk percentiles, a one standard deviation increase in annual MPU exposure produces a differential of 1.16 percent in loan dollars ($p = 0.033$) and 2.06 percent in the number of loans ($p = 0.009$).

To test whether the reallocation extends to household credit, we turn to residential mortgages in HMDA. Comparing banks that lend in the same county and year, with bank-year and bank-county fixed effects, we find that higher MPU leads less capitalized banks to reduce mortgage lending relatively more in counties with higher lagged foreclosure rates. The corresponding differential is 0.68 percent ($p = 0.019$), consistent with the same capacity constraint governing mortgage supply.

To align mortgage outcomes more closely with the monthly timing of FOMC announcements and incorporate loan pricing, we complement HMDA with CoreLogic monthly county data on average original loan balances and initial mortgage interest rates. Interacting deposit-weighted local bank capital with lagged county foreclosure risk, we find that, for a one standard deviation increase in MPU, riskier counties served by less capitalized banking systems experience a 0.37 percent relative contraction in loan sizes accompanied by a 1.53 basis point relative increase in initial interest rates. This opposite movement in quantities and prices is consistent with tighter credit supply rather than weaker borrower demand, which would push loan sizes and rates in the same direction.

We verify the robustness of these results across a wide battery of checks. First, replacing SRU with Treasury implied volatility (TIV), Eurodollar basis-point volatility (BPVol), or the MOVE index preserves the benchmark capital ordering across specifications. Second, the results hold under alternative annual shock-weighting conventions, after controlling for conforming loan limits and local house values in HMDA, when dropping one year at a time in CRA, and when measuring local mortgage risk via lagged borrower FICO scores. Third, to test whether MPU proxies for macroeconomic information released at FOMC announcements, we augment our specifications one at a time with changes in professional forecasters’ long-term inflation disagreement, macroeconomic uncertainty ([Jurado et al., 2015](#)), and the mean and dispersion of households’ long-term inflation expectations ([Fofana et al., 2025](#)), each fully interacted with bank capital and borrower risk. The capital ordering remains intact under all four information controls in DealScan, HMDA, and CoreLogic, and under three of the four in CRA, where it

attenuates only when we condition on professional forecasters' inflation disagreement.³

These findings point to an interaction between central bank communication and prudential policy. Central banks increasingly use forward guidance not only to steer the expected path of rates but also to reduce uncertainty around that path (Campbell et al., 2012; Amengual and Xiu, 2018; Ehrmann et al., 2019; Bundick et al., 2024). Our results imply that lower MPU works like a temporary relaxation of bank capital constraints: by reducing the risk of existing rate exposures, it frees risk-bearing capacity and shifts credit toward riskier borrowers, particularly at thinly capitalized banks. Communication therefore alters credit composition through a second-moment channel distinct from the expected path of rates. Because capital regulation targets the same balance-sheet margin, greater monetary predictability can encourage risk taking that is socially excessive when limited liability and deposit insurance shield banks from the full downside. While we use FOMC announcements because they provide cleanly dated changes in rate uncertainty, the same capacity mechanism should govern how banks respond to other sources of background risk.

Our paper contributes to three strands of literature. The first studies monetary policy and bank risk taking (Maddaloni and Peydró, 2011; Altunbas et al., 2014; Jiménez et al., 2014; Ioannidou et al., 2015; Dell'Ariccia et al., 2017; Paligorova and Santos, 2017; Li et al., 2026), building on theories in which low interest rates encourage risk taking through search for yield, leverage, and limited liability (Rajan, 2006; Adrian and Shin, 2010; Borio and Zhu, 2012; Dell'Ariccia et al., 2014; Martinez-Miera and Repullo, 2017). Empirically, Jiménez et al. (2014) is closest to our setup in interacting monetary policy with bank capital and borrower risk. Whereas that literature studies the level of interest rates, where search-for-yield and risk-shifting forces can make the role of bank capital ambiguous (Dell'Ariccia et al., 2014), we study uncertainty about the future policy path, for which our model delivers a single capital ordering that we find in four credit markets.⁴

The second strand measures economic and policy uncertainty and traces their real and financial effects. Building on Bloom (2009), recent studies construct market- and news-based measures of MPU to examine how central bank communication shapes rate uncertainty (Creal and Wu,

³An earlier version of this paper also studied bank credit allocation in Türkiye, measuring MPU as the monthly change in the standard deviation of the daily overnight rate (or the width of the central bank's interest rate corridor). Using credit register data on bank-firm loans from 2006 to 2014 with firm-by-time and bank-by-time fixed effects, that analysis uncovered the same capital ordering: when MPU fell, less capitalized banks expanded lending more to firms with a recent non-performing loan.

⁴The theoretical predictions also differ. In stance-based theories, lower policy rates raise risk taking by compressing yields, relaxing leverage constraints, or strengthening risk-shifting incentives, and the role of capital can be ambiguous: with fixed capital structures, easing raises risk taking at well-capitalized banks but may lower it at highly leveraged ones (Dell'Ariccia et al., 2014), whereas Jiménez et al. (2014) find that lower rates lead less capitalized banks to take more risk. In our model, MPU leaves the expected rate path unchanged and operates strictly through background risk on existing exposures, delivering a single, unambiguous ordering: higher MPU reduces risky lending more at less capitalized banks.

2017; Husted et al., 2020; De Pooter et al., 2021; Bauer et al., 2022; Bundick et al., 2024). In banking, aggregate, trade, and political uncertainty have been shown to reduce bank loan supply, tighten lending standards, and induce precautionary capital accumulation, especially at less capitalized banks (Buch et al., 2015; Bordo et al., 2016; Valencia, 2017; Alessandri and Bottero, 2020; Wu and Suardi, 2021; Correa et al., 2023; Kara and Yook, 2023; Cerqueiro et al., 2025; Pastor y Camarasa, 2025; Vansteenberghe, 2025). Closest to our mechanism, Altavilla et al. (forthcoming) show that dispersion in overnight interbank rates raises corporate loan rates and that stronger capital buffers attenuate this effect. Whereas their measure captures short-term funding-market dispersion, we isolate uncertainty about the monetary policy rate itself around FOMC announcements and show how MPU interacts jointly with bank capital and borrower risk to reshape credit allocation across corporate, small business, and mortgage markets.

The third strand examines banks' interest rate exposure and the shadow cost of intermediary capital. Drechsler et al. (2021), English et al. (2018), Hoffmann et al. (2019), and Gomez et al. (2021) document how deposit franchises, repricing structures, and hedging leave residual interest rate exposure on bank balance sheets. In theories of financial intermediation, equity supports risk taking and scarce capital assigns a positive shadow price to unhedged exposures (Holmström and Tirole, 1997; Froot and Stein, 1998; He and Krishnamurthy, 2013; Adrian and Shin, 2014; Brunnermeier and Sannikov, 2014; Rampini and Viswanathan, 2019), while empirical studies quantify the shadow cost of regulatory capital constraints (Kisin and Manela, 2016; Plosser and Santos, 2024). We bridge these literatures by showing that monetary policy uncertainty turns banks' residual interest rate exposure into time-varying background risk, which shifts the shadow price of risk-bearing capacity and, in turn, the composition of bank credit.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework. Section 3 presents the MPU shocks, data, and empirical strategy. Section 4 reports the empirical results for syndicated loans (Section 4.1), small business credit (Section 4.2), and mortgage lending (Section 4.3). Section 5 concludes.

2 Theory: Bank Risk-Bearing Capacity and Credit Allocation

In this section we develop a simple model in which a bank's equity supports a finite capacity to bear risk and MPU consumes part of that capacity. Banks lend within risk limits that tie the risk they can carry to their equity, such as risk-sensitive capital requirements and internal value-at-risk budgets (Adrian and Shin, 2010, 2014). An increase in MPU raises the risk of the rate exposure that banks already carry and so uses up part of this capacity. Once the limit binds, the same exposure absorbs a larger share of a less capitalized bank's remaining capacity and raises its shadow cost of risk by more. Because risky loans use more capacity per unit of expected surplus, this bank cuts risky credit more sharply relative to safer credit. This differential across bank capital and borrower risk is the model's main empirical prediction.

We formalize this intuition in a one-period allocation problem. Equity supports a finite risk budget. Residual interest rate exposure uses part of it, and the bank allocates the rest across lending opportunities. Intermediary capital thus supports risk taking and gives a shadow cost to exposures that cannot be fully hedged (Holmström and Tirole, 1997; Froot and Stein, 1998; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Rampini and Viswanathan, 2019). We add MPU as background risk and allow riskier loans to consume more capacity. To keep the mechanism transparent, the model focuses on relative credit allocation and loan pricing within a fixed risk budget. Appendix B.2 derives the risk limit from a continuation-value target, and Appendix B.5 examines welfare.

2.1 Risk-Bearing Capacity

We assume that a bank's equity supports a risk budget, which must cover both its existing interest rate exposure and its new lending. Let $K > 0$ denote this usable capacity, with $K = k(B)$, where B is equity to assets and $k'(B) > 0$.⁵ After feasible hedging, the bank retains a residual rate exposure of size $e > 0$, which arises from asset duration, loan repricing, or funding structure.

Banks can largely match the rate sensitivity of their interest income and expense, but the value of their fixed-rate loans and securities still moves with rates.⁶ We therefore interpret e as the rate exposure of bank capital that remains. We assume that e is common across banks, so that the comparisons below turn on capital; Appendix B.8 relaxes this common-exposure assumption and states the conditions under which the capital ordering survives.

Let $U \geq 0$ denote MPU, measured as a variance. The existing exposure then uses $e^2 U$ units of the risk budget.⁷ This formulation separates an uncertainty shock from a stance shock. A surprise change in expected rates raises or lowers bank net worth, depending on the sign of the exposure. Higher uncertainty instead raises the risk from that exposure, whatever its sign. In the baseline, we assume that rate losses on existing positions and credit losses on new loans are uncorrelated, with the standardized factor distribution held fixed, so that their variances add. Appendix B shows that the predictions carry over to any nonnegative correlation, that is, whenever existing rate exposure does not hedge credit risk.

New loans also use the budget. Lending ℓ_i dollars to borrower type i uses $q_i \ell_i$ units of capacity. We assume that $q_i > 0$ is larger for riskier borrowers or markets, as under risk-sensitive capital

⁵We compare banks at a given predetermined asset scale, so a higher equity-to-assets ratio maps into greater usable risk capacity at that scale.

⁶See Drechsler et al. (2021). The deposit franchise hedges the interest rate risk of banks' long-term assets: when rates rise, it gains value as fixed-rate assets lose value. The franchise, however, is not recorded on the balance sheet. Losses on fixed-rate assets can therefore reduce reported equity, for example through unrealized losses on securities, while the offsetting gain in franchise value is not recorded.

⁷Empirically, U corresponds to the squared conditional volatility of future short rates recorded by the SRU measure of Bauer et al. (2022). Section 3 discusses how announcement-induced changes in SRU map into changes in U .

requirements.⁸ For proportional responses, the relevant ranking also depends on lending surplus, as we show below. The bank's internal or regulatory risk limit is

$$\left(\sum_i q_i \ell_i\right)^2 + e^2 U \leq K^2.$$

The first term is the credit risk of new lending, and the second is the risk from existing rate exposure. We treat the constraint as a reduced-form risk budget, motivated by variance-based internal or regulatory limits. It follows the capital budgeting approach of [Froot and Stein \(1998\)](#): risk that cannot be hedged raises the shadow price of new risks. Appendix [B](#) derives the constraint from a normal or spherical factor model, under which it is a value-at-risk limit.⁹ Appendix [B.2](#) gives a second interpretation. Suppose the bank targets a probability of falling below a continuation threshold, and this target declines with franchise value. Under normality, the target is then equivalent to a cap on total volatility, with K increasing in equity and decreasing in franchise value. This links the risk budget to the franchise value theory of bank risk taking.¹⁰ Provided $K^2 > e^2 U$, we can write the limit as

$$\sum_i q_i \ell_i \leq C(K, U) \equiv \sqrt{K^2 - e^2 U}.$$

Uncertainty reduces the capacity left for new lending, and capital increases it: $C_U < 0$ and $C_K > 0$. Capital also cushions the loss of capacity, $C_{UK} > 0$, because the same exposure absorbs a larger share of the remaining capacity when K is small.

In terms of capacity, a change in MPU is equivalent to a change in capital. Because $C^2 = K^2 - e^2 U$, a decline in uncertainty of ΔU leaves the bank with the same capacity for credit as an increase in K of approximately $e^2 \Delta U / (2K)$. This equivalent increase is inversely proportional to K . Lower uncertainty thus works like a temporary relaxation of the capital constraint that is largest at thinly capitalized banks, and higher uncertainty like a temporary tightening.

⁸This assumption follows risk-sensitive regulation and evidence on the shadow cost of bank capital ([Basel Committee on Banking Supervision, 2006](#); [Kisin and Manela, 2016](#); [Plosser and Santos, 2024](#)). Under the internal-ratings-based approach, default probability, loss given default and other exposure characteristics determine capital for unexpected losses. Our empirical risk measures (prior-year foreclosure rates, firm balance sheet risk and local operating distress) are imperfect indicators of q_i .

⁹[Adrian and Shin \(2014\)](#) show that a limit of this kind can arise from a contracting problem with risk-shifting moral hazard.

¹⁰See [Keeley \(1990\)](#), [Hellmann et al. \(2000\)](#), and [Dell'Ariccia et al. \(2014\)](#). This precautionary interpretation applies where preserving continuation value makes additional variance costly to shareholders. Where the limited liability incentive to take risk dominates, shareholders would not choose the limit, and it binds only to the extent that capital requirements, supervisors or creditors enforce it. Appendix [B.2](#) states the boundary between these regions.

2.2 Optimal Credit Allocation

Lending yields a surplus but is costly to deploy. The bank receives marginal surplus $m_i > 0$ from loans to type i and faces a convex deployment cost with curvature $c_i > 0$. It chooses credit quantities to solve

$$\max_{\{\ell_i \geq 0\}} \sum_i \left(m_i \ell_i - \frac{c_i}{2} \ell_i^2 \right) \quad \text{subject to} \quad \sum_i q_i \ell_i \leq C(K, U).$$

Margins and deployment cost curvature may differ across lending opportunities; the constraint isolates the role of risk capacity. Let A be the set of types receiving positive lending. When the constraint has a strictly positive shadow value and this active set is locally unchanged, the first-order condition for $i \in A$ is

$$m_i - c_i \ell_i = \lambda q_i,$$

where $\lambda > 0$ is the shadow value of one unit of risk capacity. Define $\Omega_A \equiv \sum_{j \in A} q_j^2 / c_j$ and $M_A \equiv \sum_{j \in A} q_j m_j / c_j$. We obtain

$$\lambda = \frac{M_A - C(K, U)}{\Omega_A}, \quad \ell_i^* = \frac{m_i - \lambda q_i}{c_i} > 0, \quad i \in A.$$

Uncertainty makes risk capacity scarcer and raises its shadow value, λ . Lending to every active type therefore falls. More capital dampens the increase in the shadow value, so more capitalized banks contract less. Formally, $\lambda_U = e^2 / (2\Omega_A C) > 0$, $\lambda_K = -K / (\Omega_A C) < 0$, and $\lambda_{UK} = -e^2 K / (2\Omega_A C^3) < 0$. Proposition 1 states this result.

Proposition 1. *Suppose $e > 0$, available capacity is positive, the risk capacity constraint has a strictly positive shadow value, and the active set of credit opportunities is locally unchanged. Then higher MPU reduces lending to every active type, and capital attenuates that reduction:*

$$\frac{\partial \ell_i^*}{\partial U} = -\frac{q_i e^2}{2c_i \Omega_A C(K, U)} < 0, \quad \frac{\partial^2 \ell_i^*}{\partial U \partial K} = \frac{q_i e^2 K}{2c_i \Omega_A C(K, U)^3} > 0.$$

The first expression shows that lending to every active type contracts when uncertainty rises, more so for types with larger q_i / c_i . The second shows that the contraction becomes smaller as bank capital increases.

Banks that begin closer to their risk constraint respond more to the same uncertainty shock. Greater uncertainty reduces capacity for new credit and raises its shadow value; higher capital expands capacity and dampens that increase. Appendix B gives the complete Kuhn-Tucker conditions and the strict inequalities needed to keep the active set locally stable.

Whether the lending released by lower MPU is socially desirable depends on who bears the downside risk. Appendix B.5 adds a deposit insurer, which absorbs losses beyond equity, to the continuation-value setup of Appendix B.2. Limited liability then drives a wedge between the private and social values of risk capacity: shareholders value a marginal unit of capacity more than shareholders and the insurer together, and for a given level of risk the wedge is larger at thinly capitalized banks. Under a regulatory limit that does not adjust to uncertainty, lower MPU lets the bank replace background rate risk with credit risk while total risk stays at the limit. The released lending is socially excessive when the joint value of capacity is negative at the margin, and the contraction after higher MPU is excessive when that value is positive. Our estimates identify relative responses and do not determine which case applies.

2.3 Capital, Borrower Risk, and Loan Pricing

Our empirical specifications compare proportional lending responses, not level responses. Riskier loans need not receive fewer dollars in levels: the relevant comparison is capacity use relative to marginal surplus. For each active type, define $D_i \equiv m_i - \lambda q_i = c_i \ell_i^* > 0$ and $x_i \equiv q_i / D_i$. A larger q_i / m_i makes lending proportionally more exposed to the common shadow cost. We therefore compare active types H and L under the ranking $q_H / m_H > q_L / m_L$. A higher shadow cost reduces type H more in percentage terms. Capital dampens that increase in cost, making the high-risk-minus-low-risk response less negative at more capitalized banks. The level-quantity ranking instead depends on q_i / c_i , as derived in Appendix B.

Proposition 2. *Under the conditions of Proposition 1, holding e, m_i, c_i , and q_i fixed, the proportional lending response satisfies*

$$\frac{\partial^2 \log \ell_i^*}{\partial U \partial K} = -\lambda_{UK} x_i - \lambda_U \lambda_K x_i^2 > 0.$$

Moreover, $q_H / m_H > q_L / m_L$ implies

$$\frac{\partial^2 [\log \ell_H^* - \log \ell_L^*]}{\partial U \partial K} > 0.$$

For a fixed continuum of lending opportunities indexed by risk R , increasing $q(R) / m(R)$ gives the same positive local derivative in uncertainty, capital, and risk.

Intuitively, capital moderates the proportional lending cut through two reinforcing channels. It dampens the increase in the shadow cost of risk capacity ($\lambda_{UK} < 0$), and it raises the initial lending quantity against which the percentage change is measured ($\lambda_K < 0$).

2.3.1 A Pricing Implementation

Loan pricing can be derived from the same capacity-constrained problem. Suppose the bank faces residual demand $s_i(\ell_i) = a_i - d_i \ell_i$ for its spread, where $d_i > 0$, and constant expected marginal funding and loss cost f_i . Holding these primitives fixed when uncertainty changes

isolates the cost of risk capacity. Profit from type i is

$$[s_i(\ell_i) - f_i]\ell_i = (a_i - f_i)\ell_i - d_i\ell_i^2.$$

This nests the allocation problem above with $m_i = a_i - f_i > 0$ and $c_i = 2d_i$. Substituting the optimal quantity into residual demand gives

$$s_i^* = \frac{a_i + f_i + \lambda q_i}{2}, \quad \frac{\partial s_i^*}{\partial U} = \frac{q_i}{2} \lambda_U > 0, \quad \frac{\partial^2 s_i^*}{\partial U \partial K} = \frac{q_i}{2} \lambda_{UK} < 0.$$

The bank passes through part of the capacity charge because a higher spread reduces the quantity demanded. If $q_H > q_L$, the high-risk-minus-low-risk spread response is smaller at the more capitalized bank. The spread ranking depends on q , whereas the proportional quantity ranking requires higher q/m .

2.4 Empirical Predictions

Main prediction: Differential allocation by bank capital and borrower risk. When uncertainty rises, less capitalized banks shift lending away from risky borrowers more than more capitalized banks do. Equivalently, the high-risk-minus-low-risk quantity response becomes less negative as capital rises. This implies a positive coefficient on the triple interaction of uncertainty, capital, and risk in the log and Poisson pseudo-maximum likelihood (PPML) specifications.

Diagnostic implication: Mortgage loan sizes and rates move in opposite directions. When uncertainty rises, risky counties served by less capitalized banking systems should exhibit relatively smaller loan sizes and relatively higher initial rates. Weaker credit demand would instead lower both. Because county averages also reflect the composition of lenders, borrowers, and products, these opposite-signed responses provide a diagnostic of credit supply that complements the lender-level evidence.

Cross-market implication: The capital ordering is common. Because the risk budget binds at the level of the bank's balance sheet, the model predicts the same positive quantity interaction in DealScan, CRA, and HMDA.

Mapping these predictions to the data involves three considerations. First, we measure capital by lagged equity to assets, B , with $K = k(B)$ and $k'(B) > 0$; CoreLogic uses the deposit-weighted county average. We proxy for risk intensity with lagged weak firm cash flow, county small employer operating distress, and county foreclosure risk. Within the model, a positive proportional estimate implies that capacity use rises faster than lending margins as measured risk increases, so that q/m is increasing; level quantities would instead require an increasing q/c , and the rate contrast an increasing q . Second, the propositions describe local responses of lending to active borrower types, and Appendix B shows that the same shadow cost determines which types exit first. The PPML estimates for CRA and HMDA include zero originations

and therefore combine both margins, whereas the DealScan estimates use positive allocations. Third, the comparative statics hold residual exposure e and borrower primitives fixed, and the model treats U as a variance-equivalent level, whereas SRU records announcement-day changes. Our lender-level specifications therefore allow repricing, maturity, and funding exposures to enter with their own interactions, and we interpret the estimated interactions as empirical counterparts of the comparative statics rather than as structural parameters.

Two further identification problems remain. FOMC announcements can combine uncertainty, stance, and information news, and borrower demand can respond to that news. We next explain how frequency-matched controls and market-specific fixed effects separate these channels.

3 Data, Measurement, and Empirical Design

We use four datasets to study how bank capital shapes the allocation of business credit and mortgage lending. DealScan compares banks financing the same corporate borrower; CRA records annual small business originations by bank and county; HMDA provides annual lender-county mortgage originations; and CoreLogic records monthly county averages of original mortgage balances and initial rates. We first define the monetary policy measures, then present the common empirical design and its dataset-specific implementation, and finally describe the samples. Appendix A.1 gives the measurement and construction details and describes the fitted samples; the remainder of Appendix A reports additional robustness results. Table II reports summary statistics for the main variables of the four datasets; Appendix Tables A1 to A4 report the other variables.

3.1 Measuring Monetary Policy Uncertainty and the Policy Stance

Benchmark announcement shocks. Our benchmark measure of MPU is the daily change on FOMC announcement days in market-implied short-rate uncertainty (SRU) from [Bauer et al. \(2022\)](#). For announcement a , let $u_a \equiv \Delta \text{SRU}_a$ denote this change. SRU uses Eurodollar futures and options to measure uncertainty about future short-term interest rates, so $u_a > 0$ indicates that market-implied rate uncertainty rose around the announcement and $u_a < 0$ indicates that it fell. Because SRU is option-implied, it reflects both investors' beliefs and the pricing of uncertainty. Since SRU is a standard deviation, its change at an announcement has the same sign as the change in the variance that the model uses (Appendix A.1).

We distinguish this uncertainty shock from the surprise in the expected path of policy rates. Let s_a denote the orthogonalized high-frequency monetary policy surprise (MPS) of [Bauer and Swanson \(2023b\)](#), which removes the component predictable from pre-announcement macroeconomic and financial information. Related work similarly separates MPU from stance surprises using complementary information sets ([Husted et al., 2020](#)). We aggregate u_a and s_a to the frequency of each credit outcome using the timing rules below.

The MPU and stance surprises are correlated but economically distinct. Figure 1 plots both standardized shocks for the 218 FOMC announcements at which they are jointly observed. Their event-level correlation is 0.42. Because the shocks covary, omitting the stance surprise could attribute part of the stance-induced allocation response to MPU. Each benchmark specification therefore includes u_a and s_a after aggregation, together with their interactions with bank capital and borrower risk and all identified lower-order terms.

Aggregation to monthly, quarterly, and annual outcomes. For an outcome period t , we construct the MPU and stance exposures as

$$\text{MPU}_t = \sum_{a \in \mathcal{A}_t} w_{at} u_a, \quad \text{MPS}_t = \sum_{a \in \mathcal{A}_t} w_{at} s_a,$$

where $\mathcal{A}_t$ is the set of FOMC announcements assigned to period t and w_{at} is the relevant timing weight. For monthly CoreLogic and quarterly DealScan outcomes, $w_{at} = 1$ for announcements within the calendar period. The dynamic specifications include the contemporaneous exposure and four lags.

For HMDA and CRA, an announcement early in the year has more time to affect annual originations than one near year-end. We therefore set w_{at} equal to the fraction of the calendar year remaining after announcement a and sum the weighted shocks within the year. Individual announcements can raise or lower SRU, as Figure 1 shows. Because SRU tends to fall at announcements, the annual exposure is negative in every sample year. A higher, less negative, value of MPU_t therefore means that less uncertainty was resolved at the year’s announcements, and standardization preserves this ordering.

Alternative measures of MPU. To assess whether the results depend on our benchmark measure, we repeat the regressions with three alternative measures of MPU. Treasury implied volatility (TIV) is the TIV/TYVIX composite supplied in the replication data of [Bauer et al. \(2022\)](#), which combines Treasury implied volatility with Bloomberg’s TYVIX series. Basis point volatility (BPVol) is the Black implied volatility of at-the-money Eurodollar options multiplied by the futures price; it is closely related to SRU but uses only at-the-money options ([Bauer et al., 2022](#)). Where available, we also use the MOVE index, a yield-curve-weighted index of one-month implied volatilities on Treasury options. Each captures a somewhat different part of the interest rate volatility distribution. We introduce the measures separately, retain the stated controls and sample restrictions, and compare lending responses scaled by each measure’s own standard deviation.

Information controls. FOMC announcements can reveal information about the economy as well as about policy. To examine whether such information accounts for the MPU result, we use four controls: ten-year CPI forecast disagreement from the Survey of Professional Forecasters (SPF); macroeconomic uncertainty at a three-month horizon from [Jurado et al. \(2015\)](#), denoted JLN

below; and the mean and interquartile range (IQR) of long-term household inflation expectations from [Fofana et al. \(2025\)](#), denoted FPR below.¹¹ These measures capture disagreement about inflation, broader macroeconomic uncertainty, and expected inflation.

We add these controls one at a time alongside MPU and the stance surprise. Each control receives its own interaction with bank capital and borrower risk and the lower-order terms not absorbed by the fixed effects, so the displayed coefficient continues to describe the MPU interaction. The information variables enter as changes (Appendix [A.1](#)).

3.2 Empirical Specification and Estimand

Common specification. The four designs share an interaction between MPU, bank capital, and borrower risk. They also include the corresponding stance interactions. To display the common structure, let MPU_t denote the uncertainty exposure defined above, MPS_t the corresponding stance exposure, $BANK\ CAPITAL_{b,t-1}$ bank capital, and $BORROWER\ RISK_{it}$ borrower risk, measured by firm risk in DealScan and by county risk in CRA, HMDA, and CoreLogic. We write the regression index as

$$\begin{aligned}\eta_{ibt} = & \beta^{MPU} MPU_t \times BANK\ CAPITAL_{b,t-1} \times BORROWER\ RISK_{it} \\ & + \beta^{MPS} MPS_t \times BANK\ CAPITAL_{b,t-1} \times BORROWER\ RISK_{it} \\ & + \delta_1 MPU_t \times BANK\ CAPITAL_{b,t-1} + \delta_2 MPU_t \times BORROWER\ RISK_{it} \\ & + \delta_3 MPS_t \times BANK\ CAPITAL_{b,t-1} + \delta_4 MPS_t \times BORROWER\ RISK_{it} \\ & + \delta_5 BANK\ CAPITAL_{b,t-1} \times BORROWER\ RISK_{it} \\ & + \mathcal{M}_{ibt} + \Gamma' X_{ibt} + \alpha_{ibt}.\end{aligned}\tag{1}$$

The five two-way interactions are the lower-order terms associated with the two triple interactions, and $\mathcal{M}_{ibt}$ collects the main effects of MPU, MPS, bank capital and borrower risk. We include each term either explicitly or through fixed effects that absorb it. X_{ibt} contains the additional controls, and α_{ibt} denotes the fixed effects. The dynamic specifications below apply this structure at each included shock lag. In DealScan, CRA, and HMDA, each additional bank control enters with the same interactions as bank capital: its interactions with MPU, MPS, and borrower risk, including the triple interactions, together with the lower-order terms not absorbed by the fixed effects.

For log allocation regressions, η_{ibt} is the conditional mean of log lending; for PPML, it is the log conditional mean of lending in levels. For initial mortgage rates, it is the conditional mean of the rate. Bank capital is measured by equity to assets, using prior-year fourth-quarter values in HMDA and CRA and values from the quarter preceding each included shock in DealScan.

¹¹News-based measures of monetary policy uncertainty ([Baker et al., 2016](#); [Husted et al., 2020](#)) are alternative proxies for MPU, so we do not use them as controls.

CoreLogic uses the deposit-weighted county banking measure. Firm risk is the negative value of a four-quarter average of reported operating cash flow relative to current liabilities, measured before the corresponding shock; county risk is lagged, with an exact twelve-month lag in CoreLogic. In HMDA and CRA, bank capital and county risk are therefore measured before the year’s announcements. The data subsections below and Appendix A.1 describe standardization and the construction of each variable.

For lending quantities, the model predicts $\beta^{\text{MPU}} > 0$: as MPU rises, the difference in lending between more and less capitalized banks becomes more favorable to riskier borrowers or markets. This coefficient describes a relative allocation response. The fixed effects absorb common movements in lending, so it does not determine whether either capital group expands or contracts lending in absolute terms. Table I maps each object in the model to its empirical counterpart in the four designs.

Relationship-level syndicated loans. In the DealScan relationship design, $A_{b\ell t}$ is bank b ’s positive dollar allocation to borrower company f in quarter t and tranche type ℓ . We estimate

$$\begin{aligned} \log A_{b\ell t} = & \alpha_{ft} + \alpha_b + \alpha_\ell \\ & + \sum_{k=0}^4 \beta_k \text{MPU}_{t-k} \times \text{BANK CAPITAL}_{b,t-k-1} \times \overline{\text{FIRM RISK}}_{f,t-k-1} \\ & + \sum_{k=0}^4 \theta_k \text{MPS}_{t-k} \times \text{BANK CAPITAL}_{b,t-k-1} \times \overline{\text{FIRM RISK}}_{f,t-k-1} \\ & + \mathcal{L}_{b\ell t} + \Gamma' X_{b\ell t} + \varepsilon_{b\ell t}. \end{aligned} \tag{2}$$

For the shock in quarter $s = t - k$, bank capital and all included bank controls use book-quarter $s - 1$ values. $\overline{\text{FIRM RISK}}_{f,s-1}$ is the mean risk measure over the four quarters $s - 1$ through $s - 4$. Borrower-company-quarter fixed effects absorb these borrower-only states, the common shocks and their interactions with risk. The lower-order block $\mathcal{L}_{b\ell t}$ contains bank characteristics, their interactions with risk, and their interactions with each uncertainty and stance exposure, unless absorbed. Added bank characteristics receive the same timing and interaction hierarchy. We report $\sum_{k=0}^4 \beta_k$, the cumulative response over the quarter of the shock and the following four quarters.

Annual local lending. In HMDA and CRA, Y_{bct} is origination dollars or loan counts for bank b in county c and year t . We estimate an exponential conditional mean by PPML:

$$\begin{aligned} \mathbb{E}[Y_{bct} \mid \cdot] = \exp & \left(\alpha_{bc} + \alpha_{bt} + \alpha_{ct} \right. \\ & + \beta^{\text{MPU}} \text{MPU}_t \times \text{BANK CAPITAL}_{b,t-1} \times \text{COUNTY RISK}_{c,t-1} \\ & + \beta^{\text{MPS}} \text{MPS}_t \times \text{BANK CAPITAL}_{b,t-1} \times \text{COUNTY RISK}_{c,t-1} \\ & \left. + \delta \text{BANK CAPITAL}_{b,t-1} \times \text{COUNTY RISK}_{c,t-1} + \Gamma' X_{bct} \right). \end{aligned} \quad (3)$$

MPU_t and MPS_t are the annual remaining-year exposures. Bank-year fixed effects absorb bank capital, the shocks, and their interactions; county-year fixed effects absorb county risk and its interactions with the shocks. The bank capital $\times$ county risk interaction remains and enters explicitly, as shown. For each additional bank characteristic, X_{bct} includes its interaction with county risk and the two corresponding MPU and MPS triple interactions. Bank-county fixed effects absorb persistent lending relationships.

Monthly mortgage balances and rates. For CoreLogic, y_{ct} is log average original loan balance or the average initial mortgage rate in county c and month t . Let $q(t)$ denote the quarter containing month t , and let $\text{BANK CAPITAL}_{c,q(t)-1}$ be prior-quarter bank equity/assets averaged using the county's available deposit shares. We estimate

$$\begin{aligned} y_{ct} = & \alpha_c + \alpha_t \\ & + \sum_{k=0}^4 \beta_k \text{MPU}_{t-k} \times \text{BANK CAPITAL}_{c,q(t)-1} \times \text{COUNTY RISK}_{c,t-12} \\ & + \sum_{k=0}^4 \theta_k \text{MPS}_{t-k} \times \text{BANK CAPITAL}_{c,q(t)-1} \times \text{COUNTY RISK}_{c,t-12} \\ & + \mathcal{L}_{ct} + \Gamma' X_{ct} + \varepsilon_{ct}. \end{aligned} \quad (4)$$

County and month fixed effects absorb persistent county differences and common monthly conditions. The lower-order block $\mathcal{L}_{ct}$ includes county banking capital, lagged county risk, their interaction, and each separately interacted with the current and four lagged values of both shocks. The shock levels and any other terms that vary only by month are absorbed by month fixed effects. We report $\sum_{k=0}^4 \beta_k$.

Estimator choice. The four datasets record different margins of credit allocation, so the estimator follows the outcome. For DealScan, we estimate fixed-effects regressions of log positive allocations, so the estimand is the conditional mean of log allocation among participating lenders. For HMDA and CRA, we estimate an exponential conditional mean for origination dollars or counts by PPML. PPML retains eligible zero outcomes and gives proportional differentials in conditional mean lending (Santos Silva and Tenreyro, 2006). For CoreLogic, we estimate linear

fixed-effects regressions of the log mean original balance and of the average initial interest rate. Appendix A.1 discusses these choices and the weights.

Other control variables. Bank capital is correlated with other balance sheet characteristics that may shape lending responses to MPU. Depending on the dataset, the bank controls include size, profitability, liquidity, asset quality, loan composition, deposit and wholesale funding, and repricing and maturity gaps. The ladders hold the fully controlled estimation sample fixed, so the columns differ only in their controls. Appendix A.1 defines the controls and describes the CoreLogic control progression.

Economic magnitude. To gauge economic significance, we report a response differential beneath each MPU coefficient. It measures how a one standard deviation increase in MPU changes the lending gap between banks at the 75th and 25th percentiles of bank capital when borrower risk moves from its 25th to its 75th percentile. The reported magnitude therefore combines the estimated triple interaction with the observed interquartile ranges of bank capital and of borrower risk.

For PPML, $100[\exp(\Theta) - 1]$ is the percentage differential in conditional mean lending. Here Θ combines the triple-interaction coefficient with one standard deviation of MPU and these two interquartile ranges; the dynamic models use the sum of the lag coefficients. For DealScan, the same transformation gives the percentage differential in the geometric mean of positive allocations. Initial-rate responses are reported in basis points. Appendix A.1 gives the formal definition.

3.3 Identification and Inference

In the annual panels, we identify the allocation relationship by comparing banks with different capital that lend in the same county and year, and by comparing each bank’s lending across counties with different risk. Bank-year fixed effects control for conditions common to a bank’s lending in that year, county-year fixed effects control for local demand and other conditions shared by lenders in a county, and bank-county fixed effects control for persistent lending relationships. We then ask whether the difference in lending across county risk between more and less capitalized banks changes with annual MPU exposure. The regression allows the same relationship to vary with MPS and with the included bank characteristics. This comparison combines variation across banks and counties with variation across the fifteen annual shocks. Because capital is not randomly assigned, a causal interpretation requires that omitted changes in how bank capital shapes lending across county risk are not systematically related to MPU.

In DealScan, we compare lenders financing the same borrower company in the same quarter, so common changes in the firm’s demand are absorbed by borrower-company-quarter fixed effects. In CoreLogic, we instead compare counties with different deposit-weighted banking capital and lagged foreclosure risk, conditional on county and month fixed effects.

We cluster standard errors by bank and borrower company in DealScan, by bank and county in HMDA and CRA, and by county and month in CoreLogic.¹² The within-facility DealScan comparisons add calendar quarter as a third clustering dimension (Appendix Table A8). Because MPU varies across fifteen annual exposures in HMDA and CRA, we also report standard errors that add year as a third clustering dimension and, for CRA, estimates that omit one year at a time.

3.4 Data

3.4.1 DealScan Syndicated Loans

The syndicated loan panel links DealScan facilities to lender Call Reports and borrower Compustat records. Our primary observation is a lender’s positive dollar allocation to a borrower company in a calendar quarter and tranche type, summed across the borrower’s facilities and entered in logs. A lender’s allocation in a facility is the facility amount times the lender’s share. DealScan reports that share for about one third of the allocations in our sample. Where it is missing, we reconstruct it from the lender’s commitment where available, and otherwise from the lender’s role and the composition of the syndicate. Shares are normalized within each facility.

Starting from the reference panel of 103,000 positive allocations, we require complete four-quarter cash-flow histories and the lender states preceding all five included shocks. The benchmark relationship sample contains 78,306 allocations, 335 lenders and 3,539 borrower companies over 85 quarters, from 1999Q3 through 2020Q3. The reference panel starts in 1997Q3, which supplies the earlier shocks and four-quarter risk histories that the estimation quarters require. The control ladder holds this sample fixed. Appendix A.1 describes the construction and support rules.

Firm risk is the negative value of the average of four consecutive quarterly observations of reported operating cash flow divided by current liabilities. Higher values indicate weaker cash flow. We retain either sign of cash flow. The measure remains meaningful when book equity is negative, provided the required ratios are finite. Appendix A.1 describes the history and sample rules; Appendix Tables A5 to A7 report results with the average debt-to-equity ratio as the risk measure.

We interpret weak operating cash-flow coverage as a proxy for the ability to meet near-term obligations. Cash-flow ratios have a long history in failure prediction (Beaver, 1966; Bhandari and Iyer, 2013), and evidence on U.S. corporate borrowing shows that operating earnings play an important role in borrowing constraints (Lian and Ma, 2021).

¹²When a multiway clustered covariance matrix is not positive semidefinite, we apply the eigenvalue correction implemented in the R package fixest (Cameron and Miller, 2015). The correction leaves the coefficients unchanged.

3.4.2 CRA Local Small Business Lending

CRA disclosures provide annual bank-county data on small business lending and underlie studies of local small business credit supply (Chen et al., 2017; Nguyen, 2019; Greenstone et al., 2020). We use 2005 through 2019 as our benchmark period, motivated by the 2005 revision to CRA reporting requirements, which changed the population of banks required to report small business lending. CRA defines small business lending by reported original loan size bins of at most one million U.S. dollars, not by borrower employment. We use nominal origination dollars, in millions, and origination counts. We merge prior-year fourth-quarter Call Reports, FDIC Summary of Deposits branch information, and Census Business Dynamics Statistics.

We restrict potential local lending relationships to banks with an established deposit presence. A bank-county pair enters the eligible network only if the bank held at least one percent of the county's deposits in the prior year. Within that network, the panel assigns zero origination dollars and zero loans to a pair with no CRA lending record; pairs outside it remain absent. This construction lets a locally active bank reduce its recorded lending to zero without treating every U.S. bank as a potential lender in every county.

We measure local risk with a lagged small employer operating distress index from Business Dynamics Statistics for firms with 1 to 19 employees. The index combines establishment exits, job destruction, and negatively oriented net job creation; a higher value means greater distress. This employment-based definition describes local exposure, not the CRA loan category. We lag the index and standardize it within year. Bank equity and the twelve annual bank controls come from the prior-year fourth-quarter Call Report.

After removing fixed-effect groups for which PPML has no finite estimate, the common estimation sample contains 140,799 bank-county-years, including eligible zero outcomes, for 872 banks and 2,224 counties from 2005 through 2019. Appendix A.1 reports the eligible-universe and pruning counts. Because CRA disclosures are aggregated to the bank-county-year level and do not identify borrowers or loan terms, the estimates describe local origination quantities, at both the intensive and extensive margins, within banks' established deposit footprints.

3.4.3 HMDA Bank-County Mortgage Lending

Our principal household credit panel aggregates Home Mortgage Disclosure Act records by bank, county, and year from 2005 through 2019. The benchmark outcome is total nominal mortgage origination dollars, in millions. We estimate an exponential conditional mean in levels by PPML on an unbalanced panel of observed reporting cells. The appendix examines purchase and refinance origination counts, total counts, and denial shares as separate outcomes.

A cell enters when HMDA has at least one Loan/Application Register (LAR) record for a lender with a Federal Reserve RSSD identifier in a valid county. Its origination total may be zero; lender-county-years with no HMDA record are absent. We therefore estimate the conditional

mean of mortgage dollars on this support, not mean log positive lending. The outcome records originations rather than applications that do not result in a loan; counts, denial rates, purchase counts, and refinance counts provide outcome checks.

County mortgage risk is the prior calendar year average of a monthly foreclosure measure. We require at least six nonmissing source months before forming the county-year average, lag the result by one year, and standardize it within calendar year. Bank equity to assets and the twelve bank controls defined in Appendix A.1 are prior-year fourth-quarter Call Report characteristics.

The benchmark estimation sample contains 2,314,338 observed lender-county-year cells, representing 425,611 lender-county relationships, 6,357 lenders, 2,763 counties, and 15 years. Relative to the eligible sample, PPML removes singleton observations, which do not help identify the coefficients, and all-zero fixed-effect groups, for which no finite estimate exists (Correia et al., 2020). Appendix A.1 reports the eligible count and the full construction ladder.

We also examine whether conforming loan limits and local house values account for the mortgage allocation result. Section 4.3 describes these controls.

3.4.4 CoreLogic Monthly County Mortgages

CoreLogic’s Loan-Level Market Analytics (LLMA) data provide county-month means of original mortgage loan balances and initial mortgage rates. The selected origination extract covers 1990 through 2020 and is matched to monthly mortgage performance data available from January 1999 through December 2023. We estimate unweighted county-and-month fixed-effects linear projections of log mean original balance and of the average initial rate in levels. These outcomes describe the size and pricing of originated mortgages, not total county lending. The reported coefficients sum the contemporaneous MPU_t interaction and four monthly lags, with the corresponding MPS_t interactions included throughout.

Joint availability of the outcome, lagged foreclosure risk, shocks, and controls yields an estimation window from December 2000 through September 2020. The fully controlled balance and rate specifications use the same 579,668 county-months, covering 2,968 counties and 238 months. The available MPU series, rather than the performance extract, determines the September 2020 endpoint. The tables report column-specific observation counts as controls are added. Appendix Table A4 reports moments on the fully controlled fitted sample.

County mortgage risk is the foreclosure rate from the CoreLogic performance file, defined under the Office of Thrift Supervision (OTS) delinquency convention, averaged over twelve consecutive months and lagged twelve months. Local banking capital is prior-quarter Call Report equity to assets, averaged with county deposit shares from the FDIC Summary of Deposits. Appendix A.1 describes the standardization, the banking composition measures, and the county controls. As a robustness check, we also use low county FICO scores among earlier mortgage originations as an alternative risk measure (Appendix Tables A21 and A22).

Unlike HMDA, CoreLogic aggregates mortgage and banking information to the county and does not identify the originating lender. We therefore use it as a complementary comparison of mortgage balances and pricing, relying on HMDA for lender-specific mortgage allocation; Section 4.3 discusses the interpretation of the balance and rate comparison.

4 Results

We report the results for syndicated loans, small business lending and mortgage lending in turn.

4.1 Within-Borrower Evidence from Syndicated Loans

We begin with DealScan, where we can compare banks lending to the same borrower company in the same quarter. Borrower-company-quarter fixed effects absorb changes in credit demand and other conditions common to the firm’s lenders. We ask whether banks with different levels of capital respond differently to MPU.

We estimate equation (2) using each bank’s positive allocation to a borrower company in a quarter and tranche type. The variables, fixed effects, and clustering follow Section 3.

Benchmark results. Table III progressively adds bank liquidity and size, profitability and asset quality, loan composition, deposit mix, wholesale funding and repricing/maturity controls. Each added control is interacted with MPU, orthogonalized MPS, and firm risk, with the same timing as bank capital. All six columns use the same 78,306 positive allocations. The MPU-capital-risk coefficient is positive and significant at the 5 percent level or better in every column. Response differentials range from 1.36 to 1.65 percent. In the full-control column the coefficient sum is 16 (standard error 6.8), corresponding to a 1.65 percent differential for a one standard deviation increase in MPU ($p = 0.020$). The direction therefore persists after allowing these observed bank characteristics to have their own differential responses.

We also compare banks participating in the same loan facility, adding facility and bank-quarter fixed effects. Appendix Tables A8 to A10 report these supplementary cash-flow results on a common eligible sample. The full-control differential is 2.12 percent ($p = 0.091$): within the same facility, less capitalized lenders take relatively smaller allocations of loans to riskier borrowers when MPU rises. This estimate uses the debt/equity-and-timing common support, which requires four finite, nonnegative quarterly debt-to-equity observations and coverage for the alternative timing designs; cash flow itself remains signed. On the cash-flow sample without this restriction, the full-control differential is 1.40 percent ($p = 0.253$; Appendix A.2.1). Both estimates weight each facility equally.

Information controls. A potential concern is that our MPU measure may capture other information released or revealed around monetary policy announcements. If such information affects lending differently across banks or borrowers, the benchmark interaction could partly reflect these concurrent information changes rather than MPU itself. We therefore augment

the benchmark specification with several measures of information changes while continuing to include the monetary policy stance surprise.

Table V adds the four information changes one at a time. All columns, including the baseline, share 78,117 allocations and end in 2020Q2 because the JLN macro uncertainty series stops there. The baseline differential on this support is 1.64 percent. With SPF CPI disagreement, JLN macro uncertainty, the FPR long-term mean and the FPR long-term interquartile range, the differentials are 1.33, 1.46, 1.56 and 1.55 percent, respectively. They remain positive and significant at the 10 percent level or better; the SPF specification is the least precise ($p = 0.061$). The benchmark pattern is therefore not driven by these concurrent changes in disagreement, macroeconomic uncertainty, or inflation expectations.

Alternative measures of MPU. Table IV replaces SRU with the alternative MPU measures TIV, BPVol, and MOVE on a common sample of 77,577 observations through 2020Q1, the period with complete data for all four measures. The SRU differential on this sample is 1.67 percent ($p = 0.019$). The differentials are positive for all three proxies: 2.28 percent for TIV ($p = 0.086$), 1.82 percent for BPVol ($p = 0.010$) and 2.35 percent for MOVE ($p = 0.006$). BPVol and MOVE are significant at the 5 percent level or better, and TIV at the 10 percent level. Each differential scales the proxy by its own standard deviation, so the result does not depend on the particular construction of SRU.

Alternative risk measure. Appendix Tables A5 to A7 repeat the three sets of tables with the four-quarter average debt-to-equity ratio as the risk measure. Every quarterly ratio must be finite and nonnegative, so that firms with negative equity are not ranked as safe. The full-control differential is positive at 1.13 percent ($p = 0.086$); the control-ladder and alternative-MPU estimates are less precise than for cash flow.

Taken together, the DealScan evidence shows that less capitalized banks reduce lending to riskier borrowers relatively more when MPU rises. This pattern appears when comparing lenders to the same borrower in the same quarter. It is also robust to conditioning on bank characteristics and observed information around monetary policy announcements. The analysis is necessarily confined to positive syndicated-loan allocations, however. We therefore turn next to CRA data, which extend the analysis to local small business lending, broaden the set of banks and borrowers, and incorporate zero originations within predetermined local lending markets.

4.2 Local Small Business Lending

DealScan provides a demanding within-borrower comparison, but syndicated lending is concentrated among relatively large firms and banks, and the analysis observes only positive lending allocations, which excludes the extensive margin. We therefore turn to CRA data to ask whether the same response of credit allocation to MPU appears in local small business credit as well. The CRA setting broadens the bank and borrower environment and, importantly, allows us to

include zero originations, and hence the extensive margin, within banks' predetermined local lending markets.

CRA does not identify individual borrowers or report their balance sheets, so the risk comparison is across local markets rather than across firms. We measure local risk with the lagged operating distress index for small employers; higher values indicate greater distress. CRA defines small business loans by original loan size, at most \$1 million, rather than by borrower employment. The analysis therefore asks whether banks with different levels of capital adjust local small business lending differently across counties with different levels of operating distress.

Benchmark results. Table VI reports PPML estimates for origination dollars (Panel A) and loan counts (Panel B). Bank-year fixed effects absorb each lender's nationwide annual conditions, county-year fixed effects absorb local conditions common to all banks, and bank-county fixed effects absorb persistent local lending relationships. Identification therefore comes from differences in the way banks with different lagged capital positions adjust lending across counties with different lagged operating distress after the same annual MPU exposure.

The results closely mirror the pattern in syndicated lending. The coefficient on $\text{MPU} \times \text{bank capital} \times \text{local distress}$ is positive for both origination dollars and loan counts and remains positive as we progressively allow bank size, profitability, liquidity, asset quality, funding structure, repricing exposure, maturity structure, and loan composition to have their own interactions with MPU and county risk. In the fully controlled specification, the coefficient is 0.011 for origination dollars (standard error 0.0053; $p = 0.033$) and 0.020 for loan counts (standard error 0.0077; $p = 0.009$).

These estimates imply economically meaningful effects: a one standard deviation increase in annual MPU exposure raises the high-minus-low-capital lending differential by 1.16 percent for origination dollars and 2.06 percent for loan counts across the interquartile range of local operating distress. Equivalently, when annual MPU exposure increases, less capitalized banks reduce lending relatively more in high-distress local markets.

Adding calendar year as a third clustering dimension raises the full-control standard errors to 0.0062 for dollars and 0.0097 for counts (Table VI). With a t distribution with 14 degrees of freedom, the p -values are 0.091 for dollars and 0.056 for counts, so both estimates remain significant at the 10 percent level.

Information controls. A potential concern, as in DealScan, is that annual MPU exposure may covary with other information released or revealed around monetary policy announcements. Appendix Table A13 therefore adds the four information measures one at a time, allowing each measure to have its own interaction with bank capital and county risk. With SPF inflation disagreement, the dollar response differential falls from 1.16 to 0.30 percent ($p = 0.595$), and the count differential from 2.06 to 1.14 percent ($p = 0.120$). The other three information changes

leave the differentials close to the benchmark, at 1.15 to 1.23 percent for dollars and 2.06 to 2.11 percent for counts. The CRA estimates are therefore most sensitive to inflation disagreement, whereas the same control leaves the DealScan and HMDA estimates significant.

Alternative measures of MPU. We next ask whether the CRA result depends on the SRU measure of MPU. Panels A and B of Appendix Table A11 replace SRU with TIV, BPVol, and MOVE on the same sample. For origination dollars, BPVol and MOVE preserve the positive relationship, although the estimates are less precise than the SRU benchmark; the TIV estimate is smaller and statistically imprecise. For loan counts, the estimates are positive and statistically significant under SRU, BPVol, and MOVE, while TIV again produces a smaller and imprecise estimate.

Omitting individual years. Appendix Table A12 re-estimates the fully controlled specification after omitting each year in turn. The loan-count coefficient remains positive and statistically significant at the 5 percent level in every leave-one-year-out regression. The dollar-volume coefficient also remains positive in every case, although it becomes statistically insignificant at the 10 percent level in two exclusions. The estimated magnitudes remain of the same order as the benchmark.

Taken together, the CRA evidence extends the DealScan result to local small business lending, a setting that includes a broader set of banks and local markets and incorporates zero originations within predetermined lending footprints. When annual MPU exposure increases, less capitalized banks reduce lending relatively more in locally distressed markets. The pattern is especially robust for the number of loans; dollar volumes display the same sign but are less precisely estimated in some inference and robustness exercises. We next turn to mortgage lending.

4.3 Mortgage Lending

We now examine whether the same pattern of credit allocation appears in household credit. HMDA provides the main lender-specific mortgage test, in which we compare banks with different predetermined capital positions lending in the same county and year. The benchmark outcome is total mortgage origination dollars. We then examine whether the result is explained by bank balance-sheet characteristics, housing-market and conforming-loan-limit conditions, alternative measures of MPU, or information released around monetary policy announcements. Finally, CoreLogic adds complementary monthly evidence on average original loan balances and initial mortgage rates at the county level.

We estimate equation (3) using the HMDA bank-county-year panel. County-year fixed effects absorb local mortgage demand and other county conditions common to lenders operating in the same market and year, while bank-year fixed effects absorb nationwide changes in each bank's lending conditions. Identification therefore comes from differences across banks with different predetermined capital positions in how lending changes across safer and riskier counties after

the same annual MPU exposure. Our benchmark measure of local mortgage risk is the lagged foreclosure rate. A positive coefficient on $\text{MPU} \times \text{bank capital} \times \text{foreclosure risk}$ means that, as annual MPU exposure moves higher, more capitalized banks maintain relatively more lending in riskier counties than less capitalized banks do.

Benchmark results. Table VII presents the benchmark HMDA estimates. The coefficient on $\text{MPU} \times \text{bank capital} \times \text{foreclosure risk}$ is positive in every specification and changes little as we allow bank size, profitability, liquidity, asset quality, deposit and wholesale funding, repricing gaps, maturity structure, and loan composition to have their own interactions with MPU and county risk. The estimated coefficient ranges from 0.0082 to 0.0096 across the four specifications.

In the fully controlled specification, the coefficient is 0.0087 with a standard error of 0.0037. A one standard deviation increase in annual MPU exposure raises the high-minus-low-capital lending differential by 0.68 percent across the interquartile range of foreclosure risk. Equivalently, when annual MPU exposure increases, less capitalized banks reduce mortgage lending relatively more in high-foreclosure counties. Because the estimation sample is held fixed across the control ladder, the stability of the estimate is not driven by changes in bank-county coverage.

With year added as a third cluster, the full-control standard error is 0.0034 (Table VII), and the estimate remains significant at the 5 percent level with a t distribution with 14 degrees of freedom ($p = 0.021$) and at the 1 percent level under the normal approximation ($p = 0.0095$).

Conforming loan limits and local housing conditions. One concern is that mortgage lending may respond differently across banks because house-price movements and conforming loan limits affect agency eligibility and the attractiveness of originating loans for sale to the government-sponsored enterprises. Table VIII therefore allows these housing-market and conforming-limit conditions to have their own interactions with bank capital and with the MPU and stance shocks, in addition to the benchmark foreclosure-risk channel. County-year fixed effects absorb the local variables in levels; the additional interactions allow their association with mortgage lending to differ across banks with different capital positions.

The conforming-limit comparisons use the common sample reported in the table. Adding house-value growth, national conforming-limit pressure, or the hybrid conforming-limit measure leaves the estimated MPU-capital-foreclosure relationship positive and close to the benchmark. The hybrid specification uses national conforming-limit pressure through 2008 and the applicable county limits from 2009 onward. Thus, on the available common sample, the benchmark mortgage allocation result is not explained by the measured housing-market and agency-eligibility conditions.

Information controls. As in the business-credit analyses, a potential concern is that changes in MPU coincide with other information released or revealed around monetary policy announcements. Table X therefore augments the benchmark specification with measures of changes in the

information environment while retaining the orthogonalized monetary policy stance surprise. Columns 2 to 5 add changes in SPF ten-year CPI disagreement, JLN macroeconomic uncertainty, and the FPR long-term mean and interquartile range one at a time. The estimated MPU-capital-risk relationship remains positive and statistically significant in all four specifications. It is close to the benchmark with the JLN and FPR controls and larger with SPF disagreement (0.97 percent). Overall, the benchmark HMDA relationship is robust to these controls.

Alternative measures of MPU. Table IX asks whether the HMDA result depends on the particular construction of MPU. We replace SRU with TIV, BPVol, and MOVE while holding the sample, foreclosure-risk measure, stance control, fixed effects, and bank controls fixed. The interaction between uncertainty, bank capital, and foreclosure risk is positive under all four measures, and the scaled response differentials are economically similar. The SRU, BPVol, and MOVE estimates are statistically significant at the 5 percent level or better, while the TIV estimate is less precise and significant at the 10 percent level.

Additional outcome, timing, and inference checks. Appendix Table A14 examines whether other mortgage outcomes display the same ordering. Purchase-origination counts provide the clearest positive counterpart to the dollar-volume result, both in the benchmark specification and when the hybrid conforming-limit controls are added. The estimates for total counts, refinance counts and denial shares are less precise.

Appendix Table A15 examines whether the result depends on the way announcement-level changes are aggregated into annual exposure. The remaining-year exposure, the unweighted annual sum, and the 90-, 180-, and 365-day constructions all produce positive and statistically distinguishable MPU coefficients on the same sample. The estimated magnitude varies with the timing convention, but the ordering across bank capital and county risk does not reverse. These specifications therefore show that the benchmark HMDA result is not specific to a single annual exposure construction, although they do not add independent years of shock variation.

Monthly mortgage balances and rates: evidence from CoreLogic. HMDA identifies the originating lender but provides annual origination outcomes. CoreLogic offers a complementary perspective by adding monthly timing and information on average original loan balances and initial mortgage rates. CoreLogic does not identify the originating bank, so the relevant comparison is across county banking systems. We therefore use the deposit-weighted capital position of banks operating in each county and interact it with lagged county foreclosure risk.

Table XI reports the benchmark CoreLogic estimates. With the full set of controls and the orthogonalized monetary policy stance surprise, a one standard deviation increase in MPU raises the high-minus-low-capital differential in average original loan balances by 0.37 percent across the interquartile range of foreclosure risk. The corresponding differential in initial mortgage rates is -1.53 basis points. This compares high- with low-capital banking systems;

reversing the comparison gives +1.53 basis points, so the rate gradient across county risk rises relatively more where banking systems are less capitalized. Thus, as MPU moves higher, riskier counties with less capitalized banking systems experience relatively smaller originated loans and higher initial mortgage rates. This joint movement in quantities and rates is consistent with the risk-bearing-capacity mechanism.

The control progression examines whether local economic conditions or the composition of the county banking system account for these relationships. Adding county income, unemployment, and outstanding mortgage balances reduces the loan-size differential and modestly changes the rate differential, although this step also changes the fitted sample. On the same observations, allowing these county controls to interact with the shocks and foreclosure risk reduces the loan-size differential from 0.55 to 0.38 percent and changes the rate differential from -0.85 to -1.59 basis points. Adding the banking-composition controls changes the estimates little. The loan-size interaction remains positive throughout, while the negative rate interaction becomes more precisely estimated once the county-control interactions are included.

Appendix Table A19 replaces SRU with TIV, BPVol, and MOVE on the fully controlled sample through May 2020, the period with complete data for all four measures. BPVol and MOVE produce positive loan-size differentials, and BPVol preserves a negative and statistically significant rate differential. The other alternative-proxy estimates are imprecise, and the TIV loan-size estimate is negative.

Appendix Table A20 conditions on the same information changes considered in the other datasets. The four change-based information controls preserve both benchmark signs: the loan-size differentials remain positive, while the rate differentials remain negative.

The CoreLogic evidence complements HMDA in two respects. It uses monthly variation in the shocks, and it adds prices: smaller loans together with higher rates are what a tightening of supply produces, whereas weaker demand would tend to lower both. If higher MPU excludes riskier borrowers from origination, the resulting improvement in borrower composition would tend to reduce average rates, working against the rate increase we observe. Because county averages also move with the composition of lenders, borrowers and mortgage products, we treat this evidence as supporting the lender-level HMDA results rather than as a separate identification of mortgage supply.

Appendix Table A23 compares the benchmark timing with earlier banking and control dates and with shock-matched dates on a common sample. The loan-size differential remains positive and the initial-rate differential negative. With shock-matched dates, they are 0.38 percent and -1.84 basis points, and all four timing designs give estimates significant at the 1 percent level.

Alternative risk measure. Appendix Tables A16 to A18, A21 and A22 replace foreclosure risk with a county measure of borrower credit quality, low average FICO scores among earlier origi-

nations. The HMDA estimate is positive in every column of the control ladder and significant at the 10 percent level in the fully controlled specification. In CoreLogic, the loan-size and rate differentials, 0.96 percent and -1.77 basis points, are significant at the 1 percent level and larger in absolute value than the foreclosure risk responses of 0.37 percent and -1.56 basis points in Table A19.¹³ The mortgage results are therefore robust to measuring local mortgage risk by borrower credit quality.

Taken together, the mortgage evidence matches the business lending results. When MPU rises, less capitalized banks reduce mortgage lending relatively more in riskier counties, and riskier counties with less capitalized banking systems see relatively smaller loans at higher initial rates.

5 Conclusions

In this paper, we show that monetary policy uncertainty (MPU) changes the allocation of bank credit across borrower risk. We develop a tractable model in which bank equity supports a finite risk-bearing capacity and MPU acts as background risk through banks' existing interest rate exposure. When risk limits bind, higher MPU uses up capacity and raises the shadow cost of new credit, especially for riskier loans and at banks with thin capital buffers. Less capitalized banks therefore cut lending to riskier borrowers, relative to safer borrowers, more than well-capitalized banks do.

We find this pattern in four U.S. datasets covering syndicated loans (DealScan), small business lending (CRA), lender-level mortgage originations (HMDA), and county mortgage balances and rates (CoreLogic). Using announcement-day changes in short-rate uncertainty, conditioning on the orthogonalized stance surprise, and comparing lenders within the same borrower and quarter or the same county and year, we find a common ordering: when MPU rises, less capitalized banks reduce lending more to riskier firms and in riskier counties. In mortgage markets, relatively smaller loans come with relatively higher initial rates, which is consistent with tighter credit supply rather than weaker demand.

Our findings point to an interaction between central bank communication and prudential policy. Forward guidance aims to reduce uncertainty about the path of policy rates. By reducing the risk of banks' existing rate exposure, lower MPU works like a temporary relaxation of capital constraints that is largest at thinly capitalized banks, and it shifts their lending toward riskier borrowers. Because communication and capital regulation act on the same balance-sheet margin, quantifying how this reallocation affects firm investment, defaults, and financial stability would help assess monetary predictability and prudential policy together.

¹³On a common sample covering the full benchmark window (487,551 county-months in 2,554 counties, December 2000 to September 2020), the foreclosure risk responses are 0.34 percent ($p = 0.012$) and -1.35 basis points ($p < 0.001$), and the low-FICO responses are 0.95 percent ($p < 0.001$) and -1.77 basis points ($p = 0.002$). Both specifications use the same county-months and the same capital and MPU scaling. The difference in samples therefore does not by itself produce the larger low-FICO response. The two risk measures capture different dimensions of county mortgage risk, so this comparison is not a formal test of equal coefficients.

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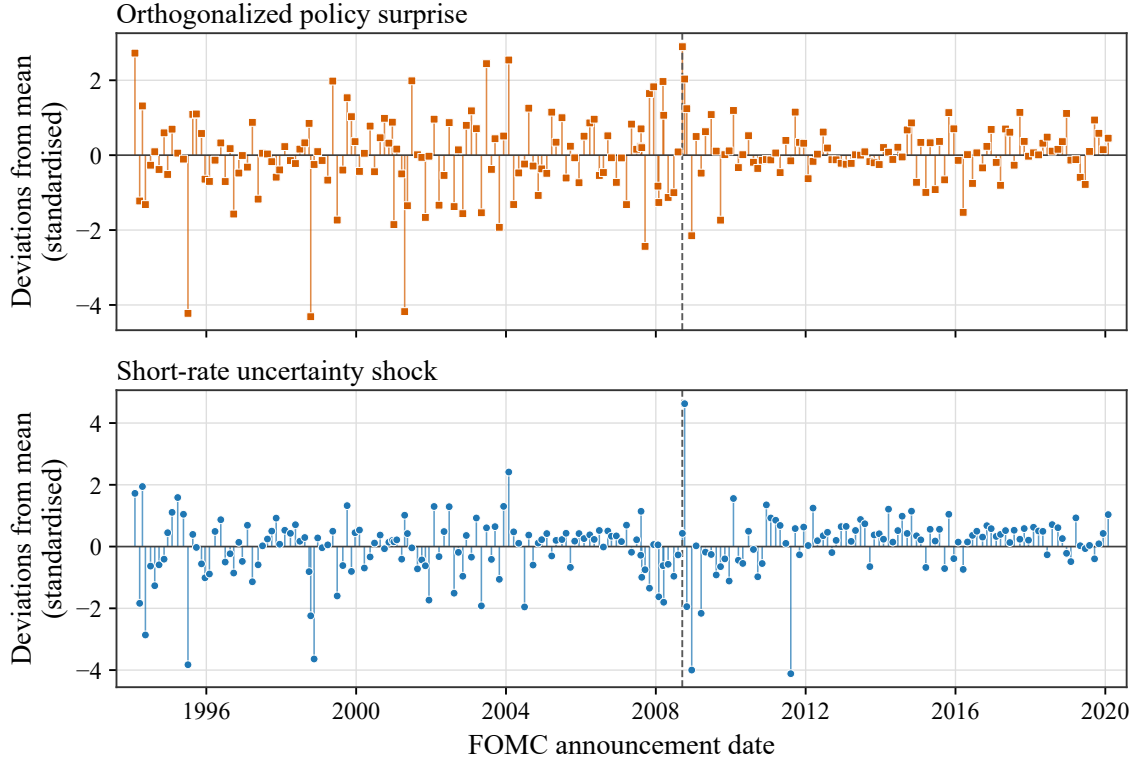
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FIGURE 1 – Benchmark FOMC Shock Series, 1994 to 2020



Notes: The figure plots the two benchmark FOMC event shocks for the 218 announcements at which both are observed. The top panel is the orthogonalized monetary policy surprise; the bottom panel is the daily SRU change used to measure benchmark MPU. For each series, we subtract its sample mean and divide by its sample standard deviation, calculated across the common sample of 218 FOMC announcements from February 1994 through January 2020. A plotted value of 1 represents a shock one standard deviation above that series' average; zero represents the average announcement shock. Each panel uses its own standard deviation. The dashed vertical line marks September 2008, the month of Lehman Brothers' bankruptcy and the acute phase of the financial crisis. Positive values of the unscaled shock $u_a = \Delta \text{SRU}_a$ represent increases in uncertainty about the future short-rate path. Throughout the paper, MPU denotes the economic construct and SRU the observed series used to construct it. The orthogonalized monetary policy surprise s_a is the stance control in all four datasets.

TABLE I – The Model's Objects and Their Empirical Counterparts

Model object	Syndicated lending to corporations (DealScan)	Small business lending by banks (CRA)	Mortgage lending by banks (HMDA)	County mortgage originations (CoreLogic)
Risk intensity q_i/m_i for quantities, q_i for rates	Negative value of the four-quarter mean of operating cash flow/current liabilities, before each shock	County small employer operating distress, lagged	County foreclosure risk, lagged	County foreclosure risk, lagged twelve months
Capital B , capacity $K = k(B)$	Lender equity to assets, prior book quarter for each shock	Lender equity to assets, prior year	Lender equity to assets, prior year	Deposit-weighted county average, prior quarter
Uncertainty U , in changes	Quarterly sum of announcement-day SRU changes	Remaining-year exposure	Remaining-year exposure	Monthly announcement changes; current month and four lags

TABLE II – Summary Statistics: Main Variables

Variable	N	Mean	SD	Min	Median	Max
<i>Panel A: Syndicated lending to corporations (reference panel)</i>						
Log bank allocation	103,000	17.199	1.122	11.494	17.158	23.392
Bank equity/assets (percent)	6,492	10.68	4.76	4.80	9.59	88.81
Firm risk (low operating cash flow)	11,974	-0.576	0.530	-3.234	-0.469	1.534
MPU change (quarterly)	93	-0.0369	0.0435	-0.2159	-0.0260	0.0479
<i>Panel B: Small business lending by banks</i>						
Small business originations (USD millions)	140,799	14.21	38.30	0.00	4.35	2,481.23
Small business originations (count)	140,799	185	979	0	44	85,510
Bank equity/assets (percent)	7,526	10.48	2.65	2.51	10.02	31.43
Lagged local small employer operating distress	29,969	-0.030	0.778	-2.998	-0.085	4.624
MPU change (remaining year)	15	-0.0607	0.0555	-0.2215	-0.0518	-0.0021
<i>Panel C: Mortgage lending by banks</i>						
Total mortgage originations (USD millions)	2,314,338	6.62	70.75	0.00	0.36	16,072.07
Bank equity/assets (percent)	58,748	10.62	3.38	2.51	9.97	76.91
Lagged county foreclosure rate (percent)	36,762	1.42	1.36	0.00	1.05	30.20
MPU change (remaining year)	15	-0.0607	0.0555	-0.2215	-0.0518	-0.0021
<i>Panel D: County mortgage originations</i>						
Log average origination balance	579,668	11.822	0.403	9.666	11.807	15.033
Initial mortgage interest rate (percent)	579,668	5.308	1.406	2.435	5.016	18.248
County bank equity/assets (percent)	579,668	10.49	1.70	2.53	10.43	68.35
Foreclosure risk (12-month lag)	579,668	-0.101	0.964	-1.180	-0.387	4.147
MPU change (monthly)	238	-0.0118	0.0241	-0.1505	-0.0034	0.0520

Notes: The table reports selected moments for the main variables of each dataset. Panels A to D cover the DealScan, CRA, HMDA, and CoreLogic datasets, in that order. They are the moments of Appendix Tables A1 to A4, which define all variables and report the other bank controls and the information changes. Moments are computed once at each variable's level of variation. For DealScan, the outcome and bank equity describe the fixed reference panel of 103,000 positive allocations and 6,492 bank-quarters, and firm risk describes 11,974 borrower-quarters with complete four-quarter histories; the benchmark estimation sample is smaller, at 78,306 allocations. Firm risk is the negative value of the four-quarter mean of operating cash flow relative to current liabilities. Bank equity and the foreclosure rate are in percent. Local operating distress and CoreLogic foreclosure risk are standardized indices. MPU is the change in short-rate uncertainty in its original units: quarterly for DealScan, remaining year for CRA and HMDA, and monthly for CoreLogic. SD is the sample standard deviation.

TABLE III – Syndicated Lending to Corporations: Average Low-Cash-Flow Risk - Benchmark Control Ladder

	Dependent Variable: Log New Loan Allocation (USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	13.4159*** (4.3487)	15.0440*** (5.3971)	13.1939** (5.4215)	14.1948** (6.4444)	14.3098** (6.9731)	16.0231** (6.8430)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	1.38%	1.55%	1.36%	1.46%	1.47%	1.65%
BORROWER-COMPANY-QUARTER FIXED EFFECTS	YES	YES	YES	YES	YES	YES
BANK FIXED EFFECTS	YES	YES	YES	YES	YES	YES
LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES	YES	YES
BANK LIQUIDITY AND SIZE CONTROLS	YES	YES	YES	YES	YES	YES
BANK PROFITABILITY AND ASSET QUALITY CONTROLS	NO	YES	YES	YES	YES	YES
BANK LOAN COMPOSITION CONTROLS	NO	NO	YES	YES	YES	YES
BANK DEPOSIT MIX CONTROLS	NO	NO	NO	YES	YES	YES
BANK WHOLESALE FUNDING CONTROLS	NO	NO	NO	NO	YES	YES
BANK INCOME, MATURITY, AND REPRICING GAP CONTROLS	NO	NO	NO	NO	NO	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES	YES
Number of Observations	78,306	78,306	78,306	78,306	78,306	78,306
Number of Banks	335	335	335	335	335	335
Number of Borrowers	3,539	3,539	3,539	3,539	3,539	3,539
R-squared	0.7860	0.7866	0.7870	0.7879	0.7881	0.7884

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q3. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the negative value of the mean of four consecutive quarterly operating-cash-flow/current-liabilities ratios. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPS interactions and identified lower-order terms. Bank-control blocks and their shock/risk interactions are included as indicated. All columns use the same sample. The response differential is defined in Appendix A.1. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE IV – Syndicated Lending to Corporations: Average Low-Cash-Flow Risk - Alternative MPU Measures

	Dependent Variable: Log New Loan Allocation (USD)			
	MPU (Benchmark) (1)	TIV (2)	BPVol (3)	MOVE (4)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	16.2387** (6.8620)	2.1284* (1.2364)	14.6402** (5.6702)	14.5159*** (5.2825)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	1.67%	2.28%	1.82%	2.35%
BORROWER-COMPANY-QUARTER FIXED EFFECTS	YES	YES	YES	YES
BANK FIXED EFFECTS	YES	YES	YES	YES
LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	77,577	77,577	77,577	77,577
Number of Banks	333	333	333	333
Number of Borrowers	3,528	3,528	3,528	3,528
R-squared	0.7868	0.7868	0.7868	0.7869

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q1. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the negative value of the mean of four consecutive quarterly operating-cash-flow/current-liabilities ratios. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPS interactions and identified lower-order terms. Every column uses the full bank-control specification. All columns use the common sample in which SRU, TIV, BPVol, and MOVE are all available; column 1 therefore re-estimates the benchmark on this sample. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The TIV standard deviation excludes quarters with incomplete announcement data. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE V – Syndicated Lending to Corporations: Average Low-Cash-Flow Risk - Uncertainty and Information Controls

	Dependent Variable: Log New Loan Allocation (USD)				
	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	15.9436** (6.8377)	12.9376* (6.8909)	14.1437** (7.1390)	15.1642** (6.8317)	15.0561** (7.0131)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	1.64%	1.33%	1.46%	1.56%	1.55%
BORROWER-COMPANY-QUARTER, BANK AND LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET	YES	YES	YES	YES	YES
AND INTERACTIONS	YES	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	78,117	78,117	78,117	78,117	78,117
Number of Banks	335	335	335	335	335
Number of Borrowers	3,537	3,537	3,537	3,537	3,537
R-squared	0.7881	0.7882	0.7881	0.7881	0.7881

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q2. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the negative value of the mean of four consecutive quarterly operating-cash-flow/current-liabilities ratios. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPS interactions and identified lower-order terms. Every column uses the full bank-control specification. Each control and its identified capital/risk interactions enter contemporaneously and with four quarterly lags, using the stated characteristic timing. SPF CPI disagreement and JLN h=3 use quarterly differences; FPR long-term mean and IQR use monthly arithmetic changes summed within quarter. All columns use the same sample. The response differential is defined in Appendix A.1. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE VI – Small Business Lending by Banks: Small Business Origination Volume and Counts

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Small Business Origination Volume (USD millions, levels)				
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0132** (0.0060)	0.0130** (0.0058)	0.0121** (0.0055)	0.0113** (0.0053)
SE adding a year cluster	–	–	–	0.00623
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	1.35%	1.33%	1.24%	1.16%
Pseudo R-squared	0.891	0.891	0.891	0.891
Panel B: Dependent Variable: Number of Small Business Originations				
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0190*** (0.0052)	0.0185*** (0.0052)	0.0210*** (0.0066)	0.0201*** (0.0077)
SE adding a year cluster	–	–	–	0.00966
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	1.95%	1.90%	2.15%	2.06%
Pseudo R-squared	0.984	0.984	0.984	0.984
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES
BANK SIZE AND PROFITABILITY CONTROLS	NO	YES	YES	YES
BANK LIQUIDITY, ASSET QUALITY, DEPOSIT, AND WHOLESALE FUNDING CONTROLS	NO	NO	YES	YES
BANK INCOME GAP, MATURITY, REPRICING, AND LOAN COMPOSITION CONTROLS	NO	NO	NO	YES
BANK CONTROL INTERACTIONS WITH MPU, MPS, AND COUNTY RISK	NO	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	140,799	140,799	140,799	140,799
Number of Banks	872	872	872	872
Number of Counties	2,224	2,224	2,224	2,224

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019. Panel A estimates nominal CRA small business origination dollars in USD millions and Panel B the corresponding number of loans; both use PPML in levels. CRA's small business category is defined by original loan size bins at most \$1 million, not borrower employment. Absent cells are coded zero only within the predetermined network where the bank's prior-year deposits are at least one percent of county deposits; pairs outside it are excluded. The reported interaction combines remaining-year MPU measured by SRU, prior-year Q4 bank equity to assets, and lagged Census Business Dynamics Statistics (BDS) operating distress for firms with 1 to 19 employees. The distress index combines establishment exits, job destruction, and negatively oriented net job creation. All columns include bank-county, bank-year, and county-year fixed effects, orthogonalized MPS interactions, and identified lower-order terms. The control ladder adds the indicated prior-year Q4 bank characteristics, each with county risk and its interactions with MPU and MPS, as defined in Appendix A.1. Both panels use the same 140,799 fitted observations in every column. Standard errors in parentheses are clustered by bank and county. The added SE row reports three-way bank, county and calendar-year clustering only for the full-control column. Significance stars refer to the two-way bank-and-county inference. The added row is a covariance sensitivity with fifteen time clusters. Adding year as a third cluster in column 4 gives standard errors of 0.00623 for dollars and 0.00966 for counts, with p-values of 0.091 and 0.056 under a t distribution with 14 degrees of freedom. The response differential is defined in Appendix A.1. Higher benchmark exposure is a smaller annual decline in announcement-day uncertainty in this sample. Fit statistics are Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels.

TABLE VII – Mortgage Lending by Banks: Mortgage Origination Volume

	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	(1)	(2)	(3)	(4)
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0082** (0.0037)	0.0090*** (0.0034)	0.0096*** (0.0035)	0.0087** (0.0037)
SE adding a year cluster	–	–	–	0.00335
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	0.64%	0.71%	0.75%	0.68%
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES
BANK SIZE AND PROFITABILITY CONTROLS	NO	YES	YES	YES
BANK LIQUIDITY, ASSET QUALITY, DEPOSIT, AND WHOLESALE FUNDING CONTROLS	NO	NO	YES	YES
BANK INCOME GAP, MATURITY, REPRICING, AND LOAN COMPOSITION CONTROLS	NO	NO	NO	YES
BANK CONTROL INTERACTIONS WITH MPU, MPS, AND COUNTY RISK	NO	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	2,314,338	2,314,338	2,314,338	2,314,338
Number of Banks	6,357	6,357	6,357	6,357
Number of Counties	2,763	2,763	2,763	2,763
Pseudo R-squared	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The dependent variable is total nominal mortgage origination dollars in USD millions per bank-county-year, estimated by PPML from 2005 to 2019. Zero originations are retained on observed HMDA reporting support; bank-county-years with no record are not imputed as zero. The reported interaction combines remaining-year MPU measured by SRU, prior-year Q4 bank equity to assets, and the prior-year county foreclosure rate. All columns include bank-county, bank-year, and county-year fixed effects, orthogonalized MPS interactions, and identified lower-order terms. Columns 2 to 4 add the indicated bank control blocks, interacted with county risk alone and together with MPU and with MPS, using the definitions in Appendix A.1. The fully controlled sample of 2,314,338 observations is fixed across the ladder; the reported sample and cluster counts are after fixed effect pruning. Standard errors in parentheses are clustered by bank and county. The added SE row reports three-way bank, county and calendar-year clustering only for the full-control column. Significance stars refer to the two-way bank-and-county inference. The added row is a covariance sensitivity with fifteen time clusters. Adding year as a third cluster in column 4 gives a standard error of 0.00335 and p-value 0.0095 under the normal approximation, or 0.021 under a t distribution with 14 degrees of freedom; the fifteen-year qualification is discussed in Appendix A.1. The response differential is defined in Appendix A.1. Higher annual benchmark exposure means less uncertainty resolution in this sample. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels.

TABLE VIII – Mortgage Lending by Banks, Robustness: Conforming Loan Limits and Local House Values

	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	(1) Benchmark	(2) House values	(3) National CLL	(4) Hybrid CLL
$\hat{\beta} : \text{MPU} \times \text{BANK CAPITAL} \times \text{COUNTY RISK}$	0.0093** (0.0039)	0.0087** (0.0037)	0.0113* (0.0060)	0.0114** (0.0055)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	0.73%	0.68%	0.88%	0.89%
LOCAL HOUSE VALUE INTERACTION	NO	YES	YES	YES
NATIONAL CLL PRESSURE INTERACTION	NO	NO	YES	PRE-2009
EXACT COUNTY CLL PRESSURE INTERACTION	NO	NO	NO	2009–2019
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	1,806,926	1,806,926	1,806,926	1,806,926
Number of Banks	6,170	6,170	6,170	6,170
Number of Counties	2,330	2,330	2,330	2,330
Pseudo R-squared	0.936	0.936	0.936	0.936

Notes: The table reports estimates of equation (3). The dependent variable is nominal mortgage origination dollars in USD millions per bank-county-year, estimated by PPML from 2005 to 2019. All columns use the same 1,806,926 observations with the conforming limit and house value information available. HMDA zeros are retained only on observed reporting support; absent reporting cells are not coded as zero. The reported interaction combines remaining-year SRU-based MPU, prior-year Q4 bank equity to assets, and prior-year county foreclosure risk. Bank-county, bank-year, and county-year fixed effects, full bank control interactions, orthogonalized MPS interactions, and identified lower-order terms are included. Column 1 has neither added house value nor limit pressure interactions. Column 2 adds prior-year local house value growth; column 3 also adds pressure based on house value relative to the national conforming loan limit. Column 4 uses national limit pressure through 2008 and applicable county limits from 2009 onward. County-year fixed effects absorb the corresponding local variables in levels. Each added county variable H enters as $B \times H$, $\text{MPU} \times B \times H$, and $\text{MPS} \times B \times H$, where B is bank capital; the other lower-order terms are absorbed by the fixed effects. House value growth is $\log \hat{H}_{c,t-1} - \log \hat{H}_{c,t-2}$, where $\hat{H}$ is the annual mean house value. Limit pressure is $\log \hat{H}_{c,t-1}$ minus the log of the national or applicable county conforming loan limit from FHFA; the 2011 county limit is 0.75 times the temporary limit plus 0.25 times the HERA limit. Because the variables are standardized within year, national limit pressure varies only with lagged house values. These controls do not replace foreclosure risk. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. The reported fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE IX – Mortgage Lending by Banks, Robustness: Alternative Proxies for MPU

MPU measure	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	(1) MPU (Benchmark)	(2) TIV	(3) BPVol	(4) MOVE
$\hat{\beta} : \text{MPU} \times \text{BANK CAPITAL} \times \text{COUNTY RISK}$	0.0087** (0.0037)	0.0069* (0.0039)	0.0117*** (0.0032)	0.0098** (0.0038)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	0.68%	0.54%	0.91%	0.77%
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	2,314,338	2,314,338	2,314,338	2,314,338
Number of Banks	6,357	6,357	6,357	6,357
Number of Counties	2,763	2,763	2,763	2,763
Pseudo R-squared	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019, and the dependent variable is nominal mortgage origination dollars in USD millions, estimated by PPML. Zero outcomes are retained only on observed HMDA reporting support; absent reporting cells are not coded as zero. Column 1 uses SRU as the MPU proxy; columns 2 to 4 replace it with Treasury implied volatility (TIV), Eurodollar option basis-point volatility (BPVol), or MOVE bond-market volatility. The measures enter separately, not jointly. All columns use the same 2,314,338 observations, prior-year bank equity to assets, prior-year foreclosure risk, bank-county, bank-year, and county-year fixed effects, full bank controls and their interactions, orthogonalized MPS interactions, and identified lower-order terms. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE X – Mortgage Lending by Banks, Robustness: Uncertainty and Information Controls

Dependent Variable: Mortgage Origination Volume (USD millions, levels)					
	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0087** (0.0036)	0.0124*** (0.0038)	0.0077** (0.0037)	0.0080** (0.0038)	0.0077** (0.0037)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	0.68%	0.97%	0.60%	0.62%	0.60%
ADDED INFORMATION INTERACTION	NO	YES	YES	YES	YES
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET	YES	YES	YES	YES	YES
AND INTERACTIONS	YES	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	2,314,338	2,314,338	2,314,338	2,314,338	2,314,338
Number of Bank-County Pairs	425,611	425,611	425,611	425,611	425,611
Number of Banks	6,357	6,357	6,357	6,357	6,357
Number of Counties	2,763	2,763	2,763	2,763	2,763
Pseudo R-squared	0.931	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The dependent variable is total mortgage origination dollars in USD millions per bank-county-year, estimated by PPML from 2005 to 2019. All columns use the reported common support of 2,314,338 observations. Zero outcomes are retained only on observed HMDA reporting cells; absent cells are not coded as zero. The reported interaction combines remaining-year SRU-based MPU, prior-year Q4 equity to assets, and prior-year foreclosure risk. Every column includes bank-county, bank-year, and county-year fixed effects, the full bank control interaction set, orthogonalized MPS interactions, and identified lower-order terms. Column 1 is the benchmark. Columns 2 to 5 separately add the indicated information change. The added variable enters interacted with bank capital and county risk. SPF ten-year CPI disagreement and JLN horizon-three uncertainty use quarterly first differences; FPR long-term mean and IQR use monthly arithmetic changes. Changes are remaining-year weighted and standardized across the fifteen years. SPF is the Survey of Professional Forecasters, JLN [Jurado et al. \(2015\)](#), FPR [Fofana et al. \(2025\)](#). Standard errors in parentheses are clustered by bank and county. Column 1 is estimated separately from Table VII column 4, so its standard error differs slightly. The response differential is defined in Appendix A.1. Higher benchmark exposure means less announcement-related uncertainty resolution. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE XI – County Mortgage Originations: Average Original Loan Balances and Initial Rates

	Dependent Variable: Log Average Origination Balance (USD)				Dependent Variable: Average Initial Mortgage Rate (percent)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum_{k=0}^4 \hat{\rho}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{COUNTY RISK}$	10.379*** (2.829)	8.957*** (2.235)	6.203*** (1.983)	6.071*** (1.972)	-14.777* (8.382)	-13.962* (7.848)	-26.096*** (6.704)	-25.143*** (6.644)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the risk IQR	0.63%	0.55%	0.38%	0.37%	-0.90 bp	-0.85 bp	-1.59 bp	-1.53 bp
MONTH FIXED EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY INCOME, UNEMPLOYMENT, AND MORTGAGE BALANCE CONTROLS	NO	YES	YES	YES	NO	YES	YES	YES
COUNTY CONTROL INTERACTIONS WITH MPU, MPS, AND COUNTY RISK	NO	NO	YES	YES	NO	NO	YES	YES
COUNTY BANK REAL ESTATE LOAN, MBS, SECURITIES, AND CONCENTRATION CONTROLS	NO	NO	NO	YES	NO	NO	NO	YES
ORTHOGONALIZED MPS INTERACTIONS	YES	YES	YES	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES	YES	YES	YES
Number of Observations	591,992	579,836	579,836	579,668	591,992	579,836	579,836	579,668
Number of Counties	3,022	2,968	2,968	2,968	3,022	2,968	2,968	2,968
Number of Months	238	238	238	238	238	238	238	238
R-squared	0.849	0.859	0.861	0.861	0.939	0.939	0.940	0.940

Notes: The table reports estimates of equation (4). The unit is a county-month from December 2000 through September 2020. Columns 1 to 4 estimate the log of the mean original loan balance, not total county origination dollars; columns 5 to 8 estimate the average initial mortgage rate in percent. All models are unweighted fixed effects OLS. The reported coefficient sums the current and four lagged monthly MPU interactions with deposit-weighted prior-quarter bank equity/assets and foreclosure risk. Foreclosure risk is the trailing twelve-month county foreclosure rate lagged exactly twelve calendar months. Its first and ninety-ninth percentile cutpoints, mean, and standard deviation use a fixed reference period, December 2000 to December 2016. All columns retain county and month fixed effects, the analogous orthogonalized MPS interactions, and identified lower-order terms. County controls are log nominal personal income, annual unemployment, and log average outstanding mortgage balance. Their interaction block interacts these controls with MPU, MPS, and county risk, and with MPU and MPS together with county risk; the final block adds real estate loan, total mortgage-backed securities, and securities shares and deposit concentration, in levels without shock or risk interactions. Deposit shares weight bank covariates, not observations. Columns 1 and 5 use 591,992 observations; columns 2, 3, 6 and 7 use 579,836; columns 4 and 8 use 579,668. Standard errors in parentheses are clustered by county and month; two-sided tests use the smaller cluster count minus one as degrees of freedom. R-squared is conventional OLS R-squared, including fixed effects. For the fully controlled benchmark, the eigenvalue correction of the clustered covariance matrix leaves the standard errors unchanged to six decimal places. The rate differential compares high- with low-capital banking systems; reversing the capital comparison reverses its sign. The response differential is defined in Appendix A.1. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

APPENDIX

A Additional Results and Robustness

The appendix collects measurement and construction details, descriptions of the DealScan reference panel and the estimation samples, and additional lending checks. Tables A1 to A4 give the descriptive statistics. Tables A5 to A7 report the debt-to-equity results, and Tables A8 to A10 report the common-sample within-facility cash-flow evidence. Tables A11 to A13 contain the CRA checks; Tables A14 to A18 contain the HMDA checks, including low-FICO risk; and Tables A19 to A22 contain the CoreLogic checks. The tables follow the order of their discussion. Table A23 gives the common-sample CoreLogic timing comparison.

A.1 Data, Measurement, and Sample Construction

This section collects the measurement, estimation, and construction details summarized in Section 3, and then describes the estimation samples.

Measured uncertainty and the model. The model expresses uncertainty as a variance, whereas SRU measures the implied standard deviation of future short rates. Let σ_{0a} and σ_{1a} denote SRU before and after announcement a , so that $u_a = \sigma_{1a} - \sigma_{0a}$. The corresponding change in implied variance is

$$\Delta v_a^Q = \sigma_{1a}^2 - \sigma_{0a}^2 = (\sigma_{1a} - \sigma_{0a})(\sigma_{1a} + \sigma_{0a}) = u_a(\sigma_{1a} + \sigma_{0a}).$$

Because standard deviations are nonnegative, $\sigma_{1a} + \sigma_{0a} > 0$ except in the degenerate case in which both are zero. Hence the SRU change and the variance change have the same sign; this statement is exact and does not require the announcement change to be small. We can therefore use the sign of u_a to test the model's directional prediction. When several announcements are summed, as in the quarterly and annual exposures, the sign correspondence is approximate, because each announcement's change in variance scales its SRU change by its own $\sigma_{0a} + \sigma_{1a}$. Squaring u_a itself would instead erase the distinction between increases and decreases in uncertainty.

Option prices also reflect compensation for bearing risk, and Eurodollar rates can move relative to policy rates. SRU therefore need not move one for one with the uncertainty banks face about future losses. We use it as a market-based measure of announcement-related rate uncertainty and interpret the estimates as tests of the model's predicted allocation pattern, rather than as estimates of its risk-capacity parameters.

Information controls. We add the four information controls one at a time alongside MPU and the stance surprise. Each control receives its own interaction with bank capital and borrower risk and all lower-order terms not absorbed by the fixed effects, so the displayed coefficient continues to describe the MPU interaction conditional on the added information measure.

The information variables enter as changes rather than levels. SPF disagreement uses quarterly first differences, and the FPR mean and interquartile range use monthly arithmetic changes. JLN uncertainty uses quarterly first differences in DealScan, HMDA, and CRA and monthly first differences in CoreLogic. DealScan aggregates the changes to calendar quarters. HMDA and CRA assign each quarterly observation to the middle of its quarter and each monthly observation to the middle of its month, then apply the same remaining-year weights used for MPU_t and MPS_t . Each measure is standardized over its stated estimation window.

The four controls cover the full HMDA and CRA windows. For the DealScan information-control tables, we hold the sample common across all four changes. Since JLN ends in 2020Q2, every column in that family, including its baseline, ends one quarter before the benchmark and MPU tables. We do not impute missing control values.

Estimator choice. The four datasets capture different margins of credit allocation, so we match the functional form to the outcome observed in each design. The DealScan sample contains positive allocations among lenders participating in the same borrower relationship. HMDA and CRA record local

origination flows and allow lending to equal zero within their respective analysis samples. In HMDA, an observed lender-county-year reporting cell contains at least one Loan/Application Register (LAR) record even though its origination total can be zero; in CRA, zero lending is defined within the bank's predetermined local deposit network. CoreLogic records county-month average original loan balances and initial mortgage rates.

For DealScan, we estimate fixed-effects regressions of log allocations. The estimand is the conditional mean of log allocation among participating lenders, not the conditional mean of dollar lending across all potential lenders. In CoreLogic, the balance outcome is the log of the county-month mean original loan balance and therefore measures average originated loan size rather than aggregate county lending. We estimate initial mortgage rates in levels.

For HMDA and CRA, we specify an exponential conditional mean for origination dollars or loan counts and estimate it by Poisson pseudo-maximum likelihood (PPML). The estimator retains eligible zero outcomes and does not require the outcome itself to follow a Poisson distribution; the identifying restriction concerns the conditional mean (Santos Silva and Tenreyro, 2006). The exponentiated triple-interaction coefficient describes a proportional differential in conditional mean lending.

A log-linear regression answers a different question, because the conditional mean of log lending is not the log of the conditional mean of lending. The former describes log lending on the positive support, whereas PPML models the conditional mean of lending in levels (Santos Silva and Tenreyro, 2006). For zero-inclusive outcomes, $\log(1 + Y)$ instead defines a transformed-outcome estimand whose coefficients depend on the units in which Y is measured, rather than the unit-invariant proportional response in the conditional mean studied here (Cohn et al., 2022; Chen and Roth, 2024). PPML also accommodates the required bank-county, bank-year, and county-year fixed effects. Singleton observations are removed during estimation, as are fixed-effect groups for which no finite estimate exists (Correia et al., 2020).

We estimate initial mortgage rates and denial shares with linear models, so their coefficients describe changes in outcome levels rather than proportional changes in lending quantities. We report initial-rate effects in basis points and weight the denial-share regressions by the number of recorded lending decisions. The DealScan relationship regressions and CoreLogic regressions are unweighted. The supplementary within-facility DealScan regressions give each retained facility total weight one. In CoreLogic, deposit shares are used to construct county banking characteristics, not to weight regression observations.

Control variables. Bank capital is correlated with other balance sheet characteristics that may shape lending responses to MPU. In the DealScan, CRA, and HMDA control ladders, each added bank characteristic enters with the shock and risk variables and the identified lower-order terms. The comparison therefore allows liquidity, funding structure, asset quality, portfolio composition, and repricing exposure to have their own differential responses, rather than controlling only for their levels. These ladders hold the fully controlled estimation sample fixed, so that columns differ only in their controls. In CoreLogic, county economic controls receive the displayed interactions with the shocks and county risk while additional county banking variables enter as controls. Adding county controls changes the sample; adding their interactions holds it fixed, and the final banking-composition block excludes a further 168 county-months. The table reports the observation count in each column.

For the annual panels, size is log total assets; profitability is net income divided by assets; liquidity is cash plus securities divided by assets; and asset quality is nonperforming loans divided by assets. Deposit and wholesale funding shares use liabilities as the denominator, with wholesale funding defined as federal funds and repo liabilities plus other borrowing. The final block contains the one-year repricing income gap divided by assets, average asset and liability maturity/repricing horizons and their difference in years, and loans and leases with horizons at most one year and above one year divided by assets. These controls use prior-year fourth-quarter Call Reports and are standardized within year. In DealScan, the bank controls are lagged quarterly Call Report ratios in source units, not standardized. Beyond size, return on assets, liquidity, and nonperforming loans, the loan-composition block contains real estate loans,

adjustable-rate mortgages, and loans and leases maturing within one year, each relative to assets. The deposit-mix block contains seven ratios covering total, savings, and time deposits relative to assets and large and long-term time deposits relative to liabilities. The wholesale-funding block contains wholesale funding relative to liabilities and federal funds and repo liabilities relative to liabilities and to assets. The gap block contains rate-sensitive assets minus rate-sensitive liabilities relative to assets, the maturity gap, and the average repricing maturities of assets and liabilities. In the relationship design, each shock lag is paired with its own lagged bank characteristics and bank-by-risk interactions. In CoreLogic, the county banking-composition controls enter in levels.

Economic magnitude. Formally, let $g(\text{MPU}, b, r)$ denote the log conditional mean of lending in a PPML model, or the conditional mean of log allocation in a DealScan model, holding the other controls fixed. The capital gap at high risk minus the capital gap at low risk is $A(\text{MPU}) = g(\text{MPU}, b_H, r_H) - g(\text{MPU}, b_L, r_H) - g(\text{MPU}, b_H, r_L) + g(\text{MPU}, b_L, r_L)$. For an increase $\Delta \text{MPU} = \text{MPU}_1 - \text{MPU}_0$, the triple interaction gives

$$\Theta = A(\text{MPU}_1) - A(\text{MPU}_0) = \beta^{\text{MPU}} \Delta \text{MPU} \Delta b \Delta r.$$

We set ΔMPU to one standard deviation and Δb and Δr to the respective interquartile ranges. In the dynamic models, we use the reported sum of lag coefficients.

For PPML, $100[\exp(\Theta) - 1]$ is the percentage differential in conditional mean lending. For the DealScan log-allocation regressions, the same transformation gives the percentage differential in the conditional geometric mean of positive allocations. Without additional assumptions about the regression error, it does not identify a percentage change in the conditional arithmetic mean of dollar lending. The tables indicate where we use the small-change approximation 100Θ .

For initial mortgage rates, we retain the level response and convert percentage points to basis points. A positive lending response differential means that, following an increase in MPU, the relative lending response of more capitalized banks becomes more favorable as borrower or local-market risk rises. It is not a change in market share or in either group's absolute lending. The calculation uses the scales described below.

In DealScan, $\Theta = (\sum_{k=0}^4 \beta_k) \text{SD}_{\text{MPU}} \text{IQR}_b \text{IQR}_r$, with the shock standard deviation and the interquartile ranges of bank capital and firm risk taken from the fixed full reference panel. For the averaged risk measure, the risk range is that of the four-quarter average. The within-facility tables use the same scales. Bank capital enters as a decimal ratio of equity to assets, although the summary tables report it in percent. The interquartile range of bank capital is 0.0427, that of firm risk is 0.550 for cash flow and 1.443 for debt-to-equity, and the standard deviations of SRU, TIV, BPVol, and MOVE are 0.0435, 0.450, 0.0524, and 0.0680. In annual CRA and HMDA, bank capital and county risk are standardized within year, and MPU is standardized across the fifteen years. For a one standard deviation higher annual MPU exposure, $\Theta = \hat{\beta} \text{IQR}(z_{\text{capital}}) \text{IQR}(z_{\text{risk}})$, with interquartile ranges from the full reference panel. In CoreLogic, the response is linear: 100 times the product of the coefficient sum, the MPU standard deviation, and the interquartile ranges of bank capital and county risk from the fixed reference sample. County bank capital is also a decimal ratio. Its interquartile range is 0.0218 for the foreclosure reference and 0.0216 for the FICO reference, and that of county risk is 1.087 for foreclosure and 1.490 for low FICO. The standard deviations of SRU, TIV, BPVol, and MOVE are 0.0257, 0.310, 0.0292, and 0.0460 for the foreclosure reference and 0.0259, 0.312, 0.0295, and 0.0464 for the FICO reference. Balance responses are therefore percent approximations, and rate responses are in basis points. When a table replaces the MPU proxy, each response uses that proxy's standard deviation and the same interquartile ranges. The coefficients then do not describe identically sized uncertainty changes.

Inference. In HMDA and CRA, the bank and county dimensions provide the cross-sectional variation in bank capital and county risk needed to identify the triple interaction, but MPU varies across only fifteen annual exposures. Cluster leverage and the effective number of clusters can therefore matter despite the size of the micro dataset (MacKinnon et al., 2023). We therefore examine sensitivity to clustering by

year in addition to bank and county and, in CRA, to the influence of individual years. For DealScan, the supplementary within-facility comparisons cluster by bank, borrower company and calendar quarter; they also change the sample, weighting, and fixed effects. These exercises diagnose sensitivity to common time shocks and influential periods.

DealScan borrower risk. The benchmark risk measure is the negative value of the mean of four finite reported operating-cash-flow/current-liabilities ratios. We use the WRDS ratio as reported. In each calendar quarter we use the latest available record; we neither carry forward a missing quarter nor substitute later accounting data. For the shock in quarter $s = t - k$, the window contains $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; the average is not winsorized again. Cash flow can have either sign. The alternative measure uses the WRDS debt-to-equity ratio. All four of its quarterly values must be finite and nonnegative before the same winsorization and averaging. Eligibility is checked at all dates used by the shock-matched design. The accounting data are not real-time vintages, and bank control dates refer to accounting quarters rather than filing dates.

CRA local risk. For firms with 1 to 19 employees, we take the county establishment exit, job destruction, and net job creation rates from the Census Business Dynamics Statistics. Each rate is winsorized at the 1st and 99th percentiles within year and standardized within year. The index is $J_{cy} = [z_y(\text{exit}_{cy}) + z_y(\text{job destruction}_{cy}) - z_y(\text{net job creation}_{cy})]/3$, which requires all three components and is standardized again within year. CRA outcome year t uses the index from year $t - 1$.

CoreLogic measurement. We measure county mortgage risk using the OTS foreclosure rate in the CoreLogic performance file. We require twelve consecutive months to form a trailing average and lag that average exactly twelve calendar months. County-months with a reported origination count below four are excluded. We winsorize and standardize foreclosure risk using a fixed reference period from December 2000 through December 2016 and apply the same transformation to the extended sample. Holding these units constant prevents changes in sample endpoints from mechanically rescaling comparisons.

Local banking capital is prior-quarter Call Report equity/assets averaged with the county deposit shares from the FDIC Summary of Deposits. Deposit weights follow the available Summary of Deposits year and are renormalized among banks with the relevant ratio. Real estate loans, total mortgage-backed securities, and securities are divided by assets using prior-quarter FDIC financial data; the county portfolio averages use the same deposit weights. Deposit concentration is the county Herfindahl index. County economic controls are log nominal personal income from the Bureau of Economic Analysis (table CAINC1), annual average unemployment from the Bureau of Labor Statistics Local Area Unemployment Statistics, and log average outstanding mortgage balance from CoreLogic. Deposit shares weight banking covariates, not regression observations.

Estimation samples. Appendix Table A1 describes the DealScan reference panel, not the cash-flow estimation sample. Tables A2, A3 and A4 describe the estimation samples for the other three datasets. Outcomes are summarized over micro observations and other variables once at their natural level. Reference-panel moments need not equal the moments of a particular history-restricted estimation sample.

The DealScan reference table contains 103,000 positive allocation cells and 6,492 lender-quarters in the reference panel. Lender equity averages 10.68 percent of assets, with a standard deviation of 4.76 percentage points. Panel C summarizes the four-quarter weak-cash-flow measure over 11,974 of the 14,138 reference borrower-quarters with complete eligible histories. Its mean is -0.576 , standard deviation 0.530 and median -0.469 . Because the ratio is sign-reversed, more negative values indicate stronger cash-flow coverage. These moments describe the reference panel, not the 78,306-allocation estimation sample; the regression tables report the estimation counts.

Table A2 shows why it is useful to examine both the dollars and number of small business loans. On the same 140,799 bank-county-years, mean originations are \$14.21 million and 185 loans, whereas the corresponding medians are \$4.35 million and 44 loans. Both distributions are strongly right-skewed, and

dollar volume need not move in proportion to loan counts. Bank equity averages 10.48 percent of assets, with a standard deviation of 2.65 percentage points. Zeros are defined only within a bank's lagged local deposit footprint. The descriptive evidence therefore concerns heterogeneous lending among locally present banks, not a universe in which every absent bank-county relationship is treated as an unused lending opportunity.

Table A3 describes the distribution behind the main mortgage comparison. Mean bank-county-year originations are \$6.62 million, compared with a median of \$0.36 million and a standard deviation of \$70.75 million. Lending is therefore concentrated in a relatively small part of the observed reporting network. Bank equity averages 10.62 percent of assets, with a standard deviation of 3.38 percentage points, providing variation in the balance sheet characteristic central to the analysis. The separate counts for bank-years, county-years, and annual shocks prevent repeated observations of the same characteristic from being mistaken for additional independent variation. The 2,314,338 fitted lending observations still share only 15 annual exposure values.

Table A4 places the monthly mortgage comparison in the context of county banking conditions and mortgage pricing. The balance and initial-rate specifications use the same 579,668 county-months, so their differences do not arise from different fitted observations. Initial rates average 5.31 percent, with a standard deviation of 1.41 percentage points; deposit-weighted bank equity averages 10.49 percent of assets, with a standard deviation of 1.70 percentage points. The policy variables have 238 distinct monthly observations. These moments describe the estimation sample, not the fixed reference period used to normalize risk and scale responses. Average loan sizes and rates also reflect borrower and product composition, not only changes in offered credit terms.

Sample availability and estimation exclusions play different roles. HMDA has 2,746,549 eligible observations and retains 2,314,338 after recursive fixed-effect pruning; the purchase-count exercise retains 1,980,199. The DealScan samples start from the reference panel of 103,000 positive allocations. Requiring complete four-quarter borrower histories and the bank states associated with all five shocks gives 78,306 cash-flow allocations and 79,666 debt-to-equity allocations in the benchmark tables. The information-control tables retain 78,117 and 79,509, respectively. CRA retains 140,799 of 153,756 eligible observations.

A.2 Additional Syndicated Lending Checks

Table A5 repeats the control ladder with the four-quarter debt/equity average, requiring every raw quarterly ratio to be nonnegative and finite, so that negative ratios are not ranked as safer than positive ones. All six columns use 79,666 allocations and match each shock to prior bank states and risk histories. The differentials remain positive, ranging from 0.74 to 1.17 percent. Four columns are significant at 10 percent or better; the loan-composition and deposit-mix columns are not. The full-control coefficient sum is 4.2 (standard error 2.4), with a 1.13 percent differential and $p = 0.086$.

Table A6 reports positive differentials for SRU, TIV, BPVol, and MOVE on a common sample of 78,964 allocations through 2020Q1. SRU (1.27 percent; $p = 0.049$) and BPVol (1.55 percent; $p = 0.018$) are significant at 5 percent, while TIV and MOVE are imprecise ($p = 0.386$ and $p = 0.174$). Table A7 holds all five columns on 79,509 allocations through 2020Q2. Its baseline is 1.15 percent ($p = 0.072$); with SPF disagreement, JLN uncertainty, FPR mean and FPR IQR the differentials are 1.04, 0.86, 1.17 and 1.33 percent. The JLN column is not significant at 10 percent ($p = 0.157$). Thus the alternative risk proxy preserves the sign but not uniform statistical significance.

A.2.1 Within-Facility Allocation Evidence

Appendix Tables A8 to A10 compare lenders within the same facility using the same shock-matched four-quarter cash-flow measure. Facility effects absorb loan-specific common conditions and bank-quarter effects absorb each bank's quarterly circumstances. Each retained bank observation in facility g receives weight $1/n_g$, where n_g is the number of retained bank observations in that facility, so each facility has

total weight one after common-support selection and recursive singleton pruning. Standard errors are clustered by bank, Compustat borrower company and calendar quarter. These estimates concern the distribution of a fixed loan among observed participating lenders, not total borrower credit or new participation. Existing final lender shares, including reconstructed shares, remain unchanged.

We use observations eligible under all three timing designs and each borrower-risk rule: cash flow, debt/equity with nonnegative quarterly inputs, and a positive average of signed debt/equity inputs. The common cash-flow sample therefore also satisfies the ratio-history restrictions. The timing comparisons fix characteristics at $t - 1$, at $t - 5$ before the full shock window, or pair each shock with its preceding states. The ladder tables contain 73,822 allocations, 274 banks, 2,451 borrower companies and 14,198 facilities from 1999Q3 to 2020Q3. The alternative-MPU table requires complete TIV data and contains 73,134 allocations, 274 banks and 2,441 borrower companies through 2020Q1. The information family contains 73,625 allocations and ends in 2020Q2. Within each table, all columns use the same observations.

With full bank controls the common-sample differential is 2.12 percent ($p = 0.091$; 95 percent interval -0.34 to 4.65 percent). The first five ladder columns are significant at 5 percent. On the sample with complete TIV data, the SRU differential is 2.19 percent ($p = 0.084$), and BPVol and MOVE give positive differentials of 2.18 and 2.46 percent ($p = 0.061$ and $p = 0.055$); TIV is imprecise ($p = 0.260$). Information-control differentials range from 1.82 to 2.18 percent, with JLN and FPR mean significant at 10 percent but SPF disagreement and FPR IQR not. The corresponding full-control result on the cash-flow sample without the common-support restriction (77,598 allocations, 280 banks, 2,533 borrower companies, and 15,073 facilities) is 1.40 percent ($p = 0.253$). We therefore treat the common-sample findings as supplementary evidence and do not interpret the sample contrast as a test of coefficient differences.

These supplementary estimates come from exploratory timing and risk comparisons. Reported significance levels are nominal and do not adjust for those comparisons.

A.3 Local Small Business Lending

Panel A of Table A11 asks whether the CRA dollar volume result depends on using SRU as the proxy for MPU. All four specifications use the common 140,799 bank-county-year observations, so sample composition does not account for differences across columns. The benchmark coefficient is 0.011 (standard error 0.0053), implying a 1.16 percent response differential across bank capital and county operating distress. BPVol and MOVE imply differentials of 1.04 and 0.94 percent, and are significant at the 10 percent level. TIV gives a smaller, imprecise 0.27 percent differential. The positive ordering extends to two alternative measures. Because each response uses its own standard deviation, the responses do not describe identical shocks.

Panel B of Table A11 repeats the proxy comparison for the number of small business originations, showing whether the allocation pattern also appears in loan counts. On the same 140,799 observations, benchmark MPU implies a 2.06 percent response differential, compared with 1.51 percent for BPVol and 1.58 percent for MOVE. Their coefficients are 0.020, 0.015, and 0.016, with standard errors of 0.0077, 0.0066, and 0.0057, respectively. All are significant at the 5 percent level. TIV produces a smaller 0.44 percent differential and is imprecisely estimated. The capital ordering across county operating distress appears in origination counts under three proxies, while the TIV estimate is imprecise.

Panel A of Table A12 examines how individual years affect the estimated CRA dollar volume relationship by excluding each year and re-estimating the fully controlled specification. All 15 coefficients remain positive, ranging from 0.0082 to 0.018, with response differentials between 0.84 and 1.82 percent. The largest differential follows exclusion of 2006 and the smallest exclusion of 2009. Omitting 2008 leaves the coefficient at 0.012, close to the benchmark, but raises its standard error to 0.0090. Thirteen estimates are significant at the 10 percent level or better. The direction survives every exclusion.

Panel B of Table A12 applies the same influential year check to origination counts. Each of the 15 exclusions leaves a positive coefficient that is significant at the 5 percent level. Coefficients range from

0.015 when 2010 is omitted to 0.026 when 2006 is omitted, corresponding to response differentials of 1.53 and 2.67 percent. Excluding 2008 gives a 2.57 percent differential, compared with 2.06 percent in the full sample. The count differential is therefore stable across exclusions.

Table A13 asks whether observed changes in disagreement, macro uncertainty, and long-run expectations account for the differential across bank capital and county risk. Column 1 is the benchmark; columns 2 to 5 retain MPU and add the four common information changes one at a time. Both outcome panels use 140,799 observations and the fully controlled specification. The exercise compares the benchmark allocation relationship after allowing each information change to have its own interaction with bank capital and county risk.

SPF inflation disagreement is the principal sensitivity among these changes. Over 2005 to 2019, its annual remaining-year change has a correlation of -0.42 with annual MPU exposure. It reduces the MPU coefficient to 0.0030 (standard error 0.0056; $p = 0.595$) for dollars and 0.011 (0.0072; $p = 0.120$) for counts, implying response differentials of 0.30 and 1.14 percent. The other three additions leave the dollar differentials between 1.15 and 1.23 percent and the count differentials between 2.06 and 2.11 percent. With SPF, the attenuation reflects smaller point estimates, not merely larger standard errors.

The added SPF interaction is negative for both outcomes, at -0.016 for dollars and -0.016 for counts, with p -values of 0.080 and 0.104. The MPU coefficient remains positive in every one of these comparisons, while its magnitude is most sensitive to inflation disagreement.

A.4 Mortgage Comparisons and Sensitivities

Table A14 separates mortgage dollars from loan counts and lending decisions to clarify which outcomes accompany the capital differential. In the full sample, the purchase count interaction is 0.011 (standard error 0.0046), whereas the total count interaction is 0.0025 (0.0054). Refinance counts and the denial share are also imprecise. On the sample with the hybrid conforming loan limit control, the purchase coefficient is 0.017 (0.0059), and refinancing is positive at the 10 percent level. Completed purchase lending thus provides the clearest count counterpart to the dollar result. Because the outcomes use different fitted samples and the denial share uses a decisions-weighted linear model on recorded decisions rather than PPML, these estimates do not establish how much of the dollar response comes from applications, approvals, or loan size.

Table A15 checks whether the annual allocation result depends on how announcement shocks are aligned with lending over the year. The remaining-year benchmark coefficient is 0.0087 (standard error 0.0037), with a 0.68 percent response differential. The unweighted annual sum implies 1.05 percent, while the 90-, 180-, and 365-day constructions imply 0.95, 1.08, and 1.52 percent. Every estimate remains positive and statistically distinguishable from zero under the reported inference, on the same 2,314,338 observations. The capital ordering therefore survives these alternative exposure conventions, although its magnitude varies.

A.4.1 HMDA Credit-Score Risk

Tables A16 to A18 replace the prior-year foreclosure rate with the negative value of the origination-count-weighted prior-year county mean FICO score. The fully controlled MPU coefficient is 0.011 (standard error 0.0062), implying a 1.30 percent response differential. The estimate remains positive under every displayed MPU proxy and information control; TIV, MOVE, and inflation disagreement produce MPU estimates that are significant at the 5 percent level.

A.5 CoreLogic Robustness

Tables A19 and A20 assess uncertainty measurement and information conditioning within the monthly foreclosure-risk design. Table A19 reports the benchmark MPU, TIV, BPVol, and MOVE in turn. Both outcomes and all four proxies use the same 570,304 county-months through May 2020. BPVol and MOVE give positive loan-size estimates, and BPVol preserves the benchmark's significant negative rate response; the TIV loan-size estimate is negative and imprecise.

Table A20 reports a benchmark and four information changes. All columns use a common sample through June 2020. The MPU loan-size differentials remain positive and the rate differentials negative across these additions.

A.5.1 CoreLogic Credit-Score Risk

The CoreLogic FICO exercise replaces lagged foreclosure risk throughout the fully controlled interaction hierarchy. On the 480,869-observation matched sample, the low-FICO specification implies a 0.96 percent loan-size differential and a -1.77 basis-point initial-rate differential. The foreclosure-risk responses in Table A19 are 0.37 percent and -1.56 basis points. Tables A21 and A22 show that the positive loan-size and negative rate ordering also survives the alternative MPU and information-control exercises. FICO measures credit quality among prior mortgage originations, whereas foreclosure risk measures subsequent loan performance; the two proxies therefore capture distinct dimensions of county mortgage risk.

A.5.2 Characteristic and Control Timing

Table A23 compares four timing conventions on the same 565,851 county-months, preserving the twelve-month risk definition and benchmark scaling. The shock-matched differentials are 0.38 percent for loan size and -1.84 basis points for rates; their signs match the benchmark timing on the same sample. Banking and annual-control dates change jointly in these comparisons.

TABLE A1 – Selected Summary Statistics: Syndicated Lending to Corporations (Reference Panel), 1997Q3 to 2020Q3

Variable	Definition	N	Mean	SD	Min	Median	Max
<i>Panel A: Outcome</i>							
Log bank allocation	Natural logarithm of new syndicated loan allocation by bank to borrower (log nominal loan amount)	103,000	17.199	1.122	11.494	17.158	23.392
<i>Panel B: Bank characteristics</i>							
Lagged bank equity/assets (percent)	Lagged equity divided by bank assets (percent)	6,492	10.68	4.76	4.80	9.59	88.81
Lagged log bank assets	Lagged natural logarithm of bank assets (log assets)	6,492	16.62	2.26	9.21	16.87	21.76
Lagged bank return on assets (percent)	Lagged net income divided by bank assets (percent)	6,492	0.24	0.25	-4.22	0.27	1.99
Lagged bank liquidity/assets (percent)	Lagged liquid assets divided by bank assets (percent)	6,492	27.84	14.26	0.83	24.53	94.15
Lagged bank nonperforming loans/assets (percent)	Lagged nonperforming loans divided by bank assets (percent)	6,492	0.80	0.96	0.00	0.52	10.93
<i>Panel C: Borrower risk</i>							
Firm risk (low operating cash-flow coverage)	Negative value of the four-quarter mean of operating cash flow/current liabilities (ratio)	11,974	-0.576	0.530	-3.234	-0.469	1.534
<i>Panel D: Policy shocks</i>							
Quarterly MPU change	Quarterly MPU change measured by short-rate uncertainty (SRU) (original units)	93	-0.0369	0.0435	-0.2159	-0.0260	0.0479
Quarterly orthogonalized MPS	Quarterly orthogonalized high-frequency monetary policy shock (native quarterly orthogonalized shock units)	93	0.0012	0.0772	-0.3466	0.0011	0.2203
<i>Panel E: Information changes</i>							
SPF ten-year CPI forecast disagreement change	Quarterly change in CPI forecast disagreement (standardized index)	93	0.000	1.000	-3.104	0.025	2.373
JLN macro uncertainty (h=3) change	Quarterly change in the JLN macroeconomic uncertainty measure (standardized index)	92	0.000	1.000	-2.956	-0.033	3.724
FPR long-term forecast mean change	Quarterly change in the FPR long-term forecast mean (standardized index)	93	0.000	1.000	-3.323	-0.109	2.400
FPR long-term forecast IQR change	Quarterly change in the FPR long-term forecast interquartile range (standardized index)	93	0.000	1.000	-2.783	0.000	2.783

Notes: This table describes the fixed DealScan reference panel for 1997Q3 to 2020Q3, not the estimation samples of the regressions. Panels A, B, D, and E report reference-panel moments: 103,000 positive allocation cells, 6,492 bank-quarters, and 93 quarters for policy shocks, from 1997Q3; the earlier start supplies the lagged shocks and risk histories for the 85 estimation quarters from 1999Q3. Zero and no-origination cells are absent. Panel C reports the four-quarter cash-flow measure over 11,974 distinct reference borrower-quarters with complete eligible histories; 2,164 of the original 14,138 borrower-quarters lack four usable prior quarters. The window ends one quarter before the reference loan quarter. Each quarterly operating-cash-flow/current-liabilities ratio is winsorized at fixed quarter-specific first and ninety-ninth percentiles before averaging and sign reversal. Either cash-flow sign is retained. Higher values indicate weaker coverage; negative risk values indicate positive average coverage. Bank ratios are in percent. Each of the four standardized information change measures is added one at a time, never jointly. JLN is observed in 92 of the 93 quarters; the missing quarter is not imputed. Short-rate uncertainty (SRU) is the benchmark measure of MPU; MPS denotes the orthogonalized high-frequency monetary policy shock, SPF the Survey of Professional Forecasters, and JLN Jurado-Ludvigson-Ng. SD is the sample standard deviation. These reference-panel moments are descriptive; response differentials use the reference scales described in Appendix A.1.

TABLE A2 – Selected Summary Statistics: Small Business Lending by Banks, 2005 to 2019

Variable	Definition	N	Mean	SD	Min	Median	Max
<i>Panel A: Outcomes</i>							
Small business loan originations (USD millions)	Small business loan dollars originated by a bank in a county-year (USD millions per bank-county-year)	140,799	14.21	38.30	0.00	4.35	2,481.23
Small business loan originations (count)	Number of small business loans originated by a bank in a county-year (loans per bank-county-year)	140,799	185	979	0	44	85,510
<i>Panel B: Bank characteristics</i>							
Bank equity/assets (percent)	Equity divided by total bank assets (percent)	7,526	10.48	2.65	2.51	10.02	31.43
Log bank assets	Natural logarithm of total bank assets (log assets)	7,526	14.74	1.44	11.57	14.42	21.52
Bank return on assets (percent)	Net income divided by total bank assets (percent)	7,526	0.17	0.42	-4.30	0.23	2.31
Bank liquidity/assets (percent)	Liquid assets divided by total bank assets (percent)	7,526	25.09	11.76	0.99	23.00	80.39
Bank nonperforming loans/assets (percent)	Nonperforming loans divided by total bank assets (percent)	7,526	1.05	1.35	0.00	0.59	13.38
<i>Panel C: Local operating distress</i>							
Lagged local small employer operating distress	Lagged county-year distress among small employers (index)	29,969	-0.030	0.778	-2.998	-0.085	4.624
<i>Panel D: Policy shocks</i>							
MPU change (remaining-year aggregate)	MPU measured by the remaining-year aggregate of short-rate uncertainty (SRU) (original units before regression standardization)	15	-0.0607	0.0555	-0.2215	-0.0518	-0.0021
Orthogonalized remaining-year aggregate MPS	Annual remaining-year orthogonalized monetary policy shock (native annual orthogonalized shock units before regression standardization)	15	0.0083	0.0451	-0.0970	0.0134	0.0761
<i>Panel E: Information changes</i>							
SPF ten-year CPI forecast disagreement change	Remaining-year change in CPI forecast disagreement (standardized index)	15	0.000	1.000	-1.827	-0.208	1.934
JLN macro uncertainty (h=3) change	Remaining-year change in the JLN macroeconomic uncertainty measure (standardized index)	15	0.000	1.000	-2.538	0.012	2.417
FPR long-term forecast mean change	Remaining-year change in the FPR long-term forecast mean (standardized index)	15	0.000	1.000	-0.967	-0.405	2.899
FPR long-term forecast IQR change	Remaining-year change in the FPR long-term forecast interquartile range (standardized index)	15	0.000	1.000	-1.866	0.268	2.099

Notes: This table describes selected variables from the common estimation sample of the benchmark Community Reinvestment Act (CRA) small business amount and count PPML regressions for 2005 to 2019. The amount outcome is nominal originations in USD millions per bank-county-year; the count outcome is the number of loans. Both outcomes use the same 140,799 bank-county-year observations. An absent CRA record is coded as zero only inside the predetermined network in which the bank held at least one percent of county deposits in the prior year; bank-county-years outside that footprint remain absent. Moments are computed once at each variable's level of variation: 7,526 bank-years for bank characteristics, 29,969 county-years for local operating distress, and 15 years for shocks and information changes. Ratios are expressed in percent; local risk is lagged county small employer operating distress. Each of the four standardized information change measures is added one at a time, never jointly. Short-rate uncertainty (SRU) is the benchmark measure of MPU; MPS denotes the orthogonalized high-frequency monetary policy shock, SPF the Survey of Professional Forecasters, and JLN Jurado-Ludvigson-Ng. SD is the sample standard deviation. These fitted sample moments are descriptive; response differentials use the reference scales described in Appendix A.1.

TABLE A3 – Selected Summary Statistics: Mortgage Lending by Banks, Total Originations, 2005 to 2019

Variable	Definition	N	Mean	SD	Min	Median	Max
<i>Panel A: Outcomes</i>							
Total mortgage originations (USD millions)	Total mortgage dollars originated by a bank in a county-year (USD millions per bank-county-year)	2,314,338	6.62	70.75	0.00	0.36	16,072.07
<i>Panel B: Bank characteristics</i>							
Bank equity/assets (percent)	Equity divided by total bank assets (percent)	58,748	10.62	3.38	2.51	9.97	76.91
Log bank assets	Natural logarithm of total bank assets (log assets)	58,748	12.92	1.82	9.07	12.53	21.61
Bank return on assets (percent)	Net income divided by total bank assets (percent)	58,748	0.14	0.41	-4.30	0.20	2.31
Bank liquidity/assets (percent)	Liquid assets divided by total bank assets (percent)	58,748	25.63	13.89	0.97	23.04	92.67
Bank nonperforming loans/assets (percent)	Nonperforming loans divided by total bank assets (percent)	58,748	1.10	1.51	0.00	0.60	13.38
<i>Panel C: Local mortgage risk</i>							
Lagged county foreclosure rate (percent)	Prior-year county mortgage foreclosure rate (percent)	36,762	1.42	1.36	0.00	1.05	30.20
<i>Panel D: Policy shocks</i>							
MPU change (remaining-year aggregate)	MPU measured by the remaining-year aggregate of short-rate uncertainty (SRU) (original units before regression standardization)	15	-0.0607	0.0555	-0.2215	-0.0518	-0.0021
Orthogonalized MPS (remaining-year aggregate)	Annual remaining-year orthogonalized monetary policy shock (native annual orthogonalized shock units before regression standardization)	15	0.0083	0.0451	-0.0970	0.0134	0.0761
<i>Panel E: Information changes</i>							
SPF ten-year CPI forecast disagreement change	Remaining-year change in CPI forecast disagreement (standardized index)	15	0.000	1.000	-1.827	-0.208	1.934
JLN macro uncertainty (h=3) change	Remaining-year change in the JLN macroeconomic uncertainty measure (standardized index)	15	0.000	1.000	-2.538	0.012	2.417
FPR long-term forecast mean change	Remaining-year change in the FPR long-term forecast mean (standardized index)	15	0.000	1.000	-0.967	-0.405	2.899
FPR long-term forecast IQR change	Remaining-year change in the FPR long-term forecast interquartile range (standardized index)	15	0.000	1.000	-1.866	0.268	2.099

Notes: This table describes selected variables from the estimation sample of the benchmark HMDA total mortgage PPML regression for 2005 to 2019. The outcome is nominal mortgage dollars originated by a bank in a county and year, reported in USD millions; zero dollar outcomes are retained only on observed HMDA reporting support, and absent bank-county-years are not imputed as zero. Moments are computed once at each variable's level of variation: 2,314,338 bank-county-years for the outcome, 58,748 bank-years for bank characteristics, 36,762 county-years for foreclosure risk, and 15 years for shocks and information changes. Ratios and the foreclosure rate are expressed in percent. Each of the four standardized information change measures is added one at a time, never jointly. Short-rate uncertainty (SRU) is the benchmark measure of MPU; MPS denotes the orthogonalized high-frequency monetary policy shock, SPF the Survey of Professional Forecasters, and JLN Jurado-Ludvigson-Ng. SD is the sample standard deviation. These fitted sample moments are descriptive; response differentials use the reference scales described in Appendix A.1.

TABLE A4 – Selected Summary Statistics: County Mortgage Originations, Average Original Loan Balances and Initial Rates

Variable	Definition	N	Mean	SD	Min	Median	Max
<i>Panel A: Mortgage outcomes</i>							
Log average origination balance	Natural logarithm of mean original loan balance in a county-month (log USD)	579,668	11.822	0.403	9.666	11.807	15.033
Initial mortgage interest rate (percent)	Average initial interest rate on new mortgages in a county-month (percent)	579,668	5.308	1.406	2.435	5.016	18.248
<i>Panel B: County banking conditions</i>							
County bank equity/assets (percent)	Deposit-weighted bank equity ratio in the county (percent)	579,668	10.49	1.70	2.53	10.43	68.35
County bank real estate loans/assets (percent)	Deposit-weighted bank real estate loans divided by assets (percent)	579,668	42.72	9.46	0.00	42.95	93.70
County bank MBS/assets (percent)	Deposit-weighted bank mortgage-backed securities divided by assets (percent)	579,668	9.84	5.16	0.00	9.51	79.70
County bank securities/assets (percent)	Deposit-weighted bank securities divided by assets (percent)	579,668	21.23	7.63	0.00	19.94	82.24
County deposit HHI	County deposit Herfindahl-Hirschman index (index)	579,668	0.280	0.175	0.044	0.231	1.000
<i>Panel C: Local mortgage risk</i>							
Foreclosure risk (12-month lag)	Standardized trailing twelve-month county foreclosure rate, lagged twelve months	579,668	-0.101	0.964	-1.180	-0.387	4.147
<i>Panel D: Local economic conditions</i>							
Log nominal personal income	Natural logarithm of county nominal personal income (log nominal dollars)	579,668	21.053	1.447	16.323	20.857	27.243
County unemployment rate (percent)	County annual average unemployment rate (percent)	579,668	6.22	2.60	1.07	5.66	29.02
Log average mortgage balance	Natural logarithm of average outstanding mortgage balance (log nominal dollars)	579,668	11.410	0.361	9.386	11.367	13.553
<i>Panel E: Policy shocks</i>							
Monthly MPU change	Monthly MPU change measured by short-rate uncertainty (SRU) (original units)	238	-0.0118	0.0241	-0.1505	-0.0034	0.0520
Orthogonalized MPS	Monthly orthogonalized monetary policy stance surprise (original units)	238	0.0007	0.0506	-0.3780	0.0000	0.1865

Notes: The table describes the exact common fitted sample of the fully controlled balance and rate specifications: 579,668 county-month observations, 2,968 counties, and 238 months from December 2000 through September 2020. The first outcome is the log of mean original loan balance, not total origination dollars. County-months with a reported origination count below four are excluded. Initial rates and displayed bank ratios are in percent; nominal personal income is expressed in dollars before taking logs. The unemployment variable is an annual county average. County variables are summarized once per fitted county-month and policy shocks once per fitted month. Foreclosure risk is the trailing twelve-month county foreclosure rate lagged exactly twelve calendar months. Its first and ninety-ninth percentile cutpoints, mean, and standard deviation use a fixed reference period, December 2000 to December 2016. The reported risk moments therefore need not have zero mean or unit standard deviation on this extended fitted sample. MPU is the monthly SRU change; MPS is the Bauer-Swanson orthogonalized stance measure. SD denotes the sample standard deviation.

TABLE A5 – Syndicated Lending to Corporations: Average Debt/Equity Risk - Control Ladder

	Dependent Variable: Log New Loan Allocation (USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ FIRM RISK	3.5880** (1.4157)	3.3264* (1.7677)	2.7344 (1.8903)	2.9139 (2.0475)	4.3411* (2.3246)	4.1879* (2.4304)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	0.97%	0.90%	0.74%	0.78%	1.17%	1.13%
BORROWER-COMPANY-QUARTER FIXED EFFECTS	YES	YES	YES	YES	YES	YES
BANK FIXED EFFECTS	YES	YES	YES	YES	YES	YES
LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES	YES	YES
BANK LIQUIDITY AND SIZE CONTROLS	YES	YES	YES	YES	YES	YES
BANK PROFITABILITY AND ASSET QUALITY CONTROLS	NO	YES	YES	YES	YES	YES
BANK LOAN COMPOSITION CONTROLS	NO	NO	YES	YES	YES	YES
BANK DEPOSIT MIX CONTROLS	NO	NO	NO	YES	YES	YES
BANK WHOLESALE FUNDING CONTROLS	NO	NO	NO	NO	YES	YES
BANK INCOME, MATURITY, AND REPRICING GAP CONTROLS	NO	NO	NO	NO	NO	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES	YES
Number of Observations	79,666	79,666	79,666	79,666	79,666	79,666
Number of Banks	335	335	335	335	335	335
Number of Borrowers	3,566	3,566	3,566	3,566	3,566	3,566
R-squared	0.7834	0.7840	0.7844	0.7852	0.7855	0.7859

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q3. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the mean of four consecutive quarterly WRDS debt-to-equity ratios. All four raw ratios must be finite and nonnegative; a negative or missing quarter makes the whole window ineligible. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPS interactions and identified lower-order terms. Bank-control blocks and their shock/risk interactions are included as indicated. All columns use the same sample. The response differential is defined in Appendix A.1. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A6 – Syndicated Lending to Corporations: Average Debt/Equity Risk - Alternative MPU Measures

	Dependent Variable: Log New Loan Allocation (USD)			
	MPU (Benchmark) (1)	TIV (2)	BPVol (3)	MOVE (4)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	4.6974** (2.3776)	0.2908 (0.3352)	4.7762** (2.0110)	2.1623 (1.5876)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	1.27%	0.81%	1.55%	0.91%
BORROWER-COMPANY-QUARTER FIXED EFFECTS	YES	YES	YES	YES
BANK FIXED EFFECTS	YES	YES	YES	YES
LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	78,964	78,964	78,964	78,964
Number of Banks	333	333	333	333
Number of Borrowers	3,556	3,556	3,556	3,556
R-squared	0.7842	0.7841	0.7842	0.7842

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q1. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the mean of four consecutive quarterly WRDS debt-to-equity ratios. All four raw ratios must be finite and nonnegative; a negative or missing quarter makes the whole window ineligible. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPS interactions and identified lower-order terms. Every column uses the full bank-control specification. All columns use the common sample in which SRU, TIV, BPVol, and MOVE are all available; column 1 therefore re-estimates the benchmark on this sample. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The TIV standard deviation excludes quarters with incomplete announcement data. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A7 – Syndicated Lending to Corporations: Average Debt/Equity Risk - Uncertainty and Information Controls

	Dependent Variable: Log New Loan Allocation (USD)				
	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ FIRM RISK	4.2836* (2.3741)	3.8602* (2.3333)	3.2000 (2.2546)	4.3467* (2.2979)	4.9260** (2.4899)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	1.15%	1.04%	0.86%	1.17%	1.33%
BORROWER-COMPANY-QUARTER, BANK AND LOAN TYPE FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES	YES
MPs SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	79,509	79,509	79,509	79,509	79,509
Number of Banks	335	335	335	335	335
Number of Borrowers	3,565	3,565	3,565	3,565	3,565
R-squared	0.7857	0.7858	0.7858	0.7858	0.7858

Notes: The table reports estimates of equation (2). The sample period is 1999Q3 to 2020Q2. The dependent variable is the log of a lender's positive U.S.-dollar allocation to a borrower company in a calendar quarter and loan type. Only positive allocations are included. Firm risk is the mean of four consecutive quarterly WRDS debt-to-equity ratios. All four raw ratios must be finite and nonnegative; a negative or missing quarter makes the whole window ineligible. For the shock in quarter $s = t - k$, bank capital and controls are dated $s - 1$, and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The reported coefficient sums MPU-capital-risk interactions for $k = 0, \dots, 4$. Every column includes borrower-company-quarter, bank and loan-type fixed effects, orthogonalized MPs interactions and identified lower-order terms. Every column uses the full bank-control specification. Each control and its identified capital/risk interactions enter contemporaneously and with four quarterly lags, using the stated characteristic timing. SPF CPI disagreement and JLN h=3 use quarterly differences; FPR long-term mean and IQR use monthly arithmetic changes summed within quarter. All columns use the same sample. The response differential is defined in Appendix A.1. Standard errors in parentheses are clustered by bank and borrower company. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A8 – Syndicated Lending to Corporations, Within-Facility: Averaged Cash-Flow Risk - Common-Sample Benchmark Ladder

	Dependent Variable: Log New Loan Allocation (USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	22.4446*** (6.3856)	22.3303*** (8.2987)	17.1700** (8.3472)	22.8843** (10.6220)	25.2614** (12.2357)	20.5476* (12.0197)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	2.32%	2.31%	1.77%	2.37%	2.61%	2.12%
FACILITY FIXED EFFECTS	YES	YES	YES	YES	YES	YES
BANK-QUARTER FIXED EFFECTS	YES	YES	YES	YES	YES	YES
LOAN TYPE EFFECTS (FACILITY ABSORBED)	ABSORBED	ABSORBED	ABSORBED	ABSORBED	ABSORBED	ABSORBED
BANK LIQUIDITY AND SIZE CONTROLS	YES	YES	YES	YES	YES	YES
BANK PROFITABILITY AND ASSET QUALITY CONTROLS	NO	YES	YES	YES	YES	YES
BANK LOAN COMPOSITION CONTROLS	NO	NO	YES	YES	YES	YES
BANK DEPOSIT MIX CONTROLS	NO	NO	NO	YES	YES	YES
BANK WHOLESALE FUNDING CONTROLS	NO	NO	NO	NO	YES	YES
BANK INCOME, MATURITY, AND REPRICING GAP CONTROLS	NO	NO	NO	NO	NO	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES	YES
Number of Observations	73,822	73,822	73,822	73,822	73,822	73,822
Number of Banks	274	274	274	274	274	274
Number of Facilities	14,198	14,198	14,198	14,198	14,198	14,198
Number of Borrowers	2,451	2,451	2,451	2,451	2,451	2,451
R-squared	0.9523	0.9523	0.9524	0.9526	0.9527	0.9527

Notes: The table reports a within-facility variant of equation (2). The sample period is 1999Q3 to 2020Q3. The dependent variable is log positive U.S.-dollar lender allocation within an exact loan facility. Allocations use existing final lender shares, including constructed shares; zeros are excluded. Firm risk is the negative value of the mean of four finite quarterly operating-cash-flow/current-liabilities ratios. For the shock in $s = t - k$, bank capital and controls are dated $s - 1$ and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The coefficient sums MPU-capital-risk terms for $k = 0, \dots, 4$. All columns include facility and bank-quarter fixed effects, orthogonalized MPS terms and identified lower-order terms. Bank-only and facility-only levels are absorbed. The indicated blocks add bank liquidity and size, profitability and asset quality, loan composition, deposit mix, wholesale funding, and repricing/maturity characteristics, with their identified uncertainty, stance and risk interactions. Each retained facility receives total weight one after support selection and recursive singleton pruning. Standard errors in parentheses are clustered by bank, borrower company, and calendar quarter. The common sample intersects all three risk rules (nonnegative quarterly debt/equity, positive-average debt/equity and cash flow) and the three timing designs described in Appendix A.2.1. It therefore imposes the debt-to-equity eligibility restrictions on the cash-flow sample. All columns use the same observations. The response differential is defined in Appendix A.1. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A9 – Syndicated Lending to Corporations, Within-Facility: Averaged Cash-Flow Risk - Common-Sample Alternative MPU Measures

	Dependent Variable: Log New Loan Allocation (USD)			
	MPU (Benchmark)	TIV	BPVol	MOVE
	(1)	(2)	(3)	(4)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	21.1982* (12.1229)	1.8355 (1.6199)	17.5214* (9.2249)	15.2118* (7.8136)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	2.19%	1.96%	2.18%	2.46%
FACILITY FIXED EFFECTS	YES	YES	YES	YES
BANK-QUARTER FIXED EFFECTS	YES	YES	YES	YES
LOAN TYPE EFFECTS (FACILITY ABSORBED)	ABSORBED	ABSORBED	ABSORBED	ABSORBED
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	73,134	73,134	73,134	73,134
Number of Banks	274	274	274	274
Number of Borrowers	2,441	2,441	2,441	2,441
R-squared	0.9524	0.9524	0.9524	0.9524

Notes: The table reports a within-facility variant of equation (2). The sample period is 1999Q3 to 2020Q1. The dependent variable is log positive U.S.-dollar lender allocation within an exact loan facility. Allocations use existing final lender shares, including constructed shares; zeros are excluded. Firm risk is the negative value of the mean of four finite quarterly operating-cash-flow/current-liabilities ratios. For the shock in $s = t - k$, bank capital and controls are dated $s - 1$ and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The coefficient sums MPU-capital-risk terms for $k = 0, \dots, 4$. All columns include facility and bank-quarter fixed effects, orthogonalized MPS terms and identified lower-order terms. Bank-only and facility-only levels are absorbed. All columns include the full bank control set, with its identified uncertainty, stance and risk interactions. Each retained facility receives total weight one after support selection and recursive singleton pruning. Standard errors in parentheses are clustered by bank, borrower company, and calendar quarter. The common sample intersects all three risk rules (nonnegative quarterly debt/equity, positive-average debt/equity and cash flow) and the three timing designs described in Appendix A.2.1. It therefore imposes the debt-to-equity eligibility restrictions on the cash-flow sample. All columns use the same observations. All columns use full bank controls and are restricted to quarters in which SRU, TIV, BPVol, and MOVE are all available, which removes 688 allocations from the sample of Table A8. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The TIV standard deviation excludes quarters with incomplete announcement data. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A10 – Syndicated Lending to Corporations, Within-Facility: Averaged Cash-Flow Risk - Common-Sample Uncertainty and Information Controls

	Dependent Variable: Log New Loan Allocation (USD)				
	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL} \times \text{FIRM RISK}$	20.4288* (11.9531)	17.7125 (12.4683)	19.7888* (11.2519)	21.0875* (11.7113)	17.6100 (11.7575)
Response differential for a 1-SD higher MPU: high versus low capital banks across the firm risk IQR	2.11%	1.83%	2.04%	2.18%	1.82%
FACILITY AND BANK-QUARTER FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	73,625	73,625	73,625	73,625	73,625
Number of Banks	274	274	274	274	274
Number of Facilities	14,162	14,162	14,162	14,162	14,162
Number of Borrowers	2,448	2,448	2,448	2,448	2,448
R-squared	0.9527	0.9527	0.9527	0.9527	0.9527

Notes: The table reports a within-facility variant of equation (2). The sample period is 1999Q3 to 2020Q2. The dependent variable is log positive U.S.-dollar lender allocation within an exact loan facility. Allocations use existing final lender shares, including constructed shares; zeros are excluded. Firm risk is the negative value of the mean of four finite quarterly operating-cash-flow/current-liabilities ratios. For the shock in $s = t - k$, bank capital and controls are dated $s - 1$ and risk averages $s - 1$ through $s - 4$. Each quarterly ratio is winsorized at fixed 1st and 99th percentiles before averaging; missing quarters are not imputed. Bank variables are not averaged. The coefficient sums MPU-capital-risk terms for $k = 0, \dots, 4$. All columns include facility and bank-quarter fixed effects, orthogonalized MPS terms and identified lower-order terms. Bank-only and facility-only levels are absorbed. All columns include the full bank control set, with its identified uncertainty, stance and risk interactions. Each retained facility receives total weight one after support selection and recursive singleton pruning. Standard errors in parentheses are clustered by bank, borrower company, and calendar quarter. The common sample intersects all three risk rules (nonnegative quarterly debt/equity, positive-average debt/equity and cash flow) and the three timing designs described in Appendix A.2.1. It therefore imposes the debt-to-equity eligibility restrictions on the cash-flow sample. All columns use the same observations. All columns use full bank controls and require all four information changes. Each added control includes its identified capital/risk hierarchy at lags zero through four. SPF CPI disagreement and JLN h=3 use quarterly differences; FPR long-term mean and IQR use monthly arithmetic changes summed within quarter. The response differential is defined in Appendix A.1. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A11 – Small Business Lending by Banks, Robustness: Alternative Proxies for MPU

	(1) MPU (Benchmark)	(2) TIV	(3) BPVol	(4) MOVE
Panel A: Dependent Variable: Small Business Origination Volume (USD millions, levels)				
$\hat{\beta}$: MPU (INDICATED MEASURE) $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0113** (0.0053)	0.0027 (0.0055)	0.0102* (0.0054)	0.0092* (0.0055)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	1.16%	0.27%	1.04%	0.94%
Pseudo R-squared	0.891	0.891	0.891	0.891
Panel B: Dependent Variable: Number of Small Business Originations				
$\hat{\beta}$: MPU (INDICATED MEASURE) $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0201*** (0.0077)	0.0043 (0.0056)	0.0147** (0.0066)	0.0155*** (0.0057)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	2.06%	0.44%	1.51%	1.58%
Pseudo R-squared	0.984	0.984	0.984	0.984
BANK-COUNTY, BANK-YEAR, AND COUNTY-YEAR FE	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	140,799	140,799	140,799	140,799
Number of Banks	872	872	872	872
Number of Counties	2,224	2,224	2,224	2,224

Notes: The table reports estimates of equation (3). Panels A and B estimate nominal CRA small business origination dollars in USD millions and loan counts by PPML from 2005 to 2019. The bank-county-year unit, lagged one percent deposit network screen, zero coding, and small employer operating distress measure match Table VI. All columns use the same 140,799 observations, prior-year Q4 bank capital and controls, bank-county, bank-year, and county-year fixed effects, orthogonalized MPS interactions, and identified lower-order terms. Column 1 uses SRU; columns 2 to 4 replace it with TIV, BPVol, or MOVE, respectively, holding the other specification elements fixed. The proxies enter separately. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. Shared control and sample rows apply to both panels; fit statistics are Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A12 – Small Business Lending by Banks, Robustness: Leave-One-Year-Out Estimates

Omitted year	Coefficient	Std. err.	Response	Observations	Banks	Counties	Years
Panel A: Dependent Variable: Small Business Origination Volume (USD millions, levels)							
2005	0.0117**	(0.0055)	1.19%	133,343	828	2,221	14
2006	0.0177***	(0.0062)	1.82%	132,061	826	2,218	14
2007	0.0124**	(0.0055)	1.27%	132,632	865	2,220	14
2008	0.0120	(0.0090)	1.23%	132,276	862	2,220	14
2009	0.0082	(0.0056)	0.84%	132,047	862	2,218	14
2010	0.0084*	(0.0051)	0.86%	132,280	867	2,218	14
2011	0.0110**	(0.0054)	1.12%	131,095	866	2,219	14
2012	0.0101*	(0.0054)	1.03%	131,055	867	2,222	14
2013	0.0111**	(0.0053)	1.13%	130,417	866	2,222	14
2014	0.0113**	(0.0054)	1.15%	130,314	867	2,223	14
2015	0.0112**	(0.0053)	1.14%	130,220	869	2,222	14
2016	0.0105**	(0.0053)	1.07%	130,190	867	2,221	14
2017	0.0114**	(0.0053)	1.16%	130,189	865	2,222	14
2018	0.0111**	(0.0053)	1.13%	129,740	853	2,209	14
2019	0.0118**	(0.0054)	1.20%	129,980	854	2,210	14
Panel B: Dependent Variable: Number of Small Business Originations							
2005	0.0206***	(0.0071)	2.11%	133,343	828	2,221	14
2006	0.0259***	(0.0067)	2.67%	132,061	826	2,218	14
2007	0.0208***	(0.0070)	2.14%	132,632	865	2,220	14
2008	0.0250**	(0.0100)	2.57%	132,276	862	2,220	14
2009	0.0189***	(0.0068)	1.94%	132,047	862	2,218	14
2010	0.0149**	(0.0070)	1.53%	132,280	867	2,218	14
2011	0.0197***	(0.0072)	2.02%	131,095	866	2,219	14
2012	0.0168**	(0.0071)	1.72%	131,055	867	2,222	14
2013	0.0201***	(0.0073)	2.06%	130,417	866	2,222	14
2014	0.0199**	(0.0083)	2.05%	130,314	867	2,223	14
2015	0.0212***	(0.0074)	2.18%	130,220	869	2,222	14
2016	0.0193***	(0.0071)	1.98%	130,190	867	2,221	14
2017	0.0196***	(0.0072)	2.01%	130,189	865	2,222	14
2018	0.0188***	(0.0067)	1.93%	129,740	853	2,209	14
2019	0.0210***	(0.0071)	2.15%	129,980	854	2,210	14
BANK-COUNTY, BANK-YEAR, AND COUNTY-YEAR FIXED EFFECTS: YES							
FULLY CONTROLLED SPECIFICATION AND FINAL SAMPLE: YES							
ORTHOGONALIZED MPS INTERACTION BLOCK: YES							

Notes: The table reports estimates of equation (3). Each row omits the indicated year from 2005 to 2019 and re-estimates the fully controlled CRA specification on its resulting fitted sample. Panel A uses nominal small business origination dollars in USD millions; Panel B uses loan counts. Both are estimated by PPML. Zero lending is defined only inside the predetermined network where prior-year bank deposits are at least one percent of county deposits. The reported interaction combines remaining-year SRU-based MPU, prior-year Q4 bank equity to assets, and lagged BDS operating distress among firms with 1 to 19 employees. Every row retains bank-county, bank-year, and county-year fixed effects, full bank control and orthogonalized MPS interactions, and identified lower-order terms. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. The fitted samples vary after each exclusion, as shown. MPU keeps its full-sample standardization in every row, and responses use the full-sample reference scaling. These overlapping fourteen-year estimates assess influence, not independent replications. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A13 – Small Business Lending by Banks, Robustness: Uncertainty and Information Controls

	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
Panel A: Dependent Variable: Small Business Origination Volume (USD millions, levels)					
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0113** (0.0053)	0.0030 (0.0056)	0.0120** (0.0055)	0.0112* (0.0060)	0.0114** (0.0054)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	1.16%	0.30%	1.23%	1.15%	1.17%
Pseudo R-squared	0.891	0.891	0.891	0.891	0.891
Panel B: Dependent Variable: Number of Small Business Originations					
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	0.0201*** (0.0077)	0.0111 (0.0072)	0.0206*** (0.0071)	0.0205*** (0.0073)	0.0201*** (0.0069)
Response differential for a 1-SD higher MPU: high versus low capital banks across the county risk IQR	2.06%	1.14%	2.11%	2.11%	2.06%
Pseudo R-squared	0.984	0.984	0.984	0.984	0.984
ADDED INFORMATION INTERACTION	NO	YES	YES	YES	YES
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET	YES	YES	YES	YES	YES
AND INTERACTIONS	YES	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	140,799	140,799	140,799	140,799	140,799
Number of Banks	872	872	872	872	872
Number of Counties	2,224	2,224	2,224	2,224	2,224

Notes: The table reports estimates of equation (3). Both panels estimate bank-county-year originations from 2005 to 2019 by PPML: dollars in USD millions in Panel A and loan counts in Panel B. The CRA category, lagged one percent deposit network screen, zero coding, prior-year bank variables, and lagged small employer operating distress index are as in Table VI. Every displayed column uses 140,799 observations, bank-county, bank-year, and county-year fixed effects, full bank control interactions, orthogonalized MPS interactions, and identified lower-order terms. Column 1 is the displayed benchmark. Columns 2 to 5 separately add an information change. Each enters interacted with bank capital and county risk. SPF ten-year CPI disagreement and JLN horizon-three uncertainty use quarterly first differences, remaining-year weighted at February 15, May 15, August 15, and November 15. FPR long-term mean and IQR use monthly arithmetic changes, weighted at the fifteenth of each month. SPF is the Survey of Professional Forecasters, JLN Jurado et al. (2015), FPR Fofana et al. (2025). Information changes are standardized across the fifteen years. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. All benchmark annual MPU exposures are negative, so higher exposure means less uncertainty resolution. Fit statistics are Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A14 – Mortgage Lending by Banks: Outcome Components under the Benchmark and Hybrid Conforming Limit Specifications

Specification	(1) Origination volume	(2) Origination count	(3) Denial rate	(4) Purchase count	(5) Refinance count
<i>Panel A: Benchmark specification (outcome-specific fitted samples)</i>					
$\hat{\beta} : \text{MPU} \times \text{BANK CAPITAL} \times \text{COUNTY RISK}$	0.0087** (0.0037)	0.0025 (0.0054)	-0.0004 (0.0008)	0.0114** (0.0046)	0.0055 (0.0042)
Number of Observations	2,314,338	2,314,338	2,150,412	1,980,199	2,075,013
(Pseudo) R-squared	0.931	0.953	0.991	0.928	0.946
<i>Panel B: Hybrid conforming limit specification (outcome-specific fitted samples)</i>					
$\hat{\beta} : \text{MPU} \times \text{BANK CAPITAL} \times \text{COUNTY RISK}$	0.0114** (0.0055)	0.0074 (0.0063)	-0.0009 (0.0008)	0.0171*** (0.0059)	0.0098* (0.0054)
Number of Observations	1,806,926	1,806,926	1,676,098	1,565,988	1,612,311
(Pseudo) R-squared	0.936	0.957	0.991	0.934	0.952

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019. Entries are the fully controlled MPU-by-bank-capital-by-county-risk coefficients: MPU uses remaining-year SRU exposure, capital prior-year Q4 equity to assets, and risk the prior-year foreclosure rate. Origination dollars in column 1 are in USD millions; columns 2, 4, and 5 are loan counts. These outcomes use PPML, retaining zeros on observed HMDA reporting support but not imputing absent reporting cells as zero. Column 3 is the denial share, estimated by a decisions-weighted linear model. Panel A uses the benchmark specification; Panel B adds the hybrid conforming limit specification on its available support. Samples are outcome-specific after fixed effect pruning, as the observation counts show. Column 1 repeats Table VII column 4 in Panel A and Table VIII column 4 in Panel B. All models include bank-county, bank-year, and county-year fixed effects, full bank control interactions, orthogonalized MPS interactions, and identified lower-order terms. Standard errors in parentheses are clustered by bank and county. Fit statistics are Poisson pseudo R-squared in columns 1, 2, 4, and 5 and OLS R-squared in column 3. Coefficients across these different outcome scales are not an additive decomposition. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A15 – Mortgage Lending by Banks, Robustness: Annual Shock Timing

Annual shock construction	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	Coefficient	Standard error	Response differential	Observations
Remaining-year weighted (Benchmark)	0.0087**	(0.0037)	0.68%	2,314,338
Unweighted annual sum	0.0135***	(0.0035)	1.05%	2,314,338
90-day window	0.0121***	(0.0035)	0.95%	2,314,338
180-day window	0.0138***	(0.0036)	1.08%	2,314,338
365-day window	0.0193***	(0.0044)	1.52%	2,314,338

Notes: The table reports estimates of equation (3). The dependent variable is nominal mortgage origination dollars in USD millions per bank-county-year, estimated by PPML from 2005 to 2019. SRU is the MPU proxy, bank capital is prior-year Q4 equity to assets, and county risk is the prior-year foreclosure rate. The first row repeats the fully controlled remaining-year benchmark in Table VII. Each subsequent row changes the annual aggregation of both MPU and the orthogonalized MPS surprise while retaining the same 2,314,338 observations, full bank controls and their interactions, bank-county, bank-year, and county-year fixed effects, and identified lower-order terms. HMDA zeros are retained on observed reporting support; absent reporting cells are not coded as zero. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. A higher remaining-year benchmark exposure means less announcement-related uncertainty resolution. For a horizon of H days, announcement a contributes to year t the share of the year covered by its window, $w_{at}(H) = \max\{0, \min(E_t, d_a + H) - \max(S_t, d_a)\} / L_t$, where $[S_t, E_t]$ is the calendar year, L_t its length in days, and d_a the announcement date; windows of the previous year's announcements that extend into year t are included. The rows change the timing convention, not the number of annual shock realizations. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A16 – Mortgage Lending by Banks, Robustness: Origination-Weighted Low-FICO Risk

	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	(1)	(2)	(3)	(4)
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ LOW-FICO RISK	0.0035 (0.0060)	0.0047 (0.0065)	0.0083 (0.0058)	0.0111* (0.0062)
Response differential for a 1-SD higher MPU: high versus low capital banks across the origination-weighted low-FICO risk IQR	0.41%	0.55%	0.97%	1.30%
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES
BANK SIZE AND PROFITABILITY CONTROLS	NO	YES	YES	YES
BANK LIQUIDITY, ASSET QUALITY, DEPOSIT, AND WHOLESALE FUNDING CONTROLS	NO	NO	YES	YES
BANK INCOME GAP, MATURITY, REPRICING, AND LOAN COMPOSITION CONTROLS	NO	NO	NO	YES
BANK CONTROL INTERACTIONS WITH MPU, MPS, AND COUNTY RISK	NO	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	2,314,276	2,314,276	2,314,276	2,314,276
Number of Banks	6,357	6,357	6,357	6,357
Number of Counties	2,762	2,762	2,762	2,762
Bank clusters	6,357	6,357	6,357	6,357
County clusters	2,762	2,762	2,762	2,762
Pseudo R-squared	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019, and the dependent variable is total nominal mortgage origination dollars in USD millions, estimated by PPML. For each county and year, monthly mean FICO is weighted by that month's number of originated mortgages, averaged over the prior calendar year, and multiplied by minus one; at least six valid months are required. Higher values therefore indicate lower borrower credit quality. The weighting constructs the risk measure and does not weight the regression. The measure is standardized within year across unique counties. All columns use the final fully controlled estimation support and include bank-county, bank-year, and county-year fixed effects, orthogonalized MPS interactions, and identified lower-order terms. Columns 2 to 4 add the indicated bank controls, interacted with low-FICO risk alone and together with MPU and with MPS. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A17 – Mortgage Lending by Banks, Low-FICO Robustness: Alternative Proxies for MPU

MPU measure	Dependent Variable: Mortgage Origination Volume (USD millions, levels)			
	(1) MPU (Benchmark)	(2) TIV	(3) BPVol	(4) MOVE
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ LOW-FICO RISK	0.0111* (0.0062)	0.0129** (0.0061)	0.0055 (0.0056)	0.0116** (0.0052)
Response differential for a 1-SD higher MPU: high versus low capital banks across the origination-weighted low-FICO risk IQR	1.30%	1.51%	0.64%	1.36%
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	2,314,276	2,314,276	2,314,276	2,314,276
Number of Banks	6,357	6,357	6,357	6,357
Number of Counties	2,762	2,762	2,762	2,762
Pseudo R-squared	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019, and the dependent variable is total nominal mortgage origination dollars, estimated by PPML. Low-FICO risk is the negative value of the origination-count-weighted prior-year county mean FICO score; at least six valid months are required, and the measure is standardized within year across unique counties. Column 1 uses SRU as the MPU proxy; columns 2 to 4 replace SRU with Treasury implied volatility (TIV), Eurodollar option basis-point volatility (BPVol), or MOVE bond-market volatility. The measures enter separately, not jointly. All columns use the same 2,314,276 fitted observations and include prior-year bank equity to assets, bank-county, bank-year, and county-year fixed effects, the full bank-control interaction hierarchy, and orthogonalized MPS interactions. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A18 – Mortgage Lending by Banks, Low-FICO Robustness: Uncertainty and Information Controls

Dependent Variable: Mortgage Origination Volume (USD millions, levels)					
Additional control	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
$\hat{\beta}$: MPU $\times$ BANK CAPITAL $\times$ LOW-FICO RISK	0.0111* (0.0063)	0.0140** (0.0065)	0.0116* (0.0068)	0.0101* (0.0060)	0.0110 (0.0070)
Response differential for a 1-SD higher MPU: high versus low capital banks across the origination-weighted low-FICO risk IQR	1.30%	1.65%	1.36%	1.18%	1.29%
ADDED INFORMATION INTERACTION	NO	YES	YES	YES	YES
BANK-COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES
BANK-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
COUNTY-YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
FULL BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES	YES
MPS SHOCK INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	2,314,276	2,314,276	2,314,276	2,314,276	2,314,276
Number of Bank-County Pairs	425,585	425,585	425,585	425,585	425,585
Number of Banks	6,357	6,357	6,357	6,357	6,357
Number of Counties	2,762	2,762	2,762	2,762	2,762
Pseudo R-squared	0.931	0.931	0.931	0.931	0.931

Notes: The table reports estimates of equation (3). The unit is a bank-county-year from 2005 to 2019, and the dependent variable is total nominal mortgage origination dollars, estimated by PPML. Low-FICO risk is the negative value of the origination-count-weighted prior-year county mean FICO score; at least six valid months are required, and the measure is standardized within year across unique counties. Every specification includes bank-county, bank-year, and county-year fixed effects, the full bank-control interaction hierarchy, orthogonalized MPS interactions, and identified lower-order terms. Columns 2 to 5 add one uncertainty or information-change interaction at a time. Only the MPU coefficient is displayed; coefficients on the added controls are omitted. All columns use the same observations. Standard errors in parentheses are clustered by bank and county. The response differential is defined in Appendix A.1. Column 1 is estimated separately, on the same observations as the control-ladder and alternative-MPU tables. The fit statistic is Poisson pseudo R-squared. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the bank controls.

TABLE A19 – County Mortgage Originations, Robustness: Alternative Proxies for MPU

	(1) MPU (Benchmark)	(2) TIV	(3) BPVol	(4) MOVE
Panel A: Dependent Variable: Log Average Origination Balance (USD)				
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL}$ $\times \text{COUNTY RISK}$	6.0332*** (1.9735)	-0.2628 (0.2010)	1.8720 (1.7934)	0.8484 (1.0988)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the risk IQR	0.37%	-0.19%	0.13%	0.09%
R-squared	0.860	0.859	0.860	0.859
Panel B: Dependent Variable: Average Initial Mortgage Rate (percent)				
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL}$ $\times \text{COUNTY RISK}$	-25.6166*** (6.6652)	-0.1168 (0.7728)	-20.4500*** (5.7222)	-4.1715 (4.0962)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the risk IQR	-1.56 bp	-0.09 bp	-1.42 bp	-0.45 bp
R-squared	0.938	0.938	0.938	0.938
COUNTY AND MONTH FIXED EFFECTS	YES	YES	YES	YES
FULL COUNTY/BANK CONTROLS AND INTERACTIONS	YES	YES	YES	YES
ORTHOGONALIZED MPS INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	570,304	570,304	570,304	570,304
Number of Counties	2,968	2,968	2,968	2,968
Number of Months	234	234	234	234

Notes: The table reports estimates of equation (4). Panels A and B estimate log average original loan balance and the average initial mortgage rate by unweighted fixed effects OLS. Column 1 uses SRU, the benchmark MPU measure; columns 2 to 4 replace it with TIV, BPVol, and MOVE, matching the ordering in Table A11. All columns and both outcomes use the same 570,304 county-month observations from December 2000 through May 2020, the period with complete data for all four measures. Column 1 therefore re-estimates the benchmark on this sample. They retain prior-quarter county banking capital, foreclosure risk, orthogonalized MPS, county and month fixed effects, full county/bank controls and interactions, and identified lower-order terms as in Table XI. Foreclosure risk is the trailing twelve-month county foreclosure rate lagged exactly twelve calendar months. Its first and ninety-ninth percentile cutpoints, mean, and standard deviation use a fixed reference period, December 2000 to December 2016. Standard errors in parentheses are clustered by county and month; two-sided tests use the smaller cluster count minus one as degrees of freedom. R-squared is conventional OLS R-squared, including fixed effects. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

TABLE A20 – County Mortgage Originations: Uncertainty and Information Controls

	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
Panel A: Dependent Variable: Log Average Origination Balance (USD)					
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	5.9676*** (1.9695)	5.5670*** (2.0112)	5.3958*** (2.0107)	5.6026*** (1.9857)	5.5873*** (1.9825)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the risk IQR	0.36%	0.34%	0.33%	0.34%	0.34%
R-squared	0.860	0.860	0.860	0.860	0.860
Panel B: Dependent Variable: Average Initial Mortgage Rate (percent)					
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK	-25.4707*** (6.6393)	-25.0443*** (6.8127)	-24.8266*** (7.5539)	-25.4918*** (6.8327)	-25.1791*** (6.7368)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the risk IQR	-1.55 bp	-1.53 bp	-1.51 bp	-1.55 bp	-1.53 bp
R-squared	0.939	0.939	0.939	0.939	0.939
ADDED INFORMATION INTERACTION	NO	YES	YES	YES	YES
COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES
MONTH FIXED EFFECTS	YES	YES	YES	YES	YES
FULL COUNTY/BANK CONTROL SET	YES	YES	YES	YES	YES
AND INTERACTIONS	YES	YES	YES	YES	YES
ORTHOGONALIZED MPS INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	572,539	572,539	572,539	572,539	572,539
Number of Counties	2,968	2,968	2,968	2,968	2,968
Number of Months	235	235	235	235	235

Notes: The table reports estimates of equation (4). Both panels estimate the fully controlled monthly specification in Table XI by unweighted fixed effects OLS. Column 1 is the benchmark; columns 2 to 5 separately add the indicated information change. Each addition enters with the current month and four monthly lags, interacted with bank capital and county risk, together with the identified lower-order terms. The MPU coefficient sum is displayed, not the added-control coefficient. All columns share 572,539 observations and 235 months through June 2020. SPF ten-year CPI disagreement enters as a quarterly first difference assigned to February, May, August, and November, with zero new change in intervening covered months. JLN and FPR enter as monthly arithmetic first differences. These timing conventions define control variables, not verified real-time information sets. SPF is the Survey of Professional Forecasters; JLN is Jurado et al. (2015), FPR Fofana et al. (2025). Foreclosure risk is the trailing twelve-month county foreclosure rate lagged exactly twelve calendar months. Its first and ninety-ninth percentile cutpoints, mean, and standard deviation use a fixed reference period, December 2000 to December 2016. Standard errors in parentheses are clustered by county and month; two-sided tests use the smaller cluster count minus one as degrees of freedom. R-squared is conventional OLS R-squared, including fixed effects. The response differential is defined in Appendix A.1. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

TABLE A21 – County Mortgage Originations, Low-FICO Robustness: Alternative Proxies for MPU

	(1) MPU (Benchmark)	(2) TIV	(3) BPVol	(4) MOVE
Panel A: Dependent Variable: Log Average Origination Balance (USD)				
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL}$ $\times \text{LOW-FICO RISK}$	11.5402*** (2.4848)	0.3208 (0.2264)	9.9142*** (2.1446)	2.0188* (1.2058)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the low-FICO risk IQR	0.96%	0.32%	0.94%	0.30%
R-squared	0.894	0.894	0.895	0.894
Panel B: Dependent Variable: Average Initial Mortgage Rate (percent)				
$\sum_{k=0}^4 \hat{\beta}_k : \text{MPU} \times \text{BANK CAPITAL}$ $\times \text{LOW-FICO RISK}$	-21.1343*** (6.6773)	-0.5717 (0.7284)	-18.8376*** (5.6735)	-6.9576* (3.8246)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the low-FICO risk IQR	-1.77 bp	-0.58 bp	-1.79 bp	-1.04 bp
R-squared	0.958	0.958	0.958	0.958
COUNTY AND MONTH FIXED EFFECTS	YES	YES	YES	YES
FULL COUNTY/BANK CONTROLS AND INTERACTIONS	YES	YES	YES	YES
ORTHOGONALIZED MPS INTERACTIONS	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES
Number of Observations	480,869	480,869	480,869	480,869
Number of Counties	2,554	2,554	2,554	2,554
Number of Months	234	234	234	234

Notes: The table reports estimates of equation (4). The sample period is 2000 to 2020. The unit is a county-month. Panel A estimates log average original loan balance, and Panel B estimates the average initial mortgage rate in percent. Low-FICO risk is the negative standardized twelve-month moving average of county-average FICO among originated mortgages, lagged exactly twelve calendar months, with equal weight on each of the twelve county-month averages rather than weights by originations. All twelve months are required, and county-months with fewer than four reported originations are excluded. All columns use the same 480,869 fitted observations from December 2000 through May 2020, the period with complete data for all four measures; column 1 therefore re-estimates the benchmark on this sample. They include county and month fixed effects, current-through-four-month MPU and orthogonalized MPS interactions, the interacted county economic controls, and the county banking-composition controls in levels. MPU measures enter separately. Standard errors in parentheses are clustered by county and month using 233 cluster-adjusted degrees of freedom. The response differential is defined in Appendix A.1. Each response uses the standard deviation of its own MPU proxy. The scales come from the fixed pre-2017 FICO-common reference. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

TABLE A22 – County Mortgage Originations, Low-FICO Robustness: Uncertainty and Information Controls

	Uncertainty and information changes				
	Benchmark (1)	SPF 10-year CPI disagreement (2)	JLN macro uncertainty (h=3) (3)	FPR long-term mean (4)	FPR long-term IQR (5)
Panel A: Dependent Variable: Log Average Origination Balance (USD)					
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ LOW-FICO RISK	11.4106*** (2.4780)	10.7827*** (2.5569)	10.8675*** (2.7769)	10.8615*** (2.5414)	11.3680*** (2.5044)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the low-FICO risk IQR	0.95%	0.90%	0.91%	0.91%	0.95%
R-squared	0.895	0.895	0.895	0.895	0.895
Panel B: Dependent Variable: Average Initial Mortgage Rate (percent)					
$\sum_{k=0}^4 \hat{\beta}_k$: MPU $\times$ BANK CAPITAL $\times$ LOW-FICO RISK	-21.1385*** (6.6793)	-18.2038** (7.2356)	-22.4182*** (7.6940)	-19.1201*** (6.9923)	-21.3843*** (6.9111)
Response differential for a 1-SD higher MPU: high versus low county bank capital across the low-FICO risk IQR	-1.77 bp	-1.52 bp	-1.87 bp	-1.60 bp	-1.79 bp
R-squared	0.959	0.959	0.959	0.959	0.959
ADDED INFORMATION INTERACTION	NO	YES	YES	YES	YES
COUNTY FIXED EFFECTS	YES	YES	YES	YES	YES
MONTH FIXED EFFECTS	YES	YES	YES	YES	YES
FULL COUNTY/BANK CONTROL SET AND INTERACTIONS	YES	YES	YES	YES	YES
ORTHOGONALIZED MPS INTERACTIONS	YES	YES	YES	YES	YES
LOWER ORDER INTERACTIONS AND LEVELS	YES	YES	YES	YES	YES
Number of Observations	482,523	482,523	482,523	482,523	482,523
Number of Counties	2,554	2,554	2,554	2,554	2,554
Number of Months	235	235	235	235	235

Notes: The table reports estimates of equation (4). The sample period is 2000 to 2020. The unit is a county-month. Panel A estimates log average original loan balance, and Panel B estimates the average initial mortgage rate in percent. Low-FICO risk is the negative standardized twelve-month moving average of county-average FICO among originated mortgages, lagged exactly twelve calendar months; all twelve months are required. Every specification includes county and month fixed effects, current-through-four-month MPU and orthogonalized MPS interactions, the interacted county economic controls, and the county banking-composition controls in levels. Columns 2 to 5 add one uncertainty or information-change interaction at a time. Only the MPU coefficient sum is displayed; coefficients on the added controls are omitted. All columns use a common sample through June 2020. Standard errors in parentheses are clustered by county and month. The response differential is defined in Appendix A.1. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

TABLE A23 – County Mortgage Originations, Robustness: Characteristic and Control Timing

Timing design	Benchmark timing (1)	Shock-matched snapshots (2)	One-month control snapshot (3)	Controls fixed before window (4)
Panel A: Log mean original mortgage balance (USD) MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK (sum over five shock lags)	6.427*** (1.982)	6.198*** (1.983)	5.216*** (1.880)	6.805*** (1.964)
Response differential (percent)	0.39%	0.38%	0.32%	0.41%
R-squared	0.859	0.858	0.858	0.857
Panel B: Mean initial mortgage rate (percent) MPU $\times$ BANK CAPITAL $\times$ COUNTY RISK (sum over five shock lags)	-26.309*** (6.596)	-30.255*** (6.681)	-26.986*** (6.438)	-32.834*** (6.565)
Response differential (basis points)	-1.60 bp	-1.84 bp	-1.64 bp	-2.00 bp
R-squared	0.939	0.939	0.939	0.939
COUNTY AND MONTH FIXED EFFECTS	YES	YES	YES	YES
FULL COUNTY AND BANK CONTROL SET	YES	YES	YES	YES
MPS AND LOWER-ORDER INTERACTIONS	YES	YES	YES	YES
Number of observations	565,851	565,851	565,851	565,851
Number of counties	2,963	2,963	2,963	2,963
Number of months	234	234	234	234

Notes: The table reports estimates of equation (4). The sample period is April 2001 to September 2020. The table compares full-control estimates on the same observations across both outcomes and all four timing designs. Mortgage risk remains the twelve-month average lagged twelve months; no one-month risk proxy is introduced. All models retain the benchmark normalization, county/month fixed effects, the orthogonalized stance surprise and the five-shock interaction hierarchy. (1) uses the benchmark outcome-date banking and control snapshots. (2) uses the banking and control snapshot from the month before each shock and the same twelve-month risk definition evaluated at that shock. (3) holds banking and control snapshots at $t - 1$ for every lag. (4) holds those snapshots at $t - 5$, before the full five-month shock window. The source month is $t - k - 1$ for shock lag k in (2), $t - 1$ in (3), and $t - 5$ in (4). Annual income and unemployment come from two years before the source month's year, and mortgage-balance controls from the source month; this is a conservative calendar lag. Banking snapshots retain prior-quarter accounts and the original deposit-weight construction. Standard errors in parentheses are clustered by county and month. The response differential is defined in Appendix A.1. Tests use 233 degrees of freedom. ***, **, and * denote two-sided significance at the 1, 5, and 10 percent levels. Appendix A.1 defines the county and bank controls.

B Model Derivations

We derive the results in Section 2 with a binding risk capacity constraint and an unchanged active set of lending opportunities. Appendix B.5 adds a deposit insurer and discusses welfare. The final subsection discusses the model's scope.

B.1 Available Risk Capacity

The quadratic risk budget can arise from a location-scale factor model. Let $X = \sum_i q_i \ell_i$ and let (Z_c, Z_r) be a centered spherical random vector with a fixed distribution, finite second moments, and covariance matrix I_2 . Independent standard normal factors are a special case; independence is not required for the broader spherical family. Suppose losses equal $L = XZ_c + e\sqrt{U}Z_r$. Spherical symmetry implies that L has the same distribution as $\sqrt{X^2 + e^2U}Z_c$. At a fixed probability level whose marginal quantile is finite and strictly positive, value at risk is therefore that quantile times $\sqrt{X^2 + e^2U}$. Dividing the available capital buffer by the quantile defines normalized capacity K and gives the reduced-form risk limit used in the paper:

$$\left(\sum_i q_i \ell_i \right)^2 + e^2U \leq K^2.$$

When $K^2 > e^2U$, the risk budget leaves the following capacity for credit:

$$\sum_i q_i \ell_i \leq C(K, U) = \sqrt{K^2 - e^2U}.$$

Differentiating available capacity gives

$$C_U = -\frac{e^2}{2C} < 0, \quad C_K = \frac{K}{C} > 0, \quad C_{UK} = \frac{e^2K}{2C^3} > 0.$$

Uncertainty leaves less capacity for credit, but the loss is smaller at banks with more capital. The cross-partial grows in magnitude as available capacity approaches zero.

B.2 Continuation Value, Franchise Value, and the Risk Limit

This subsection provides a continuation value interpretation of the maintained risk limit. We first identify when shareholders lose from additional variance, then express a reduced-form continuation condition as a cap on total risk. Let terminal net worth before limited liability be

$$N_1 = \bar{N}(B) + \Omega\epsilon, \quad \Omega^2 = \left(\sum_i q_i \ell_i \right)^2 + e^2U,$$

where $\bar{N}_B > 0$ and ϵ is the standardized factor of the previous subsection, taken to be standard normal here. Shareholders receive $N_1 + \gamma$ if $N_1 \geq 0$ and nothing otherwise, where $\gamma > 0$ is the franchise value lost in insolvency. Expected shareholder value is

$$V(\bar{N}, \Omega; \gamma) = (\bar{N} + \gamma) \Phi\left(\frac{\bar{N}}{\Omega}\right) + \Omega \phi\left(\frac{\bar{N}}{\Omega}\right),$$

and its derivative with respect to variance is

$$\frac{\partial V}{\partial \Omega^2} = \frac{\phi(\bar{N}/\Omega)}{2\Omega} \left(1 - \frac{\gamma\bar{N}}{\Omega^2} \right).$$

Shareholders lose from additional variance if and only if $\gamma\bar{N} > \Omega^2$: franchise value times expected net worth must exceed total variance. This is the precautionary region. Where $\gamma\bar{N} < \Omega^2$, limited liability convexity dominates and shareholders value additional variance, the risk shifting region of [Keeley \(1990\)](#), [Hellmann et al. \(2000\)](#) and [Dell'Ariccia et al. \(2014\)](#).

In the precautionary region, preserving continuation value gives shareholders a reason to limit risk. We represent this motive by imposing the continuation condition

$$\Pr(N_1 < \underline{N}) \leq p(\gamma), \quad p(\gamma) \in (0, 1/2), \quad p'(\gamma) < 0,$$

which assumes that banks with greater franchise value tolerate a smaller probability of falling below the continuation threshold $\underline{N}$. We assume $\bar{N}(B) > \underline{N}$, so that capacity is positive. Let $z(\gamma) = \Phi^{-1}(1 - p(\gamma)) > 0$. Under normality the condition is equivalent to

$$\Omega \leq K(B, \gamma) \equiv \frac{\bar{N}(B) - \underline{N}}{z(\gamma)},$$

which is the risk limit of the main text,

$$\left(\sum_i q_i \ell_i \right)^2 + e^2 U \leq K^2.$$

Equity increases capacity, $K_B = \bar{N}_B / z > 0$, while higher franchise value tightens the limit, $K_\gamma = -(\bar{N} - \underline{N})z'(\gamma)/z^2 < 0$, because the assumed continuation target is stricter at higher franchise value. The main text's $K = k(B)$ holds franchise value fixed across the compared banks; the comparative statics in U and B are unchanged.

Two remarks follow. First, the continuation condition is a maintained reduced form for internal risk limits, supervisory intervention and the cost of restoring capital. It also treats the surplus from current lending as separate from expected net worth, so the limit does not move with the surplus that the allocation earns. The shareholder value calculation motivates precautionary behavior; it does not solve for the probability target. Second, the condition describes voluntary precaution in the region where additional variance lowers shareholder value. A bank for which $\gamma\bar{N} < \Omega^2$ gains from variance and would not impose the limit on itself; if the limit binds for such a bank, it does so through supervision, capital requirements or limits imposed by creditors, and the allocation predictions of the main text then follow from the binding limit as before. Where no such enforcement operates, the model is silent, which is consistent with treating differentials across bank capital and borrower risk as statements about constrained lenders.

B.3 Optimal Allocation

The bank chooses lending subject to the risk budget and nonnegativity. Its Lagrangian is

$$\mathcal{J} = \sum_i \left(m_i \ell_i - \frac{c_i}{2} \ell_i^2 \right) + \lambda \left[C(K, U) - \sum_i q_i \ell_i \right] + \sum_i \mu_i \ell_i.$$

The Kuhn-Tucker conditions are

$$\begin{aligned} m_i - c_i \ell_i - \lambda q_i + \mu_i &= 0, & \lambda &\geq 0, & \mu_i &\geq 0, \\ \lambda \left(C - \sum_i q_i \ell_i \right) &= 0, & \mu_i \ell_i &= 0, & \ell_i &\geq 0, \\ \sum_i q_i \ell_i &\leq C. \end{aligned}$$

Let $A = \{i : \ell_i > 0\}$. With a binding constraint and a fixed active set, $\mu_i = 0$ for $i \in A$, so

$$\ell_i = \frac{m_i - \lambda q_i}{c_i}, \quad i \in A, \quad \sum_{i \in A} \frac{q_i m_i}{c_i} - \lambda \sum_{i \in A} \frac{q_i^2}{c_i} = C(K, U).$$

To solve for the shadow value and lending, define $M_A = \sum_{i \in A} q_i m_i / c_i$ and $\Omega_A = \sum_{i \in A} q_i^2 / c_i$. Then

$$\lambda = \frac{M_A - C(K, U)}{\Omega_A}, \quad \ell_i^* = \frac{m_i}{c_i} - \frac{q_i}{c_i} \frac{M_A - C(K, U)}{\Omega_A}, \quad i \in A.$$

A strictly positive shadow value requires $C < M_A$. At $C = M_A$, the constraint can hold with equality while $\lambda = 0$; the local derivatives below apply on the strictly constrained side of that boundary. The active types satisfy $m_i > \lambda q_i$, while inactive types satisfy $m_j \leq \lambda q_j$. Local stability of the active set requires the inactive inequalities to be strict. The objective is strictly concave because each $c_i > 0$, and the feasible set is convex, so the solution is unique. The derivatives are evaluated at positive available capacity and an interior admissible uncertainty level; at zero uncertainty, they are interpreted as right derivatives.

B.4 Uncertainty, Capital, and Borrower Risk

Uncertainty affects lending through the shadow value of risk capacity. Differentiating that value gives

$$\lambda_U = -\frac{C_U}{\Omega_A} = \frac{e^2}{2\Omega_A C} > 0, \quad \lambda_K = -\frac{C_K}{\Omega_A} = -\frac{K}{\Omega_A C} < 0, \quad \lambda_{UK} = -\frac{C_{UK}}{\Omega_A} = -\frac{e^2 K}{2\Omega_A C^3} < 0.$$

Using $\ell_i^* = (m_i - \lambda q_i) / c_i$,

$$\ell_{iU}^* = -\frac{q_i}{c_i} \lambda_U = -\frac{q_i e^2}{2c_i \Omega_A C} < 0,$$

$$\ell_{iUK}^* = -\frac{q_i}{c_i} \lambda_{UK} = \frac{q_i e^2 K}{2c_i \Omega_A C^3} > 0.$$

These derivatives establish Proposition 1. Comparing a high risk and a low risk opportunity with $q_H / c_H > q_L / c_L$ gives

$$\frac{\partial^2 (\ell_H^* - \ell_L^*)}{\partial U \partial K} = \frac{e^2 K}{2\Omega_A C^3} \left(\frac{q_H}{c_H} - \frac{q_L}{c_L} \right) > 0.$$

This is the level-quantity differential. With a continuum of borrower types, the same level result holds pointwise when $q(R) / c(R)$ is increasing and the comparison is infinitesimal relative to the aggregate portfolio.

For proportional rather than level responses, let $D_i = m_i - \lambda q_i = c_i \ell_i^* > 0$ and $x_i = q_i / D_i$. Direct differentiation gives

$$G_i \equiv \frac{\partial^2 \log \ell_i^*}{\partial U \partial K} = -\lambda_{UK} x_i - \lambda_U \lambda_K x_i^2 > 0.$$

The expression is strictly increasing in x_i . Because

$$x_i = \frac{q_i / m_i}{1 - \lambda q_i / m_i},$$

active types satisfy $x_H > x_L$ if and only if $q_H/m_H > q_L/m_L$. Equivalently,

$$G_H - G_L = (x_H - x_L) [-\lambda_{UK} - \lambda_U \lambda_K (x_H + x_L)] > 0.$$

This establishes Proposition 2. Along a fixed continuum of lending opportunities indexed by risk, an increasing $q(R)/m(R)$ gives the corresponding positive third derivative locally.

B.5 Deposit Insurance and the Social Value of Risk Capacity

This subsection adds a deposit insurer to the continuation value setup of Appendix B.2 and asks when the lending that uncertainty releases or withdraws is socially excessive. Under limited liability, the insurer absorbs negative terminal net worth. Its expected loss is

$$I(\bar{N}, \Omega) = E[\max(-N_1, 0)] = \Omega \phi\left(\frac{\bar{N}}{\Omega}\right) - \bar{N} \Phi\left(-\frac{\bar{N}}{\Omega}\right).$$

We call the joint value of shareholders and the insurer social value. It omits borrower surplus and spillovers, which we discuss at the end of this subsection. Social value equals expected net worth plus franchise value times the probability of survival:

$$V - I = \bar{N} + \gamma \Phi\left(\frac{\bar{N}}{\Omega}\right).$$

Differentiating with respect to variance gives

$$\frac{\partial I}{\partial \Omega^2} = \frac{\phi(\bar{N}/\Omega)}{2\Omega} > 0, \quad \frac{\partial(V - I)}{\partial \Omega^2} = -\frac{\gamma \bar{N} \phi(\bar{N}/\Omega)}{2\Omega^3} < 0.$$

With $\bar{N} > 0$, variance always lowers social value, whereas shareholders gain from it in the risk-shifting region. The difference between the private and the social effect of variance is $\partial I/\partial \Omega^2$, the sensitivity of the insurer's expected loss to variance. For given Ω , it decreases in $\bar{N}$, so it is larger at banks with thinner capital.

To link these values to lending, let $Q = \sum_i q_i \ell_i$, so that $\Omega^2 = Q^2 + e^2 U$, and keep lending surplus separate from expected net worth, as above. At a binding limit, one more unit of Q yields lending surplus λ . Its value to shareholders, w_P , and its social value, w_S , are

$$w_P = \lambda + \frac{Q \phi(\bar{N}/\Omega)}{\Omega} \left(1 - \frac{\gamma \bar{N}}{\Omega^2}\right), \quad w_S = \lambda - \frac{\gamma \bar{N} Q \phi(\bar{N}/\Omega)}{\Omega^3}.$$

Their difference, $w_P - w_S = Q \phi(\bar{N}/\Omega)/\Omega$, is the increase in the insurer's expected loss from one more unit of Q .

Proposition 3. *Suppose that the risk limit binds, is imposed by regulation or supervision, and does not depend on U , and that the active set is locally unchanged. A decline in uncertainty of $\Delta U > 0$ then raises Q by $\Delta Q = e^2 \Delta U / (2Q)$ to first order, while total risk Ω and the insurer's expected loss are unchanged. Relative to keeping the reduction in risk, this use of the released capacity changes shareholder value by $w_P \Delta Q$ and social value by $w_S \Delta Q$. If the bank is in the risk-shifting region, $\gamma \bar{N} < \Omega^2$, then $w_P > \lambda > 0$. If in addition $\lambda < \gamma \bar{N} Q \phi(\bar{N}/\Omega)/\Omega^3$, then $w_S < 0$: the released lending raises shareholder value but lowers social value.*

For a given total risk Ω , both elements of this comparison are larger at thinly capitalized banks. The capacity released by a given decline in uncertainty, $e^2 \Delta U / (2Q)$, is larger where available capacity is small. For given total risk, the wedge $w_P - w_S$ is larger where expected net worth is low. The excess of private over social value, $(w_P - w_S) \Delta Q = e^2 \Delta U \phi(\bar{N}/\Omega) / (2\Omega)$, equals the reduction in the insurer's expected loss that the decline in uncertainty would otherwise have delivered.

The comparison also applies in reverse. When uncertainty rises, a fixed limit forces the bank to reduce Q by ΔQ rather than bear more risk. Relative to bearing that risk, the reduction lowers social value by $w_S \Delta Q$, so the contraction is socially excessive when $w_S > 0$. Social value as defined here also omits borrower surplus. When borrowers cannot easily switch lenders, or when lending cuts depress collateral values or aggregate demand, the social cost of a contraction exceeds the lending surplus the bank gives up. The welfare effect of the reallocation is therefore state dependent. Lower uncertainty can release excessive risk taking at thinly capitalized banks, and higher uncertainty can force an excessive contraction there. The empirical analysis identifies relative responses and does not determine which case applies.

B.6 Loan Pricing with Residual Demand

Let residual demand for type i be $s_i(\ell_i) = a_i - d_i \ell_i$ and let f_i be constant expected marginal funding and loss cost. Profit is $(a_i - f_i)\ell_i - d_i \ell_i^2$. Setting $m_i = a_i - f_i$ and $c_i = 2d_i$ recovers the strictly concave capacity-constrained allocation problem. For an active loan, its first-order condition and optimal allocation are

$$a_i - f_i - 2d_i \ell_i = \lambda q_i, \quad \ell_i = \frac{a_i - f_i - \lambda q_i}{2d_i}.$$

Substituting into residual demand gives $s_i^* = (a_i + f_i + \lambda q_i)/2$. Holding residual demand and expected cost primitives fixed,

$$s_{iU}^* = \frac{q_i}{2} \lambda_U = \frac{q_i e^2}{4\Omega_A C} > 0, \quad s_{iUK}^* = \frac{q_i}{2} \lambda_{UK} = -\frac{q_i e^2 K}{4\Omega_A C^3} < 0.$$

For $q_H > q_L$,

$$\frac{\partial^2 (s_H^* - s_L^*)}{\partial U \partial K} = \frac{q_H - q_L}{2} \lambda_{UK} < 0.$$

Higher uncertainty thus raises spreads more on loans with larger risk capacity weights and at banks with less capital. This derivation obtains partial pass-through from the lending problem; it does not establish that linear demand describes mortgage origination or that a county mean rate is a marginal loan spread.

B.7 Correlated Background Risk

Allow correlation $\rho \in (-1, 1)$ between standardized rate and credit losses, holding ρ fixed and taking $U > 0$. With $Q = \sum_i q_i \ell_i$, the risk limit is

$$Q^2 + 2\rho e\sqrt{U}Q + e^2U \leq K^2.$$

Under $K^2 > e^2U$, zero lending is feasible and the upper endpoint of the nonnegative feasible interval is

$$C_\rho = -\rho e\sqrt{U} + D, \quad D = \sqrt{K^2 - (1 - \rho^2)e^2U}.$$

Differentiating gives

$$C_{\rho,U} = -\frac{\rho e}{2\sqrt{U}} - \frac{(1 - \rho^2)e^2}{2D}, \quad C_{\rho,UK} = \frac{(1 - \rho^2)e^2 K}{2D^3} > 0.$$

For nonnegative correlation, uncertainty still reduces available capacity and capital attenuates that reduction. Since $C_{\rho,K} = K/D > 0$, the shadow cost signs and proportional risk differential are preserved on a binding segment with a fixed active set. With sufficiently negative correlation, existing rate exposure can instead hedge credit losses, and $C_{\rho,U}$ can be nonnegative. The contraction and proportional risk differential conclusions are then not guaranteed. The baseline's uncorrelated loss assumption makes clear which exposure comparison delivers its prediction.

B.8 Capital and Residual Exposure across Banks

Uncertainty enters the shadow cost only through e^2U , so, holding capital fixed, a bank with larger residual exposure loses more capacity from the same shock and shows a larger differential across bank capital and borrower risk.

The baseline compares capital while holding residual exposure fixed. If exposure instead varies systematically with capitalization, write $e = e(B) > 0$ and $K = k(B)$, holding the opportunity set fixed. Then

$$C(B, U) = \sqrt{k(B)^2 - e(B)^2 U}, \quad C_{UB} = \frac{e^2 K k' - e e' (2K^2 - e^2 U)}{2C^3}.$$

The loss of available capacity is moderated by capital if and only if

$$\frac{k'}{K} > \frac{e'}{e} \left(2 - \frac{e^2 U}{K^2} \right).$$

The baseline positive cross-partial is recovered when $e' = 0$. If exposure rises sufficiently rapidly with capitalization, this capacity comparison can reverse. A proportional lending differential also depends on the effect of capital on the level of the shadow cost, as in Proposition 2. Capital is consequently informative about capacity under the maintained exposure conditions, rather than a sufficient statistic for it when net exposure varies freely.

As an illustration, suppose residual exposure reflects leverage, so that $e(B) = \delta + 1 - B$, where $\delta \geq 0$ measures the rate sensitivity of assets and $1 - B$ is the share of debt funding. Then $e' < 0$, the condition above holds for every $k' > 0$, and $C_B > 0$ as well, so both propositions keep their signs: a thinner capital buffer then means both less capacity and more rate exposure. Actual exposure also depends on asset and liability repricing, deposit behavior and hedging, so the example indicates a direction rather than a measurement.

B.9 Scope

The shadow cost also determines which types remain active. Holding the active set fixed until an exit occurs, type i leaves the portfolio when λ reaches m_i/q_i , which happens at the uncertainty level $U_i^* = [K^2 - (M_A - \Omega_A m_i/q_i)^2]/e^2$, provided $M_A > \Omega_A m_i/q_i$. Since $\partial U_i^*/\partial K = 2K/e^2 > 0$, a more capitalized bank keeps a type active over a wider range of uncertainty, and among active types those with the highest q_i/m_i exit first. The empirical specifications do not separate this margin from the intensive one: the PPML estimates include zero originations but do not identify exit separately, and the DealScan designs use positive allocations only.

On a binding segment with a fixed active set, total modeled lending $L = \sum_{i \in A} \ell_i^*$ satisfies

$$L_U = -\lambda_U \sum_{i \in A} \frac{q_i}{c_i} < 0.$$

Within this single-bank problem with fixed opportunities and uncorrelated background risk, as uncertainty raises the common shadow cost, inactive types do not enter and every modeled lending quantity weakly falls. Total lending in that opportunity set is therefore non-increasing in uncertainty.

The empirical triple interaction identifies only a relative differential, not either capitalization group's absolute response. Endogenous hedging, capital issuance, loan sales, securitization, and general equilibrium feedback remain outside this one-period partial equilibrium model.