The Bank Churn Channel

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Abstract

Banks have heterogeneous exposures to short rate changes: the difference in the effect of 100bps short rate changes on net interest margins is more than 70bps per dollar of assets across banks. Heterogeneity in interest rate exposure interacts with imperfect competition between banks. Rate changes that negatively affect some banks generate positive spillovers for their competitors. However, these spillovers do not fully counteract the negative direct effect. Consequently, the average interest rate exposure of banks is not a sufficient statistic for the effects of monetary policy. When banks have more disperse rate exposures, rate changes in either direction have more negative effects on lending. We build a model that incorporates both the direct and the competition effects that generate the above results and empirically test them using IV strategies. Together, our results suggest that heterogeneity in banks' interest rate exposures and imperfect competition between banks are important for understanding the effects of monetary policy on the banking sector.

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1 Introduction

This paper studies how heterogeneity in banks' short rate exposures interacts with imperfect competition between banks, affecting monetary policy transmission. On average, banks' net interest margins have low exposure to short rate changes, but there is substantial dispersion in banks' rate exposures: some banks are positively exposed, while others are negatively exposed.[1] We show that short rate changes that negatively affect some banks generate positive spillovers for their competitors: when a bank experiences a negative shock from short rate changes, this increases profits for the banks' competitors, who expand and increase lending. However, bank loans appear to be *imperfectly* substitutable, so the positive spillovers to competitors cannot fully counteract the lending reduction from the negatively affected banks.

Our findings have important implications for monetary policy. First, the findings imply that dispersion in banks' interest rate exposures affects policy transmission. When banks have more disperse rate exposures, rate changes in either direction - increases or decreases - affect lending more negatively, because rate changes harm negatively affected banks more than they help positively affected banks. Therefore, the average net interest margin of banks is not sufficient to summarize monetary policy transmission: the *distribution* of NIM betas across banks - in particular, its dispersion - also matters. We show that, in response to short rate changes, regions with more heterogeneous banks in terms of interest rate exposure experience reduction in lending relative to regions with more homogeneous banks.

Second, since short rate exposures are correlated with features of banks, such as bank age, monetary policy affects the banking industry dynamics: short rate increases lead to exit of old banks, and short rate decreases lead to exit of young banks. We further show that old banks are the major acquirers in most mergers and acquisitions with either a young or an old bank being the target. This implies that monetary policy may impact market structure in the banking sector, through its effects on entry, exit, and M&A.

We begin with a simple theoretical framework to illustrate how the Fed funds rate changes affect banks' profits through the balance sheet channel (Begenau et al., 2015; Drechsler et al., 2018; Begenau and Stafford, 2019; Williams, 2020; Begenau and Stafford, 2021). Banks

[1] Drechsler et al. (2018), Begenau et al. (2015), Begenau and Stafford (2019), Gomez et al. (2020), Williams (2020), Hoffmann et al. (2019).

borrow at the Fed funds rate to make loans with fixed interest rates. Their wealth depends on retained earnings. When the Fed funds rate rises, in the short-run, banks experience a decrease in net interest margins on their outstanding loans because they have to borrow at higher rates while the interest rates on the outstanding loans are fixed. This negative effect is larger for banks with a larger maturity mismatch. In the long-run, however, banks' profits may increase or decrease depending on how the loan spread on newly originated loans changes with the level of the Fed funds rate. The balance sheet channel focuses on the short-run effects: the equity capital of banks doing more maturity transformation is more negatively affected by Fed funds rate increases.

We then analyze how banks' interest rate exposures affect lending, entry, and exit, in an model of imperfect competition between banks. We assume a continuum of banks engage in monopolistic competition. Banks have leverage constraints, so negative wealth shocks inhibit incumbent banks' ability to make loans. Thus, when incumbents' wealth is negatively affected by interest rate changes, incumbents' leverage constraints are more binding, causing them to scale down lending and possibly exit the market. Since bank loans are substitutes, this leads competitor banks to scale up lending, and also promotes the entry of new banks.

Our model thus makes three predictions, which we bring to the data. First, interest rate exposures have a direct effect on lending: when incumbent banks have low (high) NIM betas, interest rate increases will lead incumbents to decrease (increase) lending. Second, banks' responses to interest rates also depend on the interest rate exposures of their competitors. When a bank's competitors tend to have low (high) NIM betas, the bank will tend to scale up (down) lending in response to rate increases. Third, new bank entry should also be sensitive to incumbents' interest rate exposures: when incumbent banks have low (high) NIM betas, interest rate increases tend to increase (decrease) entry. Finally, the model predicts that all three effects should be larger when incumbent banks are poorly capitalized, since their leverage constraints are more likely to be binding, so lending will respond more to changes in wealth.

We test the model predictions using data complied from multiple data sources on bank structural changes, balance sheets, income statements, and loan origination activities. To measure incumbent banks' exposures to interest rate risk, we use the *cash flow approach* widely adopted by policy makers and academic literature.[2] The approach analyzes the

[2]See, for example, Drechsler et al. (2018); Williams (2020); Claessens et al. (2018); Altavilla et al. (2018).

impact of interest rates on banks' income net of expense. We estimate the sensitivity of banks' net interest margin (NIM) to interest rate changes. We find substantial cross-sectional variation in banks' NIM betas: when the Fed Fund rate increases by 100bps, the 1st percentile bank experiences a 31bp drop in net interest revenue per dollar of assets, whereas the 99th percentile bank experiences a 40bp increase in net interest revenue for each dollar of assets.

We begin by testing the direct effect of rate changes on banks. In the baseline OLS specification, we confirm that banks with negative NIM betas experience reduction in net interest margins and equity capital when the short rate rises. We show that, when the short rate increases, banks with lower NIM betas are more likely to exit through mergers and acquisitions or liquidations and lend less. The results are mostly driven by less capitalized banks.

While NIM betas nicely reflect banks' balance sheet exposure to interest rate changes, banks do not choose their balance sheets exogeneously. The identification concern is the possibility that banks' inability to hedge against interest rate shocks, risk taking incentives, or other unobserved bank characteristics are correlated with both their NIM betas and their survival probabilities over monetary cycles.

To address the identification concerns, we adopt an instrumental variables (IV) strategy that exploits variation in the maturity structure of a bank's assets that are driven by local borrowers' maturity preferences for bank loans. To the extent that the geographic distribution of a bank's network is fixed in the short run, the instruments generate variation in banks' balance sheet exposure to short rate changes that are orthogonal to banks' characteristics. We construct the average share of manufacture firms and the average share of small businesses in banks' branch networks in the past five years and show that the two measures significantly affect banks' NIM betas.

With the two instruments, we estimate the two-stage least squares (2SLS) specification. Consistent with the OLS results, when the short rate rises, banks with negative balance sheet exposure to short rate increases are more likely to exit and reduce loan and liquidity provision relative to other banks. Suppose bank X has an NIM beta one standard deviation lower than bank Y. Quantitatively, for every percentage-point increase in the short rate, bank X are 6.6pp more likely to exit than bank Y. At the intensive margin, it reduces balance sheet lending by 1.1 percent and reduces liquidity provision by 5.6 percent.

We then test the competition effect that interest rate changes affect banks by influencing their competitors. We show that a bank's branching and lending decisions are affected more positively by interest rate shocks when these shocks negatively affect their competitors. In our baseline OLS specification, we exploit within-bank variation. We find that, when the short rate increases, the net branch growth and the loan growth of the same bank are higher in counties where competitors have more negative NIM betas.

In the OLS specifications, bank-year fixed effects absorb most of the time series variation in demand factors and profitability at bank-level and county fixed effects absorb time-invariant county characteristics. However, the results are subject to potential identification concerns arising from unobserved county characteristics. For example, credit demand in counties with high NIM beta incumbents may comove less with the short rate than demand in counties with low NIM beta. Such demand effects may bias the OLS estimates – the lending and branching decisions may be driven by changes in local demand rather than the competition effect as desired.

To address the identification concerns, we need to find variation in local incumbents' balance sheet exposure to rate changes orthogonal to local economic conditions. We instrument the NIM betas of banks' in county k using their branch-weighted local manufacturing firms shares and branch-weighted local small business shares. In calculating the instruments, we use incumbents' branches outside county k. By construction, the instruments help identify the variation in local banks' balance sheet exposure to rate changes orthogonal to local economic conditions, to the extent that there is little correlation between county k's demand and the manufacturing firm share and the small business share in other counties.

The IV results confirm our model prediction: When the short rate rises, banks experience higher net branch growth and more lending growth in counties where incumbents have more negative NIM betas, and are thus more negatively affected by the rate increase. For every 100bps increase in the short rate, a bank opens 0.04 more branches and make 126 more loans, if local incumbents' average NIM betas are 1 unit lower. Again, the effect on branching is largely driven by less capitalized banks, which is almost twice the average effect.

Our findings have important implications for monetary policy. First, the results suggest that measuring the effect of monetary policy on single banks is not sufficient due to the spillover effect through competition. When a bank is negatively affected by the short rate changes, its competitor can partially pick up the slack in lending. When the competition is imperfect, the average interest rate exposure is not a sufficient statistic for the effects of monetary policy. An economy with more dispersion in banks' exposures to interest rate shocks tends to have negative aggregate effect of short rate changes on lending.

Empirically, we show that regions with more disperse NIM betas have more negative lending responses to the short rate changes. When the short rate rises, counties with more negatively exposed banks experience reduction in lending relative to counties with less negatively exposed banks, and vice versa. Yet, regardless of a rate increase or decrease, counties with more heterogeneous banks in terms of interest rate exposure experience reduction in lending relative to counties with more homogeneous banks.

Second, we find that short rate exposures are correlated with bank age. This age-interest rate exposure relation, together with our above findings, suggests that monetary policy affects the banking industry dynamics. It implies that short rate increases lead to exit of old banks, and short rate decreases lead to exit of young banks. We further show that old banks are the major acquirers in most mergers and acquisitions with either a young or an old bank being the target. This implies that expansionary monetary policy may lead to increasingly concentrated banking sector. When short rate decreases, more young banks are acquired by old banks, and potential entrants are less likely to enter. As a result, the banking sector becomes more concentrated. The second implication is consistent with rising banking concentration after the financial crisis.

Together, our results suggest that imperfect competition interacting with heterogeneity in banks' interest rate exposures is important for understanding the effects of monetary policy.

Related Literature. This paper mainly contributes to three strands of literature. The empirical banking literature has looked at effect of interest rate changes on the banking sector. An extensive literature finds that bank profits have low exposure to interest rate shocks (Flannery, 1981, 1983; Flannery and James, 1984a,b; English, 2002; English et al., 2018; Purnanandam, 2007; Rampini et al., 2020). Drechsler et al. (2018) provides a risk-management view of banks' maturity mismatch. They argues that banks' deposit franchise gives them market power, making deposits resemble long-term debt and leading banks to hold long-term assets to hedge interest rate risks. They empirically show that there is one-for-one matching between the interest sensitivities of income and expense. On the other hand, some papers find that bank balance sheets are heavily exposed to interest rates. There are also evidence that there are cross-sectional heterogeneity in banks' exposure. Begenau et al. (2015) and Begenau and Stafford (2019) attempt to measure the banking sector's exposure to interest rate risk and find that bank balance sheets are heavily exposed to interest rates. Gomez et al. (2020) argue that banks have heterogeneous exposures to interest rate gaps, and more exposed banks' lending decisions are more sensitive to interest rate changes. Similarly, Williams (2020) and Hoffmann et al. (2019) emphasize that there is substantial cross-sectional heterogeneity in banks' exposures to interest rate risk. Our contribution to this literature is to show that shocks to existing banks also create incentives for new bank entry. This, over longer time horizons, can buffer the effect of shocks on existing banks.

This paper also contributes to a literature on monetary policy pass-through to banks. This literature includes Kashyap and Stein (1995), Bernanke and Gertler (1995), Kashyap and Stein (2000), Kishan and Opiela (2000), Altunbas et al. (2009), Gambacorta (2005), Cetorelli and Goldberg (2012), Brunnermeier and Koby (2018), Williams (2018), Wang (2018), Wang et al. (2020), Zentefis (2020), Balloch and Koby (2020). Another paper studying monetary policy and bank entry is Bisetti et al. (2020). Their paper focuses on regulatory barriers to bank entry and how entry costs affect the transmission of monetary policies, whereas we focus on the asymmetric effects of monetary policies on the banking sector across entrants and incumbents.

This paper contributes to the literature on heterogenoeus banks, and firm dynamics in the banking industry (Corbae, 2013; Coimbra and Rey, 2017; Jamilov, 2020; Jamilov and Monacelli, 2020; Villa, 2020). Relative to these papers, our model is very stylized, and it is not meant to be calibrated in a quantitatively realistic manner. Our main contribution to this literature is to make a simple stylized point: when banks have wealth constraints and do maturity transformation, interest rate changes affect incumbent banks and entrant banks asymmetrically: since incumbents have portfolios with positive duration, interest rate shocks decrease incumbents' weath, and thus stimulate entry. Carlino and DeFina (1998), Gambacorta and Mistrulli (2004), Ashcraft (2006), and Gambacorta and Shin (2018) argue that that monetary policy has heterogeneous effects, depending on bank capitalization.

Outline. The paper proceeds as follows. Section 2 contains our model and its predictions. Section 3 discusses our data, how we measure banks' interest rate exposures, and the determinants of these rate exposures. Section 4 tests our model predictions. Section 5 discusses implications of our results. We conclude in Section 6. Proofs and other supplementary material are presented in the appendix.

2 Model

This section presents our theoretical frameworks in two steps. In subsection 2.1, we use a simple framework to show how short rate changes affect individual banks' net interest margins and wealth. The model distinguishes between the short-run effects and the long-run effects and illustrates that the balance sheet channel focuses on the short-run effects. The model predicts that banks with longer loan maturity are more negatively exposed to interest rate increases: rate hikes will tend to decrease these banks' net interest margins temporarily, which will negatively impact bank wealth.

In subsection 2.2, we construct a model of banking industry equilibrium. The model features imperfect competition between banks, which have heterogeneous interest rate exposures and leverage constraints on lending. We show that, if a bank is negatively exposed to interest rates, rate increases will tend to cause the bank to scale down lending and exit the market, but will cause the bank's competitors, as well as potential entrants, to scale up lending.

2.1 Loan maturity, net interest margins, and bank capital

This subsection constructs a simple model illustrating how interest rate shocks affect banks' net interest margins and wealth. Time is discrete, $t = 1, 2, \ldots \infty$. The Fed Funds rate in period t is ρ_t. Loan rates depend on the Fed Funds rate, according to some function $r(\rho_t)$. We assume $r(\rho_t)$ is strictly increasing, so loan rates increase when the Fed Funds rate increase, but otherwise impose no restrictions on $r(\rho)$.[3]

We consider a single bank, which makes a measure $\frac{1}{M}$ of new loans in each period, funded by borrowing at the Fed Funds rate. The bank receives interest on loans, and pays interest on its Fed Funds borrowing, at the end of each period. We assume banks borrow at floating rates, but that loans take M periods to mature, and loan rates are fixed for M periods.

[3] In particular, the long-run net interest margin $r(\rho) - \rho$ may depend on ρ in an arbitrary manner. This accomodates a variety of arguments in the literature suggesting that net interest margins are affected by the level of interest rates; see, for example, Wang (2018), Ampudia and Van den Heuvel (2018), and Whited et al. (2021)

Thus, when a bank initiates a new loan at rate r, she commits to funding the loan at rate ρ and receiving interest r per period, for M periods.

At the end of period $t > M$, the bank has a unit measure of loans outstanding, from periods $t - M - 1$ to period t. Loans made in period $\tilde{t} < t$ pay the loan rate $r(\rho_{\tilde{t}})$ from period $\tilde{t}$, but the bank must fund them at the current Fed Funds rate ρ_t. Thus, the bank's net interest margin in period t is:

$$NIM_t = \frac{\sum_{\tilde{t}=t-M+1}^{t} \left(r(\rho_{\tilde{t}}) - \rho_t\right)}{M} = \frac{\sum_{\tilde{t}=t-M+1}^{t} r(\rho_{\tilde{t}})}{M} - \rho_t \tag{2.1}$$

Bank wealth. The bank begins with wealth (equivalently, equity capital) $w_{i,0}$. We assume the bank commits to paying out a dividend in each period of

$$r(\rho_t) - \rho_t$$

That is, banks pay out in dividends the long-run average of anticipated earnings per unit of loans made. Since all banks have a unit measure of loans outstanding, this is simply $r(\rho_t) - \rho_t$. This process captures the idea that dividends are related to the long-run profitability of the banking sector; it is also the only dividend process under which banks' wealth stay constant over time, if interest rates are constant. Dividends can alternatively be thought of as investments in capital growth or expansion.

Changes in bank wealth depend on retained earnings from lending and dividend payouts. Banks' wealth evolves as:

$$w_{t+1} = w_t + \left[\underbrace{\sum_{\tilde{t}=t-M+1}^{t} \frac{1}{M}\left(r_{\tilde{t}} - \rho_t\right)}_{Loan\ interest}\right] - \underbrace{\left(r(\rho_t) - \rho_t\right)}_{Dividends} \tag{2.2}$$

Hence, if interest rates are fixed at $\rho_t = \rho$, bank capital stays fixed, since (2.2) is:

$$w_{t+1} = w_t + \sum_{\tilde{t}=t-M+1}^{t} \left(r(\rho) - \rho\right) - M\left(r(\rho) - \rho\right) = w_t$$

Changes in interest rates. Suppose that interest rates are fixed at $\rho_t = \rho$ for $t < \tau$, and increase to $\rho_t = \tilde{\rho} > \rho$ in period $t = \tau$. Thus, the dividends paid out by banks also immediately increase to $r(\tilde{\rho}) - \tilde{\rho}$ for periods $t \geq \tau$. Figure 1 illustrates the effects of this change on banks' average loan rates, net interest margins, and wealth. The bank's average loan rate in period $t \geq \tau$ is the average of new loan rates in periods from $t - M - 1$ to t:

$$\frac{\sum_{\tilde{t}=t-M+1}^{t} r(\rho_{\tilde{t}})}{M}$$

This rearranges to:

$$\bar{r}_t = \max\left[\min\left[\frac{\tau - (t - M + 1)}{M}, 1\right], 0\right] r(\rho) + \max\left[\min\left[\frac{t - \tau + 1}{M}, 1\right], 0\right] r(\tilde{\rho}) \quad (2.3)$$

In words, (2.3) says that, $t - \tau$ periods after the rate changes, the bank will have a fraction $\frac{\tau-(t-M+1)}{M}$ of outstanding loans still paying the old rate $r(\rho)$, and a fraction $\frac{t-\tau+1}{M}$ at the new post-change loan rate $r(\tilde{\rho})$. Once $t > \tau + M - 1$, the bank will have all loans at the new rate $r(\tilde{\rho})$. The second panel of figure 1 illustrates this graphically. Banks with one-period loans, $M = 1$, have no outstanding loans, so their loan rates immediately update to the new loan rate $r(\tilde{\rho})$. Banks with $M > 1$ have average loan interest rates increasing gradually from $r(\rho)$ towards $r(\tilde{\rho})$, because a fraction of loans outstanding are fixed at the old interest rate $r(\tilde{\rho})$.

The third panel shows banks' net interest margins:

$$NIM_t = \max\left[\min\left[\frac{\tau - (t - M + 1)}{M}, 1\right], 0\right] \big(r(\rho) - \tilde{\rho}\big) + \max\left[\min\left[\frac{t - \tau + 1}{M}, 1\right], 0\right] \big(r(\tilde{\rho}) - \tilde{\rho}\big) \quad (2.4)$$

Interest rate changes have short-run and long-run effects on net interest margins. In the long run, net interest margins shift from their initial value $\big(r(\rho) - \rho\big)$ to $\big(r(\tilde{\rho}) - \tilde{\rho}\big)$. This may be an increase or a decrease, depending on the shape of the $r(\rho)$ function, and this change is constant for all banks. However, for $t \leq \tau + M - 1$, there is an additional short-run effect, arising from the fact that banks have outstanding loans. Since $r(\rho)$ is always lower than $r(\tilde{\rho})$, the short-run effect is always negative when rates rise. The effect is larger for banks that do more maturity transformation, since they have a larger fraction of loans at the lower pre-change interest rates.

The bottom panel of figure 1 shows the effect of rate changes on banks' wealth, calculated using (2.2). After rates change, banks with $M > 1$ temporarily make net interest margins lower than the dividend rate $\left(r(\tilde{\rho}) - \tilde{\rho}\right)$, so their wealth declines. Once all outstanding loans have matured, wealth becomes constant over time. Thus, banks that make longer maturity loans experience larger wealth drops, from a change in interest rates.

Discussion. The framework of this section essentially illustrates that banks that do more maturity transformation will have larger negative short-run NIM responses to interest rate increases, and also larger wealth drops from rate increases. This motivates our use of net interest margin betas, calculated as high-frequency correlations of NIMs with interest rates, as a measure of a bank's wealth exposure to interest rate changes. Practically, the model suggests that the horizon of the short-run effect is approximately equal to the maturity of banks' outstanding loans. Empirically, following Drechsler et al. (2018), we measure NIM betas using 3-quarter lags in Fed Funds rate changes, which is likely to capture these short-run effects.

We have considered the effect of interest rate increases; when rates decrease, banks with longer average maturity benefit, because they have some loans with rates higher than market rates. Also, we have assumed that banks always borrow at floating rates and lend at fixed rates. In the data, we find that some banks have positive NIM betas, suggesting these banks engage in a kind of "reverse maturity transformation", with fixed-rate liabilities and floating-rate assets (or, at least, liabilities with more duration exposure than assets). Our model, extended to allow fixed-rate borrowing, would produce the result that banks with more fixed-rate liabilities would have more positive exposure to interest rate increases.

We also note that, as Drechsler et al. (2018) discuss, the "cash flow" approach we use here is essentially isomorphic to an approach measuring the effective duration of banks' portfolios. We use the cash flow approach because it is closer to the NIM betas that we measure empirically.

2.2 Imperfect competition between banks

The model in this subsection builds on the insights from the previous subsection, shows how banks' interest rate exposures affect lending, entry, and exit in industry equilibrium.

2.2.1 Model setup and equilibrium

There is a continuum of infinitisemally small, infinitely long-lived banks. The model is static, and there is a single time period; equivalently, the model can be interpreted as a stationary equilibrium in which all quantities are fixed over time. Banks provide loans to a representative firm, which produces output consumed by a representative consumer. The representative firm behaves competitively, maximizing output taking loan rates as given. The firm produces output using a CRS technology, using only loans as input. Banks produce differentiated varieties of loans l_i, which aggregate to output Λ through a CES aggregator:

$$\Lambda = \left(\int_0^n (l_i)^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}}$$

With slight abuse of notation, we will sometimes call Λ "aggregate loans". We assume $\sigma > 1$. There is a representative consumer with quasilinear utility, who demands output. Consumers' utility for money M and output is:

$$U(\Lambda, A, M) = M + A \frac{\Lambda^{1-\eta} - 1}{1-\eta} \tag{2.5}$$

Intuitively, (2.5) simply implies that consumers have decreasing marginal utility of output. The parameter A affects the level of consumers' utility for output; it can be thought of as an aggregate demand parameter, capturing macroeconomic conditions, such as business-cycle movements in output (and thus credit) demand. The parameter η determines the elasticity of consumer demand. We will assume that:[4]

$$0 < \eta < \sigma \tag{2.6}$$

[4]Expression (2.6) implies that consumers' utility for output is concave, but the concavity of output is not too large, relative to the elasticity of substitution σ between different loan varieties. This assumption implies that bank loans are gross substitutes: if bank j raises r_j, bank i's loan quantity l_i increases.

Since firms behave competitively, loans produced solve the following optimization problem:

$$\Lambda = \max_{l_i} A \frac{\left(\left(\int_0^n (l_i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}\right)^{1-\eta} - 1}{1-\eta} - \int_0^n l_i r_i di \tag{2.7}$$

Given prices posted by all banks r_i, we can define a price index:

$$R \equiv \left(\int_0^n r_i^{1-\sigma} di\right)^{\frac{1}{1-\sigma}} \tag{2.8}$$

R is the optimized unit cost of loans Λ, if the representative firm chooses the loan product mix l_i optimally given prices r_i. Given the price index R, (2.7) can be written as:

$$\max_{\Lambda} A \frac{\Lambda^{1-\eta} - 1}{1-\eta} - R\Lambda$$

Aggregate output is thus a function of A and the price index R:

$$\Lambda (A, R) = \left(\frac{A}{R}\right)^{\eta} \tag{2.9}$$

Banks. There is a continuum of differentiated banks, who set interest rates and supply loans to firms. There are N types of incumbents, indexed by i; incumbents can differ in their initial wealth w_i, their interest rate exposure ν_i, and their operating costs c_i. All banks' cost of funds is the fed funds rate, ρ; that is, to provide loans l_i to firms, the bank borrows l_i and pays back $(1 + \rho) l_i$ at the end of the period, for a net cost of ρl_i.

Bank i has some equity capital w_i. Bank capital is important because it constrains banks' ability to make new loans. We assume banks face a simple leverage constraint on new loans: the volume of loans made to young firms that a bank makes in period t must satisfy:

$$l_i^Y < \Phi w_i$$

where Φ is some positive constant. This leverage constraint can be thought of as a reduced-form model of various intermediation frictions in the banking literature, such as risk limits or moral hazard, or a regulator-imposed capital requirement. We assume that banks cannot raise capital by issuing new equity.

Banks have heterogeneous interest rate exposures. For simplicity, we adopt a reduced-form model of wealth exposures, motivated by the model in the previous subsection. We assume bank i's wealth has some sensitivity ν_i to interest rates: if interest rates increase from ρ to $\tilde{\rho} = \rho + \Delta$, i's wealth changes to

$$\tilde{w}_i = w_i + \nu_i \Delta \tag{2.10}$$

From the previous subsection, we can think of heterogeneity in ν_i as being driven by differences the amount of maturity transformation banks are doing: banks with long loan maturity will tend to have more negative values of ν_i. Banks set interest rates r_i to maximize profits, given their wealth-linked capacity constraints. Given the CES structure of demand, and residual loan demand facing bank i is:

$$l_i(r_i) = \frac{A^\eta R^{\sigma-\eta}}{(r_i)^\sigma} \tag{2.11}$$

If i's capacity constraint is not binding, i optimally set interest rates at a constant markup above their cost of funds ρ:

$$r_i = \rho\left(\frac{\sigma}{\sigma - 1}\right) \tag{2.12}$$

If the rate (2.12) causes banks' leverage constraint to bind, banks instead set r_i so that loan quantity is equal to the constraint; that is,

$$l_i = \Phi w_i, \;\; r_i = \left(\frac{A^\eta R^{\sigma-\eta}}{\Phi w_i}\right)^{\frac{1}{\sigma}}$$

Bank i's gross profits in equilibrium are:

$$\Pi_i = l_i(r_i - \rho)$$

Bank i operates if she anticipates that profits Π_i are at least equal to her operating cost c_i; otherwise, bank i exits and does no lending.

Entrant banks. We assume that there is an infinite mass of potential entrant banks. For simplicity, entrants enter with a large amount of wealth, and are not constrained; this also implies entrants' interest rate exposures are irrelevant, since rate exposures only affect outcomes through their effect on wealth. Entrants enter if they expect gross profits to be at least c_{ent}; we can think of c_{ent} as capturing operating costs and fixed entry costs.

PROPOSITION 1. *Given primitives $\sigma, \eta, \Phi, A, \rho$, incumbent banks' parameters $\{(w_i, c_i)\}_i$, and entrants' cost c_{ent}, there is a unique stationary equilibrium, characterized by price index R, masses of active incumbents $\{n_i\}_i$, loan prices and quantities for each incumbent type $\{l_i, r_i\}_i$, a mass of entrants n_{ent}, and entrants' loan quantities and prices l_{ent}, r_{ent}.*

In words, proposition 1 states that there is always a unique equilibrium of the model, in which incumbents' and entrants price-setting, entry, and exit decisions are optimal, given the equilibrium price index R. To analyze how interest rates affect equilibrium outcomes, we will solve the model given some parameters, and then perturb interest rates, changing incumbents' wealth using (2.10), and then solve again for equilibrium and see how outcomes vary with interest rates.

2.2.2 Predictions

Direct effect of interest rate changes. First, we show how incumbents are affected directly by interest rate changes. Figure 2 solves for equilibrium with a single kind of bank, with negative, zero, and positive exposure to interest rates. We initialize incumbent banks' wealth at different values, making wealth constraints more or less tight. For simplicity, we set $c_{ent} = \infty$, so there are no entrants.

The top-middle plot shows the case in which $\nu_i = 0$. Here, banks' lending is affected by interest rates essentially because of an aggregate demand effect. When rates are higher, loan prices are higher, causing output demand to decrease; banks thus scale down lending.

The top-left plot shows the case in which banks have negative exposure to interest rates, $\nu_i < 0$, so rate increases decrease banks' wealth. If banks are well-capitalized – the yellow line – the left plot is identical to the middle plot, since small changes in bank wealth from interest rate shocks do not affect lending. However, when banks are poorly capitalized and close to their wealth constraints, interest rate increases lead banks to scale down lending more than they do in the middle panel. This is because interest rate increases cause banks' wealth constraints to bind, forcing them to lower lending. The bottom-left panel shows that, when ρ increases sufficiently, incumbent banks begin to exit the market, since they cannot make sufficient profits to cover their operating costs.

The top right panel shows the case when banks have $\nu_i > 0$, so rate hikes increase bank wealth. In this case, when banks are close to wealth-constrained, lowering interest rates ρ can actually decrease banks' lending. The bottom right plot shows that rate decreases eventually lead incumbent banks to exit the market. This leads to our first set of predictions.

PREDICTION 1. *If incumbent banks are negatively (positively) exposed to interest rates, rate increases will decrease (increase) lending and increase (decrease) exit. Both effects are stronger when incumbent banks are poorly capitalized.*

Competitive effects of interest rate changes. Next, we explore how incumbents are affected by interest rate shocks to their *competitors*. Figure 3 solves for equilibrium with two kinds of banks: incumbents who are poorly capitalized and exposed to interest rates, and incumbents who have no exposure. The middle panel shows the case in which both kinds of incumbents have no interest rate exposure. For simplicity, we set $c_{ent} = \infty$.

As we showed in the previous subsection, the left panel shows that, when interest rates increase, incumbents who have $\nu_i < 0$ scale down. However, their *competitors* scale up lending. Intuitively, this is because loans are substitutes: when some banks are forced to scale down due to negative wealth shocks, this generates upwards pressure on loan prices R, and increases loan quantities and profits for unaffected incumbents.[5]

The right panel shows that the case where some incumbents have $\nu_i > 0$ is analogous: interest rate increases cause exposed incumbents to scale down, and causes their competitors to scale up. This leads to our second set of predictions.

PREDICTION 2. *If a given bank's competitors are negatively (positively) exposed to interest rates, rate increases will increase (decrease) lending and decrease (increase) exit. Both effects are stronger when the bank's competitors are poorly capitalized.*

Finally, we show that the effects of rate shocks on entrants are similar to the effects on unexposed competitors. Figure 4 solves for equilibrium with a single set of incumbents, who have negative, zero, or positive, interest rate exposures, allowing for entry. Comparing the middle panels to the left panels, when incumbents are negatively exposed to interest rates, rate increases tend to promote entry, since rate increases force incumbents to scale

[5]If the unaffected incumbents are at their wealth constraints, they cannot scale up lending; however, their prices r_i will increase, and thus their profits will increase.

down, increasing potential profits for entrants. Analogously, when incumbents are positively exposed, rate decreases promote entry. Both effects are stronger when incumbents' wealth constraints are more binding. This leads to our third set of predictions.

PREDICTION 3. *If incumbent banks are negatively (positively) exposed to interest rates, rate increases are associated with higher (lower) bank entry. Both effects are stronger when incumbent banks are poorly capitalized.*

3 Data and Estimation

3.1 Data

Bank Balance Sheet. Data on quarterly banks' balance sheet and income statement data are compiled using FFIEC-031, and FFIEC-041 forms. Where available, we calculate the variables as in Drechsler et al. (2017) and Drechsler et al. (2018). Where variable codes for banks with domestic offices only (reporting FFIEC 041) and banks with domestic and foreign offices banks (reporting FFIEC 031) differ, we standardize the codes to the latter's. Where variable codes change over time, we use multiple codes. Second,

Bank Structural Change. Data on bank structural changes are from the Federal Financial Institutions Examination Council. The Transformation table provides information on mergers and failures in the banking sector that occurred since 1976. We obtain the data from National Information Center. Using this data set, we define bank exits as (1) mergers in which the bank ceases to exist or transfers at least 95 percent of its assets to other banks; or (2) failure in which the bank fails and ceases to exist and government assistance was provided. In the case of mergers, we also collect acquirer information to analyze asset disposition when banks exit.

We complement the above data with bank branching information from 1994 to 2019 from the FDIC Summary of Deposits. The data covers the universe of bank branches. We use this data to find branch opening and closures for every bank in each county from 1994 to 2019.

Bank Lending. We obtain small business lending data collected under the Community Reinvestment Act from the Federal Financial Institutions Examination Council. The CRA requires periodic evaluation of each insured depository institution's record in helping meet the credit needs of its entire community. We obtain the data from 1996 to 2016.

County Business Patterns. We construct local manufacturing firm share and small business share using County Business Patterns (CBP) data published by the US Census Bureau. The data track employment by county and industry from 1946 to the present. The original data are subject to data limitations: (1) suppressed employment information for the majority of county-industry due to confidentiality, and (2) industry classifications change over time. Therefore, we use the data sets complied by Eckert et al. (2020) that address these issues.

Fed Funds Rate Data. We obtain the monthly effective Fed funds rate from Federal Reserve Economic Data (FRED). We take the December rate of each year to convert the data to annual frequency for the main analysis. For estimation of bank betas, we take the quarter-end rate to convert the data to quarterly frequency.

County Controls. We obtain data on county-level economic conditions, such as income per capita, population, and employment, from the Bureau of Economic Analysis and the Bureau of Labor Statistics.

3.2 Banks' Interest Rate Exposures

To measure banks' exposures to interest rate risk, we use the *cash flow approach* widely adopted by policy makers and academic literature.[6] The approach analyzes the impact of interest rates on banks' income net of expense. We estimate the sensitivity of banks' net interest margin (NIM) to interest rate changes:

$$\Delta NIM_{it} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i\tau} \Delta FedFunds_{t-\tau} + \varepsilon_{it} \tag{3.1}$$

$\Delta NIM_{i,t}$ is the change in bank i's net interest margin. $\Delta FedFunds_t$ is the change in the Fed funds rate from t to $t-1$. α_i and η_t are bank and time fixed effects, respectively. Equation 3.1 effectively estimates the cumulative effect of four quarters of Fed Funds rate shocks on banks' income and expense, which captures the persistent effect of interest rate changes.

[6] See, for example, Drechsler et al. (2018); Williams (2020); Claessens et al. (2018); Altavilla et al. (2018).

We then find the sensitivity of bank i's net interest margin to interest rate changes by summing over the estimated $\beta_{i,\tau}$'s for each bank:

$$\beta_i \equiv \sum_{\tau=0}^{3} \beta_{i,\tau}$$

The NIM beta measures the sensitivity of a bank's interest revenue to the Fed funds rate. For example, a bank with a beta of -0.1 experiences a reduction of net interest margin - interest revenue per dollar of assets - by 10bps for every 100bps increase in the Fed funds rate.

For our panel analysis, we estimate Equation 3.1 using 3-year quarterly rolling samples proceeding each period of estimation to obtain time series interest rate exposure for each bank. This ensures that we capture the existing balance sheet exposure to interest rate changes.

To analyze the competition channel, i.e., rate changes that negatively affect a bank's competitors generate positive spillovers for itself, we construct a beta for each county as the weighted average of NIM betas of all banks that conduct business in that county:

$$\beta_k = \sum_{i \in \mathbb{I}^k} s_{ik} \beta_i \tag{3.2}$$

Therefore, a high-beta county is the one whose incumbent banks have higher ex-ante balance sheet exposure to interest rate changes. Figure 7 shows the geographic distribution of banking sector's exposure to interest rate shocks. There are many markets in which the local banking sector has positive or negative exposure to interest rate risk.

3.3 Summary Statistics

Figure 5 shows the distribution of NIM betas across banks. Panel (a) is estimated using the full time series from 1984 to 2019. Panel (b) is estimated using 3-year rolling samples from 1984 to 2019. Consistent with the existing literature, the average effect of changes in the Fed Fund rate on banks' net interest margin is small. The average NIM beta is 0.01 in Panel (a): A 100 basis-point increase in the Fed Fund rate leads to a 0.8 basis-point increase in the net interest margin for an average bank. However, there is substantial dispersion in

NIM betas: the 1st percentile of NIM betas is -0.31, and the 99th percentile is 0.4.[7] In other words, when the Fed Fund rate increases by 100bps, the 1st percentile bank experiences a 31bp drop in net interest revenue per dollar of assets, whereas the 99th percentile bank experiences a 40bp increase in net interest revenue for each dollar of assets. We reach similar conclusions from the rolling-window estimates in Panel (b): in response to a 100 basis-point increase in the Fed Fund rate, the average bank experiences only 2 basis-point reduction in net interest margin, but the impact ranges from -167 basis points to 103 basis points across banks.[8]

To understand the fundamental differences across banks with positive and negative interest rate exposures, we present balance sheet compositions for banks in each NIM beta quintile in Table 1. We find the average balance sheet compositions from 1984 to 2019 for every bank, and then find the group average for every NIM beta quintile. Table 1 highlights the heterogeneity in banks' asset holdings across NIM beta quintiles. Banks with negative NIM betas tend to hold more residential mortgage loans and less commercial real estate loans: total real estate loan share is identical across NIM beta quintiles, whereas the residential mortgage loan share declines as banks move from the lowest NIM beta quintile to the highest NIM beta quintile. Banks with negative NIM betas also tend to hold more consumer loans, agricultural loans, and securities, which are typically long term, whereas banks with the most positive NIM betas hold more cash and reserves as well as more commercial and industrial loans. In contrast to the heterogeneous asset composition, the liability side is rather homogeneous. Banks across NIM beta buckets have nearly identical financial structure in terms of core deposit-wholesale funding ratios and equity ratios. The homogeneous financing structure is in line with the literature on bank capital structure (Hanson et al., 2015; Jiang et al., 2020). In Appendix B we confirm the above findings in regression settings; we also find that the majority of variation in NIM betas across banks is driven by differences in the sensitivity of interest income to interest rates.

[7] For panel (a), NIM betas are truncated at the 1st and 99th percentiles to remove outliers.

[8] Beta estimates are truncated at 5th and 95th percentiles to remove outliers.

4 Empirical results

Given the cross-sectional variation in banks' interest rate exposure, we study the heterogeneous effects of monetary policies in this section. First, subsection 2.1 tests the direct effect of interest rates on banks, prediction 1 of the model: when rates increase, banks with more negative NIM betas tend to reduce lending and exit. Subsection 4.2 then tests predictions 2 and 3, stating that incumbent banks tend to increase lending, and new bank entry increases, when competitors in a market are negatively affected by interest rate changes. In each subsection, we start with the baseline OLS specification. We then discuss the identification concerns and present instrumental variable (IV) results.

4.1 Baseline Effects of Monetary Policy

4.1.1 OLS Specification

Prediction 1 of the model states that incumbent banks are more likely to exit when the fed fund rate increases if their profits are more negatively affected by the interest rates, that is, if they have more negative NIM betas, and if they are poorly capitalized. We test this prediction by examining (1) exit through liquidation or mergers and acquisitions and (2) lending and liquidity provision.

We estimate the following specification at bank-year level:

$$Outcome_{it} = \alpha_t + \eta\beta_{it}^{NIM} + \gamma\left(\beta_{it}^{NIM} \times \Delta FF_t\right) + X_{it}\Gamma + \epsilon_{it} \tag{4.1}$$

The outcome variable is either bank exit - an indicator for whether bank i is acquired or liquidated in year t - or growth in lending and liquidity provision. $\beta_{i,t}^{NIM}$ is bank i's net interest margin sensitivity to interest rate changes in the three years proceeding year t. ΔFF_t is the change in fed fund rates from $t-1$ to t. α_t are year fixed effects. X_{it} are bank controls, including lagged size and capitalization.

Panel A of Table 2 reports the exit results. We estimate 4.1 using various forms of NIM betas and changes in the Fed Fund rate. Column 1 interacts NIM betas with changes in the Fed Funds rate: the coefficient is negative and significant. To interpret this, consider two banks, X and Y, where X's NIM beta is one standard deviation lower than Y's: that is, X's

NIM is more negatively affected by short rate increases. Column 1 implies that, for every percentage-point increase in the short rate, bank X becomes 22bps more likely to exit the market, relative to bank Y.[9]

Prediction 1 also states that the exit effect should be stronger for less well-capitalized banks. Column 4 further interacts NIM betas and Fed Funds rate shocks with an indicator, which is equal to 1 if the bank's capital ratio is in the top quartile among banks in the same year. The interaction effect is positive and significant, in line with prediction 1. Quantitatively, if banks X and Y are poorly capitalized, a percentage point increase in the short rate makes X 81bps more likely to exit than Y; if both banks are in the top quartile of capitalization, X is only 16bps more likely to exit than Y.

Columns 2, 3, 5, and 6 show that these results are robust to different ways to measure the interaction effect between NIM betas and Fed Funds rate shocks. In columns 2 and 5, we replace the raw value of NIM beta with an indicator that equals 1 if the NIM beta is positive. In columns 3 and 6, we replace the raw value of the Fed Fund rate change with an indicator that equals 1 if the Fed Fund rate increases. In all cases, results are qualitatively and quantitatively similar to the findings from the baseline specification. All coefficients are significant except for the interaction effect in column 6.

Next, in Panel A of Table 3, we study how interest rate exposures affect banks' loans and liquidity provision responses to interest rate changes. In columns 1 and 2, we first confirm that banks with negative NIM betas experience reduction in net interest margins and equity capital (wealth) when the short rate rises. We then show the effects on banks' loans and liquidity provision in columns 3 and 4. Once again, consider two banks, X and Y, where X's NIM beta is one standard deviation lower than Y's (so X is more negatively affected by rate increases). Column 3 shows that, when the short rate rises by 1 percentage point, bank X experiences 0.3 percent reduction in balance sheet lending relative to bank Y. Column 4 shows that bank X's liquidity provision decreases by 0.08 percent relative to bank Y's. The effect on lending is statistically significant but economically small, while the effect on liquidity provision is neither statistically nor economically significant. In the following subsection, we show that both effects are statistically and economically significant in IV specifications and discuss the possible reasons.

[9] The standard deviation of NIM betas estimated using the three-year rolling samples is 1.37. Thus, with the estimated coefficient of -0.16 in column 1, the effect on banks with one standard deviation lower NIM beta is $1.37 \times 0.16 = 22bps$. The average exit rate is about 4.6% since 1980s.

4.1.2 2SLS Specification

To interpret the above results correctly, we need to address potential identification concerns. While NIM betas nicely reflect banks' balance sheet exposure to interest rate changes, banks do not choose their balance sheets exogeneously. The balance sheets' exposure to changes in the short rate may vary across banks for many fundamental reasons besides the observed balance sheet characteristics as discussed in the previous section. The identification concern is the possibility that banks' inability to hedge against interest rate shocks, risk taking incentives, productivity in lending long-term (e.g., if some banks are better at monitoring), or other unobserved bank characteristics are correlated with both their NIM betas and their survival probabilities over monetary cycles.

To address the identification concerns, we adopt an instrumental variables (IV) strategy that generates variation in lenders' balance sheet exposure to rate changes orthogonal to unobserved bank characteristics.

Our IV strategy exploits variation in the maturity structure of a bank's assets that are driven by local borrowers' maturity preferences for bank loans. To the extent that the geographic distribution of a bank's network is fixed in the short run, the instruments generate variation in banks' balance sheet exposure to short rate changes that are orthogonal to banks' characteristics. Literature shows that small firms reply more on bank loans due to lack of access to capital market, and borrower industry affects their preferences for debt maturity. Motivated by this fact, we construct the average share of manufacture firms and the average share of small businesses in banks' branch networks in the past three years and show that the two measures are significantly associated with banks' NIM betas:

$$\begin{aligned}\%Manufacture_{jkt} &= \sum_k w_{jkt} \times \frac{ManufactureFirms_{kt}}{TotalFirms_{kt}} \\ \%SmallBusiness_{jkt} &= \sum_k w_{jkt} \times \frac{\#EmployeeSmallBusiness_{kt}}{\#EmployeeTotal_{kt}}\end{aligned} \tag{4.2}$$

Manufacture firms include firms in sectors like agriculture, forestry, fishing, hunting, mining, construction, and manufacturing. *Small businesses* are defined as establishments with less than 10 employees, which is the sample median number of employees. Figure 6 visualizes the relationship between NIM beta and our two instruments. Banks in areas with more manufacturing firms or small businesses tend to have more negative NIM betas.

With the measures for local borrowers' maturity preference, we estimate the following two-stage least squares (2SLS) specifications:

$$
\begin{aligned}
\beta_{jt}^{NIM} =& \alpha\% Manufacture + \beta\% Manufacture \times \Delta FF \\
& + \delta\% SmallBusiness + \gamma\% SmallBusiness \times \Delta FF + X_{jt}\Gamma + \mu_t + \epsilon_{it} \\
\beta_{jt}^{NIM} \times \Delta FF =& \alpha\% Manufacture + \beta\% Manufacture \times \Delta FF \\
& + \delta\% SmallBusiness + \gamma\% SmallBusiness \times \Delta FF + X_{jt}\Gamma + \mu_t + \epsilon_{it} \\
Outcome_{jt} =& \eta(\widehat{\beta_{jt}^{NIM} \times \Delta} FF) + \gamma\widehat{\beta_{jt}^{NIM}} + X_{jt}\Gamma + \mu_t + \epsilon_{it}
\end{aligned}
\tag{4.3}
$$

The first two equations are the first-stage. The first equation is for NIM beta, and the second one is for its interaction with short rate changes. There are four instruments in total: share of manufacturing firms, share of small businesses, and their interactions with short rate changes. The last one is the second-stage equation. $Outcome_{jt}$ are exit indicator, loan growth, changes in loan to assets ratio, deposit growth, and deposit to leverage ratio, respectively. X_{jt} are bank controls like lagged log assets and lagged capital ratios.

Panels B of Table 2 report the exit results from the 2SLS specification. In Panel B, columns 1-2 show the first stage, and column 3-5 shows the second stage. Column 3 uses the full sample of banks, in which the NIM betas are estimated using three year rolling samples from 1984 to 2019. Columns 4-5 then divide banks into less capitalized and more capitalized, depending on whether a bank's capital ratio is above median among all banks in a particular year. All columns include year fixed effects and bank controls.

The first-stage results are strongly negative, similar to what we showed in Figure 6. Column 3 shows that, consistent with the OLS results, banks with negative balance sheet exposure to short rate increases are more likely to exit when the short rate rises. The IV result is somewhat larger than the OLS results: quantitatively, when bank X has a 1 standard deviation lower NIM beta than bank Y, for every percentage-point increase in the short rate, bank X becomes 6.6pp more likely to exit than bank Y.[10] Column 4 shows that the effect is stronger for less capitalized banks; the coefficient in column 5, for banks with above-median

[10] The standard deviation of NIM betas estimated using the three-year rolling samples is 1.37. Thus, with the estimated coefficient of -4.8 in column 3, the effect on banks with one standard deviation lower NIM beta is $1.37 \times 4.8 = 6.6pp$. The average exit rate is about 4.6% since 1980s.

capitalization, is smaller and insignificant.

Panel B of Table 3 reports the second stage for lending and liquidity provision analyses. The first stage is the same as the exit analysis. Columns 1 and 2 confirm that banks with negative NIM betas experience reduction in their net interest margin and wealth when the short rate rises. For every percentage point increase in the short rate, a bank experience 6.1 percentgae points reduction in its net interest margin and 8.4 percent reduction in its equity capital, if its NIM beta is 1 unit lower. Columns 3 and 4 show the effects on lending and liquidity provision. In response to one percentgae point increase in the short rate, a bank reduces loan provision by 1.1 percent and reduces liquidity provision by 5.6 percent if its NIM beta is one unit lower.

Besides the deposit growth result, all effects have the same sign as the OLS results, but are somewhat larger in magnitude. This could be because IV estimates the local average treat effect, while OLS estimates are the average treatment effect over the entire population of banks. Local manufacture and small business shares shift the behavior of a subgroup of banks for whom the effect of interest rate exposure is larger than average. In other words, the IV estimate is the effect of interest rate exposure for banks whose NIM betas are affected by the local manufacture and small business shares. IV estimates are larger than OLS estimates because of heterogeneity in the studied groups.[11]

To summarize, both the OLS and 2SLS results suggest that, when interest rates increase, banks with lower NIM betas tend to exit more, lend less and lower loan-to-assets ratios, and lower wholesale funding as a fraction of their liabilities. These results are mostly driven by low-capitalization banks.

[11]The measurement errors and the omitted variable concerns may lead to an upward bias, instead of a downward bias, and thus are not likely explain the difference between the OLS and the 2SLS estimates. For example, negative NIM betas may reflect banks' inability to hedge against interest rate shocks or risk taking incentives. Since expansionary monetary policies usually take place during economic downturns, the OLS estimates could also capture the effects of banks' lack of hedging or risk taking. In other words, such measurement errors could lead to an overestimate of the baseline effects predicted by our model; whereas the difference between the 2SLS estimates and the oLS estimates suggest an underestimate of the OLS specification.

4.2 Spillover Effects on Competitors

4.2.1 OLS Specification

Predictions 2 and 3 of the model show that interest rate changes also affect banks by influencing banks' *competitors*. We test this prediction empirically by showing that a bank's branching and lending decisions are affected more negatively by interest rate shocks, when these shocks have more positive impacts on the bank's competitors. We estimate specifications at the bank-county-year level, of the following form:

$$Outcome_{jkt} = \alpha_{jt} + \mu_k + \eta(LocalBeta_{kt} \times \Delta FF_t) + X_{kt}\Gamma + \epsilon_{jkt} \tag{4.4}$$

$LocalBeta \equiv \sum_{i \in \mathbb{I}^k} w_{ikt}\beta_{it}^{NIM}$ is the weighted average of local incumbents' NIM betas in county k in year t; it thus captures the average exposure of banks in county k, year t to interest rate shocks.

We examine two outcome variables, $Outcome_{jkt}$. The first is the net change in bank j's branch number in county k in year t: this captures j's decisions to open new branches, or close existing branches. For the branching analysis, incumbents $i \in \mathbb{I}^k$ are defined as banks with at least one branch in county k in year t; and incumbents' NIM betas are weighted by their numbers of branches in county k.

The second dependent variable is the change in small business lending volume of bank j, in county k, from year $t-1$ to t. For the lending analysis, incumbents are defined as banks that provide a loan in county k in year t; and incumbents' NIM betas are weighted by their numbers of loans in county k.

If prediction 2 holds, η should be negative: when the short rate increases, a given bank j tends to have higher branch growth (loan growth) when the bank's competitors have lower NIM betas, since j's competitors in these counties are more negatively affected by rate increases.[12]

In specification 4.4, μ_k are county fixed effects, which control for time-invariant county-level variation, such as market size and baseline economic conditions. X_{kt} is a set of county-year controls like income per capita, employment rate, log population, and average capital

[12]Ideally, we would like to compute the average NIM betas using bank j's competitors in county k; i.e., $\sum_{j'} w_{j'kt}\beta_{j't}^{NIM}$. Since we include bank-year fixed effects, the current specification yields the same interpretation.

ratios of incumbent banks. Lastly, α_{jt} is bank-year fixed effects. Since we include bank-year fixed effects, η are identified from variation within banks across counties: whether, when rates rise, a given bank tends to have higher branch growth (loan growth) in counties where the bank's competitors have lower NIM betas.

Columns 1-3 of Table 4 presents the results on bank branching. For the estimation, we construct a balanced sample to capture the entry and exit decisions. A bank-county pair appears in every year as long as the bank presents in that county over our sample period. In columns 1, the estimate of η is negative, consistent with our prediction: when the short rate increases, banks' net branch growth is higher in counties where competitors have more negative NIM betas. Columns 2 and 3 split the sample based on whether local incumbents' capitalization is above median among all counties: once again, the effect is largely driven by low-capitalization banks. The estimate of η in column 4 is smaller than the estimate in column 3. We formally discuss the economic magnitude of the results in the next section, in which we discuss the IV results.

Panel A of Table 5 presents the lending results. We estimate Equation 4.4 using bank-county level lending in every year from 1999 to 2016 from the Community Reinvestment Act (CRA) database. Column 1 reports the full sample results, and columns 2-4 report the results by loan size bucket. The estimate of η is negative: when rates increase, banks' net loan growth is higher in counties where their competitors have more negative NIM betas. Quantitatively, consider two counties, X and Y, and suppose the average NIM beta of banks in county X is one unit higher than that of incumbents in county Y. For every one percentage point increase in the short rate, a bank will makes 15 fewer loans in county X compared to county Y. The effect is more salient for loans below \$100,000, as shown in column 2. The estimated η is close to zero for loans above \$100,000, reported in columns 3-4.

4.2.2 2SLS Specification

In the OLS specifications, bank-year fixed effects absorb most of the time series variation in demand factors and profitability at bank-level and county fixed effects absorb time-invariant county characteristics. However, the results are subject to potential identification concerns arising from unobserved county characteristics. For example, credit demand in counties with high NIM beta incumbents may comove less with the short rate than demand in counties with low NIM beta. Such demand effects may bias the OLS estimates - the lending and branching decisions may be driven by changes in local demand rather than the competition effect as desired.

To address the identification concerns, we need to find variation in local incumbents' balance sheet exposure to rate changes orthogonal to local economic conditions. Following our estimation of the baseline effects in Section 4.1, we instrument the NIM betas of banks' in county k using their branch-weighted local manufacturing firms shares and branch-weighted local small business shares. In calculating the instruments, we use incumbents' branches outside county k, that is,

$$\begin{aligned} IV^M_{kt} &= \sum_{j \in \mathbb{J}^k} w_{jkt} \sum_{k'} w_{jk't} \% Manufacture_{jk't} \\ IV^S_{kt} &= \sum_{j \in \mathbb{J}^k} w_{jkt} \sum_{k'} w_{jk't} \% SmallBusiness_{jk't} \end{aligned} \tag{4.5}$$

To construct the IVs for county k's NIM beta, we begin with the set of banks in market k in year t, indexed by $j \in \mathbb{J}^k$. For each bank in this set, we find the manufacturing firm share $\%Manufacture_{jk't}$ in each of the counties outside county k where it conducts business. We weight each market k' by its weight $w_{jk't}$ in bank j's branching to account for geographic concentration. Lastly, we find the weighted average NIM betas of all banks in county k. By construction, the instruments help identify the variation in local banks' balance sheet exposure to rate changes orthogonal to local economic conditions, to the extent that there is little correlation between county k's demand and the manufacturing firm share and the small business share in other counties.

With the instruments for local banks' NIM betas, we estimate the following IV specifications:

$$Outcome_{jkt} = \alpha_{jt} + \mu_k + \eta(\widehat{LocalBeta_{kt}} \times \Delta FF_t) + \delta \widehat{LocalBeta}_{kt} + X_{kt}\Gamma + \epsilon_{jkt} \tag{4.6}$$

where the average NIM beta of banks in county k, $LocalBeta$, and its interaction with short rate changes, $LocalBeta \times \Delta FF$, are instrumented by IV^M_{kt}, IV^s_{kt}, and their interactions with the Fed funds rate changes.

Columns 4-6 of Table 4 reports the branching results from the 2SLS specification. Column

4 uses the full sample of banks, in which the NIM betas are estimated using three year rolling samples from 1984 to 2019. Columns 5-6 divide banks into less capitalized and more capitalized, depending on whether local incumbents' capitalization is above median among all counties in a particular year. All columns include year fixed effects and bank controls.

The results from the 2SLS specifications are consistent with the OLS results. Column 4 shows that, when the short rate rises, banks have higher net branch growth in counties where incumbents have more negative NIM betas, and are thus more negatively affected by the rate increase.For every percentage point increase in the short rate, a bank closes 0.4 more branches, if its competitors' average NIM betas are 1 unit higher. Columns 5 and 6 split the sample depending on incumbents' capitalization. The effect is largely driven by low-capitalization banks: the estimate of η in column 5 is almost twice the effect in column 4, whereas the estimate in column 6 is smaller and insignificant.

Panel B of Table 5 reports the lending results from the 2SLS specification. Column 1 reports the full sample results, and columns 2-4 report the results by loan size bucket. The estimate of η in column 1 shows that, when the short rate increases by 100bps, a bank makes 126 more loans in counties where their competitors' NIM betas are one unit lower. The effect is more salient for loans below \$100,000, as shown in column 2. The estimated η is significantly smaller for loans above \$100,000 in column 3 and close to zero for loans above \$250,000 in column 4.

The IV results are larger than the OLS results. There are two possible reasons.[13] First, the omitted variable, such as local demand responses to monetary policy, could be negatively correlated with local incumbents' NIM betas, which leads to a downward bias in the oLS estimate. Lastly, IV estimate could be large than the OLS because IV estimates the local average treat effect, while OLS estimates are the average treatment effect over the entire population. Local manufacture and small business shares shift the behavior of a subgroup of banks for whom the effect of interest rate exposure is larger than average. In other words, the IV estimate is the effect of local incumbents' interest rate exposure for counties whose

[13] While incumbents' NIM beta is a noisy predictor of incumbents' interest rate exposures, the measurement errors may lead to an upward bias, instead of a downward bias, and thus are not likely explain the difference between the OLS and the 2SLS estimates. For example, negative NIM betas may reflect banks' inability to hedge against interest rate shocks or risk taking incentives. Since expansionary monetary policies usually take place during economic downturns, the OLS estimates could also capture the positive spillover effects of competitors' lack of hedging or risk taking. In other words, such measurement errors could lead to an overestimate of the spillover effects predicted by our model; whereas the difference between the 2SLS estimates and the oLS estimates suggest an underestimate of the OLS specification.

incumbents' NIM betas are affected by the local manufacture and small business shares. IV estimates are larger than OLS estimates because of heterogeneity in the studied groups.

Overall, we have shown that, when rates increase, banks open more branches, and increase lending, in counties where incumbents are more negatively affected by rate increases. This provides evidence that bank loans are substitutes: banks respond to interest rate-induced shocks to their competitors.

5 Discussion and Implications

5.1 Regional Aggregate Effects

An implication of our results is that, in a banking market with more dispersion in NIM betas across banks, the aggregate effect of interest rate changes - either increases or decreases - on lending should be more negative. Intuitively, this occurs because negatively affected banks scale down lending more than positively affected banks scale up. We formally demonstrate this effect within our model, in appendix A.2.

To test the implication, we estimate the effects of the absolute value of Fed Funds rate changes, interacted with the mean and standard deviation of incumbent banks' NIM betas, on county aggregate loan supply:

$$\begin{aligned} LendingPerCapita_{kt} =& \alpha_k + \eta(LocalBeta_{kt} \times |\Delta FF_t|)) \\ &+ \delta(LocalBetaDispersion_{kt} \times |\Delta FF_t|)) + X_{kt}\Gamma + \mu_t + \epsilon_{kt} \end{aligned} \tag{5.1}$$

$LendingPerCapita_{kt}$ is the total lending, measured as either loan counts or dollar volume, scaled by population in county k in year t. As before, $LocalBeta_{kt}$ is the lending weighted average NIM beta of incumbents in county k in year t. $LocalBetaDispersion \equiv Dispersion(\beta_{it}^{NIM}, i \in \mathbb{I}^k)$ is the standard deviation of incumbents' NIM betas in county k in year t. $|\Delta FF_t|$ is the absolute value of short rate changes in year t.

Table 6 reports the results. Panel A shows the effects on loan counts per thousand population. Panel B shows the effects on dollar volume. Across both panels, the coefficient estimate on the mean NIM beta, η, is insignificant in most specifications, but the coefficient estimate on the dispersion in NIM betas, δ, is negative and significant in all specifications:

regions with more disperse NIM betas have more negative lending responses to Fed Funds rate shocks. We then divide the sample into years with short rate increases and years with short rate decreases in panel C. Consistent with our baseline effect, when the short rate rises (columns 1 and 3), counties with more negatively exposed banks experience reduction in lending relative to counties with less negatively exposed banks, and vice versa (columns 2 and 4). Yet, regardless of a rate increase or decrease, counties with more heterogeneous banks in terms of interest rate exposure experience reduction in lending relative to counties with more homogeneous banks.

The results imply that the average net interest margin in a region is not sufficient to summarize monetary policy transmission: the *distribution* of NIM betas across banks - in particular, its dispersion - also matters for policy transmission.

5.2 Reallocation Across Bank Types

Banks' interest rate exposures are correlated with features of banks, such as bank age. As a result, interest rate changes induce reallocation within the banking sector, favoring younger or older banks.

Figure 8 shows that NIM beta decreases with bank age. We make simple cuts of raw data and plots banks' NIM beta by age. Betas are estimated using quarterly bank call report data from 1984 to 2019. Age is the number of years since the establishment date by 2020. We group banks into 5-year age bucket and find the average NIM beta in each age bucket. Panel A shows a strong negative correlation between NIM beta and bank age. Moreover, the negative relationship holds in each asset size bucket, as shown in Panel B-E.

Since old and young banks have different NIM betas, monetary policy affects banking industry dynamics: short rate increases lead to exit of old banks and short rate decreases lead to exit of young banks. Figure 9 confirms this intuition: it shows that young banks (less than 50 year old) and old banks (180-200 year old) are most likely to exit. Figure 9 further shows that old banks are the major acquirers in most M&A deals with either a young or an old bank being the target.

This has important, different implications for expansionary monetary policy and contractionary monetary policy. On the one hand, it implies that expansionary monetary policy may lead to increasingly concentrated banking sector. When the short rate decreases, more young banks are acquired by old banks, and potential entrants are less likely to enter. As a result, the banking sector becomes more concentrated. This is consistent with the rising banking concentration after the financial crisis.

On the other hand, it implies that contractionary monetary policy may result in lending supply reductions, and lower credit access for certain borrower types. When the short rate increases, old banks exit. Although this creates entry opportunities and helps young banks enter the market, young banks cannot completely pick up the slack in old banks' lending for two reasons. Firstly, lending relationships differentiate individual lenders. Secondly, young banks do less maturity transformation, as reflected in their NIM betas (Figure 8), and do different types of lending. As Table A1 shows, banks with positive NIM betas tend to hold more C&I loans, whereas banks with negative NIM betas tend to hold more residential mortgage loans, consumer loans, and agricultural loans. Thus, lending reduction and exits of one particular type of banks may result in lack of credit access for certain borrower types.

6 Conclusion

In this paper, we have shown that bank heterogeneity in interest rate exposures, and imperfect competition between banks, affects monetary policy pass-through. Banks have different interest rate exposures: interest rate increases cause some banks to scale down and exit, and others to scale up. Since banks compete with each other, shocks to one bank spills over to its competitors. When a bank's competitors are negatively shocked by a rate increase, the bank tends to increase branch growth and loan growth.

Our results have two implications. First, dispersion in banks' interest rate exposures affects policy transmission. We show that the average net interest margin of banks is not sufficient to summarize monetary policy transmission: the *distribution* of NIM betas across banks - in particular, its dispersion - also matters. In response to short rate changes, regions with more heterogeneous banks in terms of interest rate exposure experience reduction in lending relative to regions with more homogeneous banks.

Second, since short rate exposures are correlated with bank age, monetary policy affects the banking industry dynamics: short rate increases lead to exit of old banks, and short rate decreases lead to exit of young banks. We further show that old banks are the major acquirers in most mergers and acquisitions with either a young or an old bank being the target. This implies that expansionary monetary policy may lead to increasingly concentrated banking sector. When short rate decreases, more young banks are acquired by old banks, and potential entrants are less likely to enter. As a result, the banking sector becomes more concentrated.

References

Altavilla, Carlo, Miguel Boucinha, and José-Luis Peydró, 2018, Monetary policy and bank profitability in a low interest rate environment, *Economic Policy* 33, 531–586.

Altunbas, Yener, Leonardo Gambacorta, and David Marques-Ibanez, 2009, Securitisation and the bank lending channel, *European Economic Review* 53, 996–1009.

Ampudia, Miguel, and Skander Van den Heuvel, 2018, Monetary policy and bank equity values in a time of low interest rates .

Ashcraft, Adam B, 2006, New evidence on the lending channel, *Journal of Money, Credit and Banking* 751–775.

Balloch, Cynthia, and Yann Koby, 2020, Low rates and bank loan supply: Theory and evidence from japan, *Unpublished Manuscript* .

Begenau, Juliane, Monika Piazzesi, and Martin Schneider, 2015, Banks' risk exposures, Technical report, National Bureau of Economic Research.

Begenau, Juliane, and Erik Stafford, 2019, Do banks have an edge?, *Available at SSRN 3095550* .

Begenau, Juliane, and Erik Stafford, 2021, Stable nim and interest rate exposure of us banks, Technical report, Tech. rep., Stanford working paper.

Bernanke, Ben S, and Mark Gertler, 1995, Inside the black box: the credit channel of monetary policy transmission, *Journal of Economic perspectives* 9, 27–48.

Bisetti, Emilio, Stephen A Karolyi, and Stefan Lewellen, 2020, The bank entry channel of monetary policy transmission, *Available at SSRN 3710500* .

Brunnermeier, Markus K, and Yann Koby, 2018, The reversal interest rate, Technical report, National Bureau of Economic Research.

Carlino, Gerald, and Robert DeFina, 1998, The differential regional effects of monetary policy, *Review of economics and statistics* 80, 572–587.

Cetorelli, Nicola, and Linda S Goldberg, 2012, Banking globalization and monetary transmission, *The Journal of Finance* 67, 1811–1843.

Claessens, Stijn, Nicholas Coleman, and Michael Donnelly, 2018, “low-for-long” interest rates and banks’ interest margins and profitability: Cross-country evidence, *Journal of Financial Intermediation* 35, 1–16.

Coimbra, Nuno, and Hélène Rey, 2017, Financial Cycles with Heterogeneous Intermediaries, Technical Report w23245, National Bureau of Economic Research.

Corbae, Dean, 2013, A Quantitative Model of Banking Industry Dynamics 74.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The deposits channel of monetary policy, *The Quarterly Journal of Economics* 132, 1819–1876.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2018, Banking on deposits: Maturity transformation without interest rate risk, Technical report, National Bureau of Economic Research.

Eckert, Fabian, Teresa C Fort, Peter K Schott, and Natalie J Yang, 2020, Imputing missing values in the us census bureau’s county business patterns, Technical report, National Bureau of Economic Research.

English, William B, 2002, Interest rate risk and bank net interest margins, *BIS Quarterly Review* 10, 67–82.

English, William B, Skander J Van den Heuvel, and Egon Zakrajšek, 2018, Interest rate risk and bank equity valuations, *Journal of Monetary Economics* 98, 80–97.

Flannery, Mark J, 1981, Market interest rates and commercial bank profitability: An empirical investigation, *The Journal of Finance* 36, 1085–1101.

Flannery, Mark J, 1983, Interest rates and bank profitability: additional evidence: note, *Journal of Money, Credit and Banking* 15, 355–362.

Flannery, Mark J, and Christopher M James, 1984a, The effect of interest rate changes on the common stock returns of financial institutions, *The journal of Finance* 39, 1141–1153.

Flannery, Mark J, and Christopher M James, 1984b, Market evidence on the effective maturity of bank assets and liabilities, *Journal of Money, Credit and Banking* 16, 435–445.

Gambacorta, Leonardo, 2005, Inside the bank lending channel, *European Economic Review* 49, 1737–1759.

Gambacorta, Leonardo, and Paolo Emilio Mistrulli, 2004, Does bank capital affect lending behavior?, *Journal of Financial intermediation* 13, 436–457.

Gambacorta, Leonardo, and Hyun Song Shin, 2018, Why bank capital matters for monetary policy, *Journal of Financial Intermediation* 35, 17–29.

Gomez, Matthieu, Augustin Landier, David Sraer, and David Thesmar, 2020, Banks' exposure to interest rate risk and the transmission of monetary policy, *Journal of Monetary Economics* .

Hanson, Samuel G, Andrei Shleifer, Jeremy C Stein, and Robert W Vishny, 2015, Banks as patient fixed-income investors, *Journal of Financial Economics* 117, 449–469.

Hoffmann, Peter, Sam Langfield, Federico Pierobon, and Guillaume Vuillemey, 2019, Who bears interest rate risk?, *The Review of Financial Studies* 32, 2921–2954.

Jamilov, Rustam, 2020, A Macroeconomic Model with Heterogeneous Banks, SSRN Scholarly Paper ID 3732168, Social Science Research Network, Rochester, NY.

Jamilov, Rustam, and Tommaso Monacelli, 2020, Bewley Banks, SSRN Scholarly Paper ID 3732172, Social Science Research Network, Rochester, NY.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2020, Banking without deposits: Evidence from shadow bank call reports, Technical report, National Bureau of Economic Research.

Kashyap, Anil K, and Jeremy C Stein, 1995, The impact of monetary policy on bank balance sheets, in *Carnegie-rochester conference series on public policy*, volume 42, 151–195, Elsevier.

Kashyap, Anil K, and Jeremy C Stein, 2000, What do a million observations on banks say about the transmission of monetary policy?, *American Economic Review* 90, 407–428.

Kishan, Ruby P, and Timothy P Opiela, 2000, Bank size, bank capital, and the bank lending channel, *Journal of Money, credit and banking* 121–141.

Purnanandam, Amiyatosh, 2007, Interest rate derivatives at commercial banks: An empirical investigation, *Journal of Monetary Economics* 54, 1769–1808.

Rampini, Adriano A, S Viswanathan, and Guillaume Vuillemey, 2020, Risk management in financial institutions, *The Journal of Finance* 75, 591–637.

Villa, Alessandro T, 2020, Macro Shocks and Firm Dynamics with Oligopolistic Financial Intermediaries 73.

Wang, Olivier, 2018, Banks, low interest rates, and monetary policy transmission, *Available at SSRN 3520134* .

Wang, Yifei, Toni M Whited, Yufeng Wu, and Kairong Xiao, 2020, Bank market power and monetary policy transmission: Evidence from a structural estimation, Technical report, National Bureau of Economic Research.

Whited, Toni M, Yufeng Wu, and Kairong Xiao, 2021, Low interest rates and risk incentives for banks with market power, *Journal of Monetary Economics* .

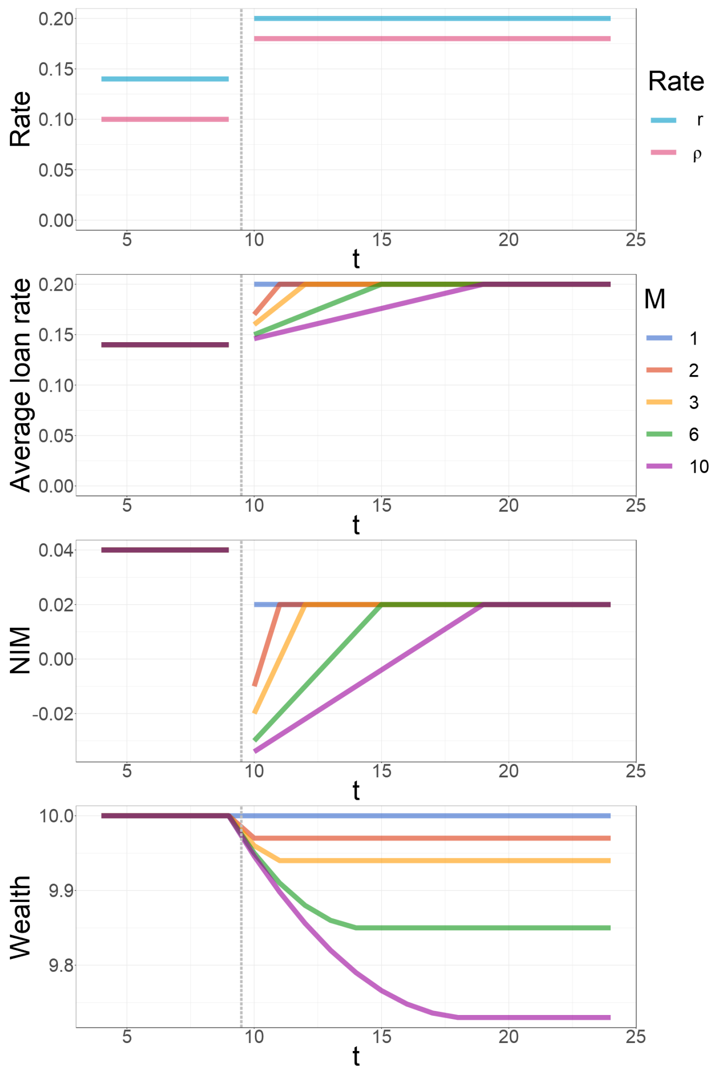
Williams, Emily, 2018, Monetary policy transmission and bank financing frictions .

Williams, Emily, 2020, Heterogeneity in net-interest income exposure to interest rate risk and non-interest expense adjustment, *Available at SSRN 3559364* .

Zentefis, Alexander K., 2020, Bank net worth and frustrated monetary policy, *Journal of Financial Economics* 138, 687–699.

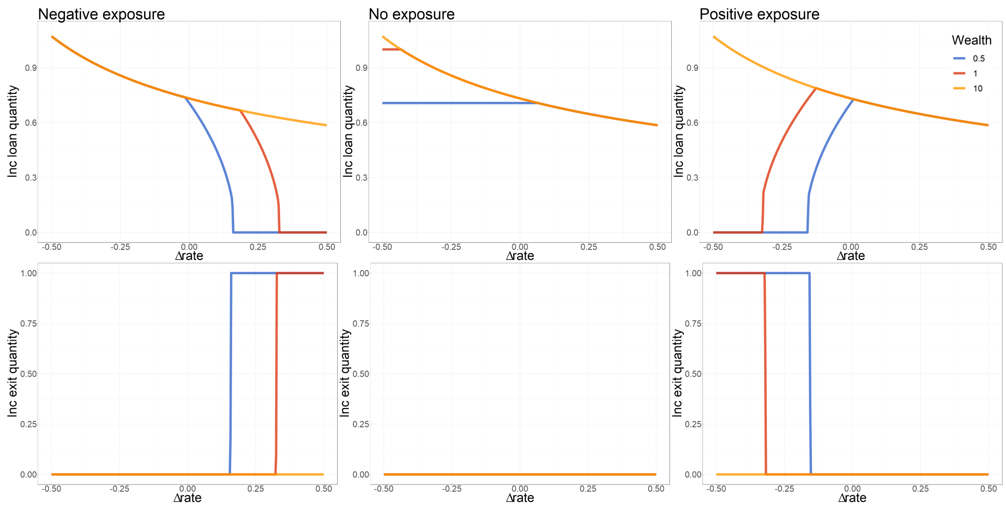
Figures

Figure 1. Interest rates, net interest margins, and wealth



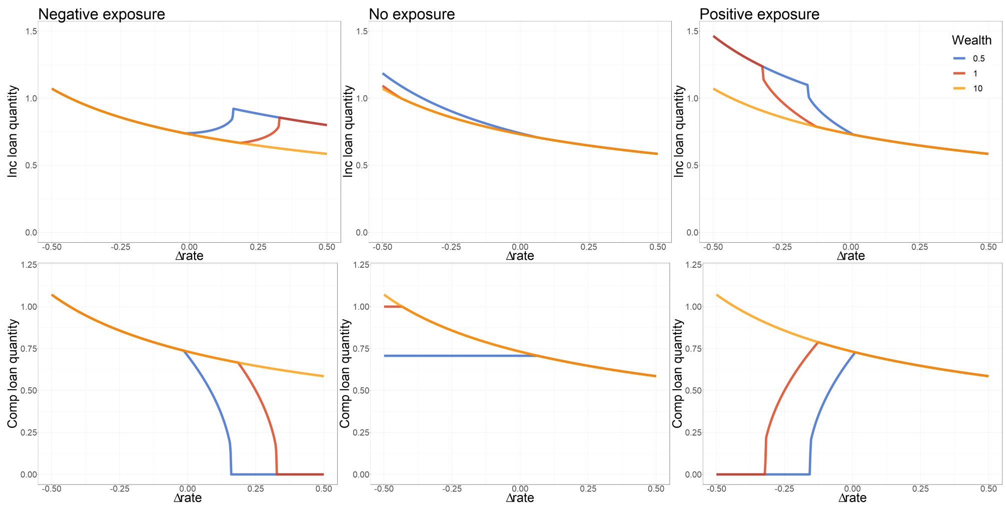
Notes. Effects of interest rate changes on net interest margins and wealth, for different values of loan maturity M. The x axis is time; the interest rate changes at $t = 10$, indicated by the gray dotted line. The top panel shows the Fed Funds rate ρ_t (pink), and the new loan rate r_t (light blue). The second panel shows average loan rates for incumbents with different loan maturities. The third panel shows NIM_t, over time by maturity, and the fourth panel shows how wealth w_t evolves over time.

Figure 2. Interest rates and incumbents



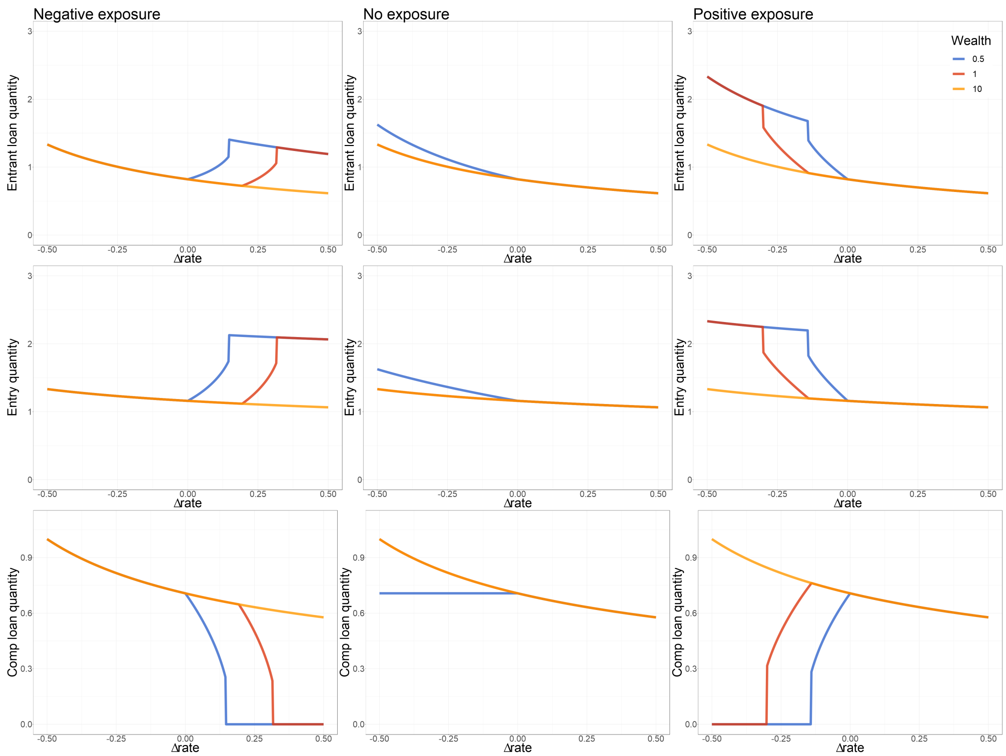
Notes. Interest rate effects on incumbents. We assume there are a set of competitors to the unexposed incumbents in the simulation, who face no operating costs and have no interest rate exposures. The three columns show the case in which incumbents have negative (left), zero (middle), and positive (right) NIM betas. The top row shows total loan quantity of all exposed incumbents, $nl_i^{\frac{\sigma-1}{\sigma}}$: this can be thought of as the contribution of exposed incumbents to aggregate loan quantity. The bottom row shows the equilibrium measure of incumbents that exit. Different colored lines show the effects of interest rate changes for different values of incumbents' original wealth. We set $A = 2, \eta = 1.1, \sigma = 2, \Phi = 1, c_i = 0.3$. The initial measure of exposed incumbents and competitors is 1, and the initial value of ρ is 1.

Figure 3. Interest rates and competitors



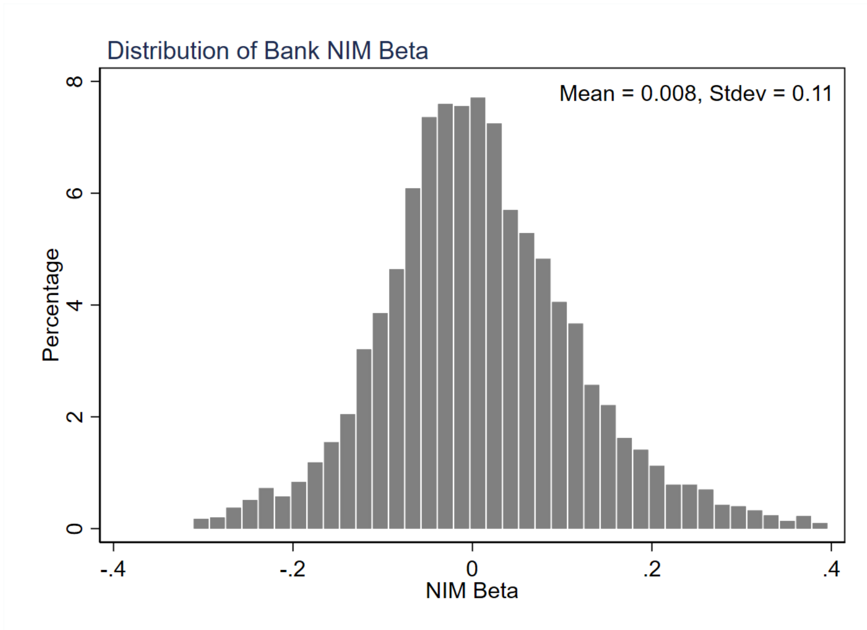
Notes. Interest rate effects on incumbents' competitors, and effects on incumbents. The incumbents in the top row face no operating costs, have infinite wealth, and have no interest rate exposures. The three columns show the case in which competitors have negative (left), zero (middle), and positive (right) NIM betas. The top row shows total loan quantity of all unexposed incumbents, $nl_i^{\frac{\sigma-1}{\sigma}}$. The bottom row shows total loan quantity of incumbents' exposed competitors, $nl_i^{\frac{\sigma-1}{\sigma}}$. Different colored lines show the effects of interest rate changes for different values of exposed competitors' original wealth. We set $A = 2, \eta = 1.1, \sigma = 2, \Phi = 1, c_i = 0.3$. The initial measure of exposed incumbents and competitors is 1, and the initial value of ρ is 1.

Figure 4. Interest rates and entry

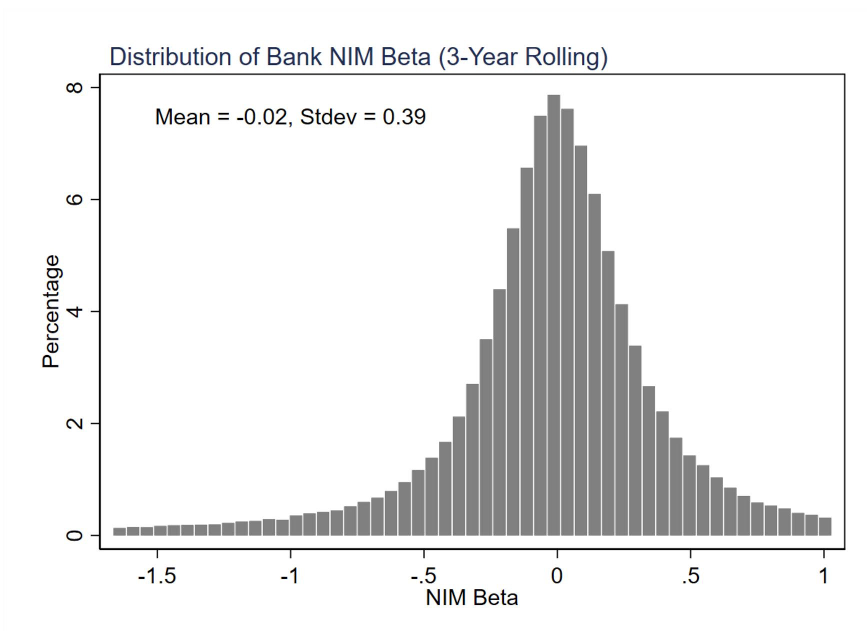


Notes. Interest rate effects on entrants. The entrants have operating cost 0.5, and have no interest rate exposures. The incumbents are exactly as in Figure 2. The three columns show the case in which incumbents have negative (left), zero (middle), and positive (right) NIM betas. The top row shows total loan quantity of all entrants $nl_i^{\frac{\sigma-1}{\sigma}}$. The middle row shows the equilibrium mass of entrants. The bottom row total loan quantity of all exposed incumbents, $nl_i^{\frac{\sigma-1}{\sigma}}$. Different colored lines show the effects of interest rate changes for different values of exposed incumbents' original wealth. We set $A = 2, \eta = 1.1, \sigma = 2, \Phi = 1, c_i = 0.3$. The initial measure of exposed incumbents is 1, and the initial value of ρ is 1.

Figure 5. Interest Rate Exposure



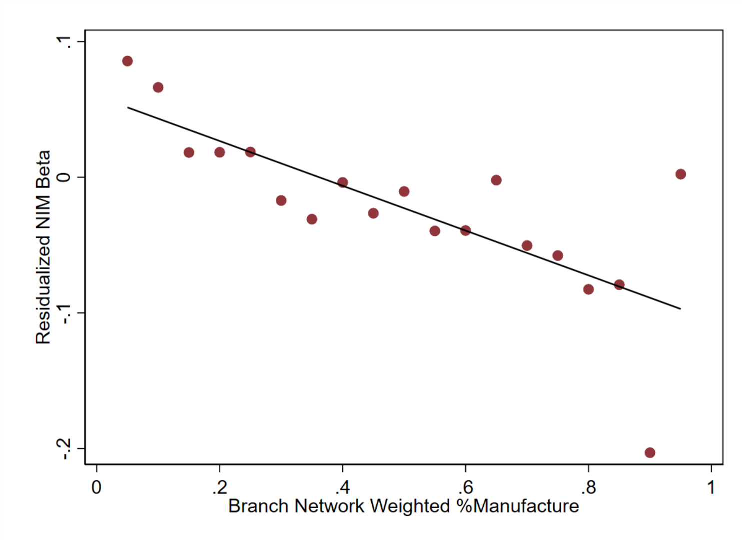
(a) Bank NIM Beta 1984-2019



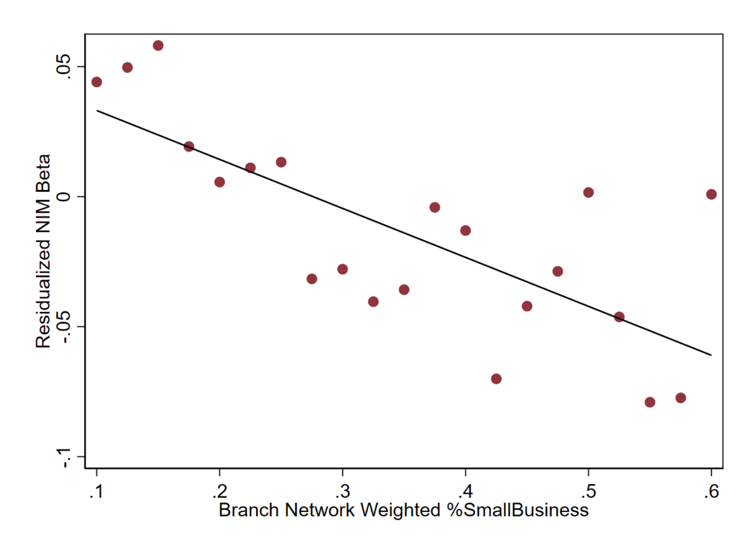
(b) 5-Year Rolling Bank NIM Beta

Note: This figure shows the distribution of estimated NIM betas. Betas are estimated using quarterly bank call report data from 1984 to 2019. Panel A plots the histogram of bank betas estimated over the entire sample. Panel B plots the 5-year rolling bank NIM betas.

Figure 6. Instrument Relevance



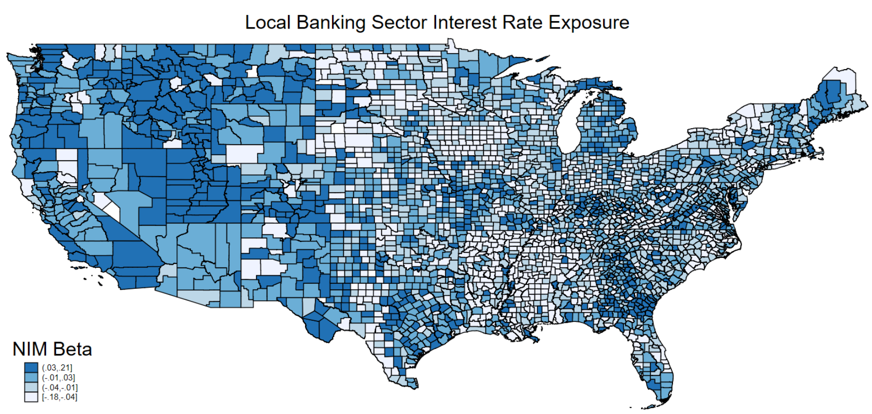
(a) Branch Network-Weighted Manufacture Share



(b) Branch Network-Weighted Small Business Share

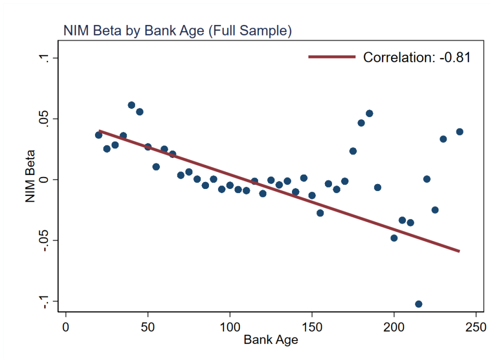
Note: This figure shows how NIM beta is driven by the two instruments. NIM betas are estimated using 3-year rolling quarterly bank call report data from 1984 to 2019, which are then residualized by year, asset size, and capitalization. Branch network-weighted manufacture share and branch network-weighted small business share, defined in equation 4.2, are divided into 20 buckets (0.05 for %manufacture and 0.025 for %small business). Each dot represents the average residualized NIM beta values in each bucket.

Figure 7. Geographic Distribution of Banking Sector Interest Rate Exposure

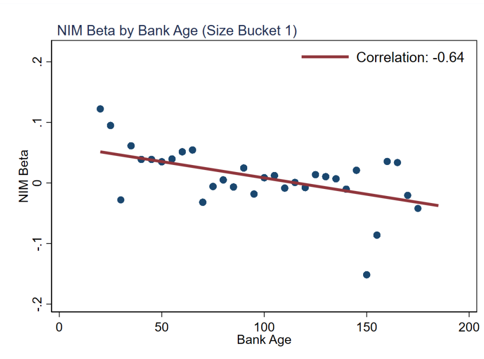


Note: The figure shows geographic distribution of NIM betas at the county level. Betas are estimated from equation (3.1) using quarterly bank call report data from 1984 to 2019. County-level betas are branch-weighted averages of local banks' NIM betas.

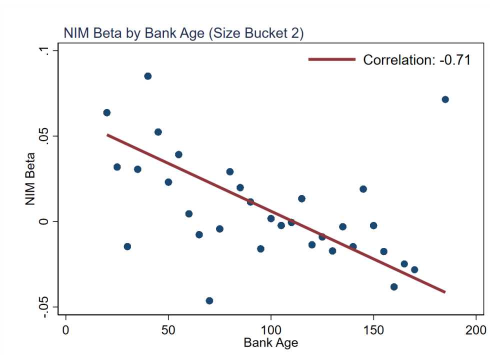
Figure 8. Bank Age and Interest Rate Exposure



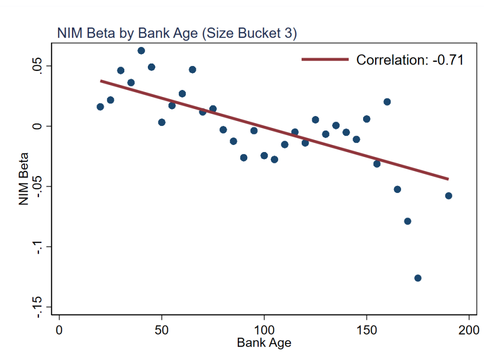
(a) Full Sample



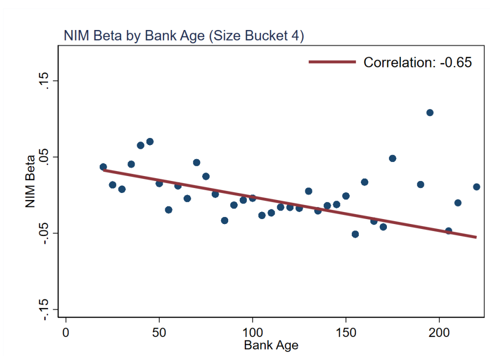
(b) Size Bucket 1



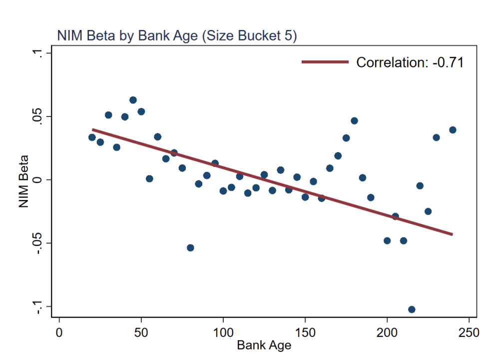
(c) Size Bucket 2



(d) Size Bucket 3



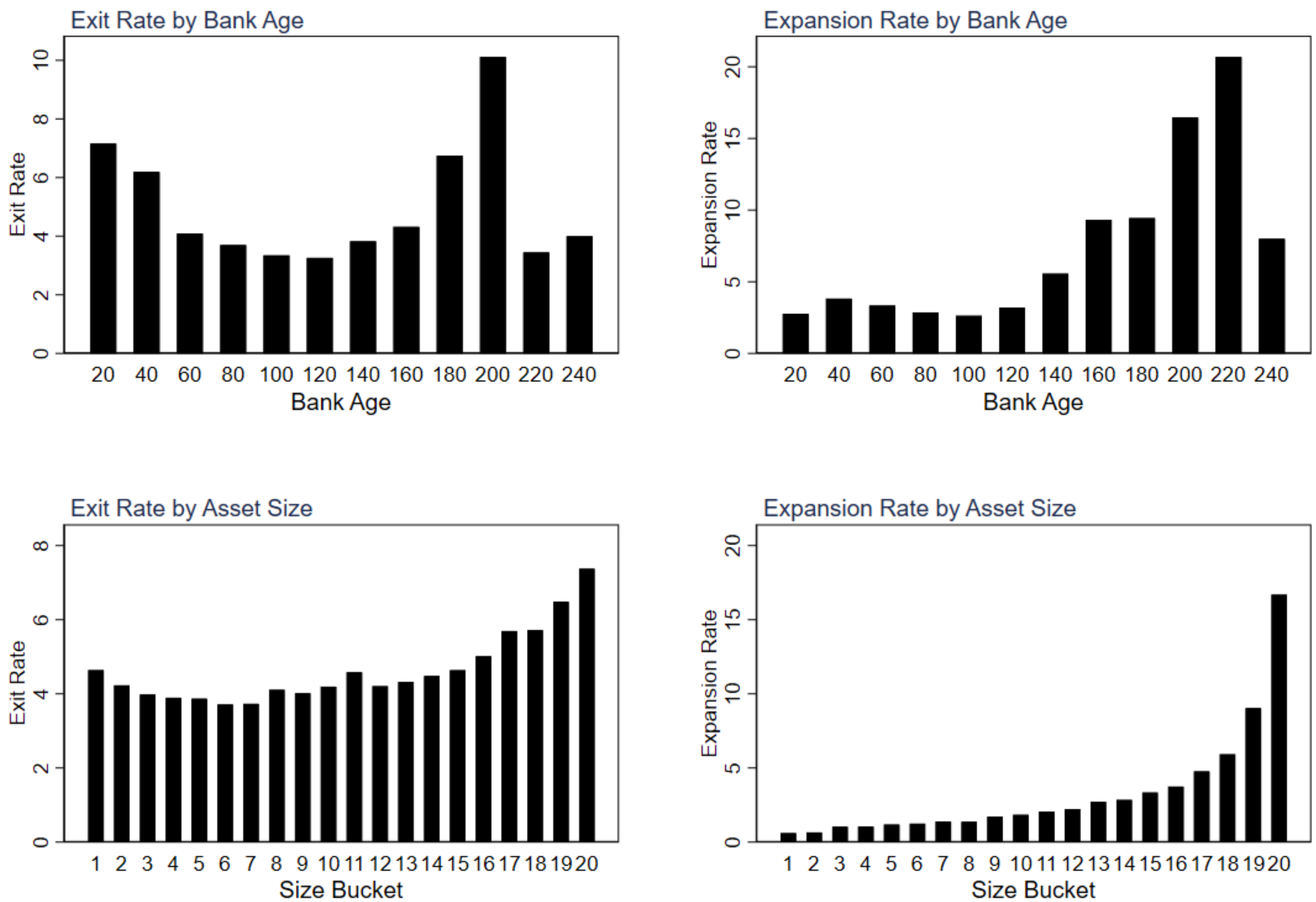
(e) Size Bucket 4



(f) Size Bucket 5

Note: This figure plots banks' NIM beta by age. Betas are estimated using quarterly bank call report data from 1984 to 2019. Age is the number of years since the establishment date by 2020. We group banks into 5-year age bucket and find the average NIM beta in each age bucket. Panel A uses all banks. Panel B-E uses banks in each asset size quintile to ensure the NIM beta-age relation holds in each assrt size bucket.

Figure 9. Exit and Expansion by Age and Size



Note: This figure plots exit and expansion rates. Exit is defined as being acquired or liquidated. Expansion is defined as being an acquirer in a merger. The top panels plot the rates for every 20-year age bucket. The bottom panels plot the rates for every size bucket, where banks are divided into 20 equal-sized buckets based on their asset sizes in each year. The sample covers years from 1987 to 2019, which is the same sample for our bank exit analysis with NIM betas estimated using 3-year rolling samples.

Tables

Table 1: Distribution of NIM Sensitivity to Short Rate Changes and Bank Characteristics

This table reports the average bank characteristics for banks in each NIM beta quintile. Betas are estimated using the full sample from 1984 to 2019. For each bank, we find the average balance sheet composition over the sample period and then find the group average for banks in every NIM beta quintile.

NIM Beta Quintile	1	2	3	4	5
Total Asset (Billion)	0.8	1.4	1.3	0.7	0.6
Percentage of total assets					
Real Estate Loans	0.34	0.34	0.34	0.34	0.34
Residential Real Estate Loan	0.17	0.17	0.17	0.16	0.13
C&I Loans	0.13	0.14	0.14	0.15	0.16
Consumer Loans	0.08	0.07	0.07	0.07	0.06
Agricultural Loans	0.06	0.05	0.05	0.04	0.03
Securities	0.25	0.25	0.25	0.23	0.21
Cash and Reserves	0.09	0.08	0.09	0.10	0.13
Deposit	0.85	0.85	0.85	0.86	0.85
Core Deposit	0.72	0.74	0.74	0.74	0.73
Wholesale funding	0.14	0.13	0.13	0.13	0.13
Equity	0.10	0.10	0.10	0.10	0.11
β_{NIM}	-0.15	-0.05	0.00	0.06	0.18
β_{IIM}	0.21	0.29	0.34	0.38	0.51
β_{IEM}	0.35	0.34	0.33	0.33	0.33
Number of Banks	1,636	1,636	1,636	1,636	1,636

Table 2: Incumbent Exit and NIM Beta

This table presents the results of incumbent exit. Panel A reports the OLS results. Panel B and C report the IV results, in which we use banks' branch-weighted local manufacture firms shares, branch-weighted local small business shares, and their interactions with changes in the Fed Funds rate as instruments in the first stage. In panel C, we further include their interactions with high-capital ratio indicators in the first stage. In Panel A, the dependent variable is an exit indicator that equals 100 if the bank exits through mergers and acquisition or liquidation. The independent variable of interest is bank's NIM beta, or a positive NIM beta indicator that equals 1 if the bank's NIM beta is positive, interacting with changes in the Fed Fund rate, or a rate increase indicator that equals 1 if the Fed Fund rate rises; and the triple interaction with high capital ratio indicator that equals 1 if the bank's capital ratio is in the top quartile among all banks in a particular year. Bank controls include lagged capital ratio for specifications without the triple interaction, lagged log assets, high capital indicator interacting with beta and changes in the Fed fund rate, respectively, and NIM beta. Observations are at bank-year level from 1987 to 2019. Standard errors are clustered at bank level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Panel A: OLS Specification

	Exit					
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_{NIM} \times \Delta$FF	-0.16**			-0.59***		
	(0.06)			(0.12)		
Positive $\beta_{NIM} \times \Delta$FF		-0.14***			-0.42***	
		(0.04)			(0.07)	
Positive $\beta_{NIM} \times$ Positive ΔFF			-0.39***			-0.85***
			(0.119)			(0.203)
$\beta_{NIM} \times \Delta$FF $\times$ High Capital				0.47***		
				(0.16)		
Positive $\beta_{NIM} \times \Delta$FF $\times$ High Capital					0.39***	
					(0.09)	
Positive $\beta_{NIM} \times$ Positive ΔFF $\times$ High Capital						0.34
						(0.291)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.003	0.003	0.003	0.008	0.008	0.008
Observations	259,191	259,191	259,191	268,738	268,738	268,738

Panel B: 2SLS Specifications

	First Stage		Second Stage		
	(1)	(2)	(3)	(4)	(5)
	β_{NIM}	$\beta_{NIM}\times$ ΔFF	Exit Full Sample	Exit Less Capitalized	Exit More Capitalized
$\widehat{\beta_{NIM} \times \Delta FF}$			-4.74***	-4.66**	-2.60
			(1.56)	(2.11)	(1.79)
%Manufacture $\times$ ΔFF	-0.02***	-0.11***			
	(0.00)	(0.01)			
%Manufacture	-0.24***	0.01			
	(0.03)	(0.01)			
%Small Business $\times$ ΔFF	-0.03***	-0.05***			
	(0.01)	(0.01)			
%Small Business	-0.27***	-0.00			
	(0.04)	(0.01)			
Year FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Observations	218269	218269	218269	110933	107336

Table 3: Lending and Liquidity Provision

This table presents the results of lending and liquidity provision. Panel A reports the OLS results. Panel B reports the IV results, in which we use banks' branch-weighted local manufacture firms shares, branch-weighted local small business shares, and their interactions with changes in the Fed Funds rate as instruments in the first stage. The first stages are the same as in Table 2 Panel B. In both panels, the dependent variable in column (1) is change in net interest margins, in column (2) is percentage change in equity capital, in column (3) is percentage change in loans and leases, and in column (4) is percentgae change in deposits. All information are obtained from bank call reports. Observations are at bank-year level from 1987 to 2019. Bank controls include NIM beta, lagged log assets, and lagged capital ratio. Standard errors are clustered at bank level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Panel A: OLS Specification

	(1) ΔNIM	(2) $\frac{\Delta Equity}{Equity}$	(3) $\frac{\Delta Loans}{Loans}$	(4) $\frac{\Delta Deposits}{Deposits}$
$\beta_{NIM} \times \Delta$FF	0.030***	0.348***	0.201***	-0.062
	(0.007)	(0.057)	(0.063)	(0.060)
Year FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
R2	0.028	0.052	0.042	0.014
Observations	228,963	228,963	228,963	228,963

Panel B: 2SLS Specification

	(1) ΔNIM	(2) $\frac{\Delta Equity}{Equity}$	(3) $\frac{\Delta Loans}{Loans}$	(4) $\frac{\Delta Deposits}{Deposits}$
$\widehat{\beta_{NIM} \times \Delta} FF$	6.093***	8.378***	1.136***	5.559***
	(1.800)	(1.589)	(0.150)	(1.746)
Year FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Observations	202,954	202,954	202,954	202,954

Table 4: Competition Channel - Branch Network

This table presents the results of branching through the competition channel. Columns 1-3 report the OLS results. Columns 4-6 report the IV results. The dependent variable is the bank's branch growth in a given county. The independent variable of interest is Local Beta - the average NIM beta of banks in county k - interacting with changes in the Fed Fund rate. In columns 4-6, we instrument Local Beta using their branch-weighted local manufacture firms shares, branch-weighted local small business shares, and their interactions with changes in the Fed Funds rate as instruments in the first stage. In calculating the instruments, we use incumbents' branches outside county k. *Less Capitalized* sample includes counties with the average bank capital ratio below median of all counties. *More Capitalized* sample includes counties with the average bank capital ratio above median of all counties. County controls include local incumbents' lagged average capital ratio, log of population, income per capita, employment rate, and county NIM beta. We construct a balanced sample from years 1994 to 2019. Standard errors are clustered at county level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	OLS			2SLS		
	(1) Full Sample	(2) Less Capitalized	(3) More Capitalized	(4) Full Sample	(5) Less Capitalized	(6) More Capitalized
Local Beta $\times \Delta FF$	-0.03***	-0.03***	-0.02*			
	(0.01)	(0.01)	(0.01)			
Local $\widehat{\text{Beta} \times}$ ΔFF				-0.38***	-0.73***	-0.05
				(0.13)	(0.22)	(0.23)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.14	0.16	0.16	-	-	-
Observations	0.8M	0.4M	0.35M	0.8M	0.4M	0.35M

Table 5: Competition Channel - Lending

This table presents the results of lending. Panel A reports the OLS results. Panel B reports the IV results. In both panels, column 1 shows changes in total loan volume; and columns 2-5 show changes in loan volume in each loan size bucket. The observations are at bank-county-year level from 1999 to 2016, acquired from the Community Reinvestment Act (CRA) database. The independent variable of interest is the average NIM beta of banks in county k interacting with changes in the Fed Fund rate. County controls include local incumbents' lagged average capital ratio, log of population, income per capita, employment rate, and county NIM beta. Standard errors are clustered at county level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Panel A: OLS

	Δ Loan Counts			
	(1)	(2)	(3)	(4)
	Full Sample	Below 100k	100k-250k	250k-1M
Local Beta $\times \Delta FF$	-14.978***	-15.571***	-0.035**	-0.038**
	(2.670)	(2.277)	(0.016)	(0.016)
Bank-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
R2	0.042	0.043	0.053	0.060
Observations	1.8M	1.8M	1.8M	1.8M

Panel B: 2SLS

	Δ Loan Counts			
	(1)	(2)	(3)	(4)
	Full Sample	Below 100k	100k-250k	250k-1M
Local $\widehat{\text{Beta}} \times \Delta FF$	-1260.958**	-938.552**	-2.004**	-0.615
	(593.539)	(459.087)	(0.988)	(0.696)
Bank-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Observations	1.8M	1.8M	1.8M	1.8M

Table 6: Local Interest Rate Exposure Dispersion and Lending

This table presents the results of county-level lending and local interest rate exposure dispersion. Panel A reports the loan counts results. The dependent variables are the number of loans provided in each county each year divided by county population in thousand. Panel B reports the dollar volume results. The dependent variables are the dollar volume of loans in million provided in each county each year divided by county population in thousand. In both panels, the independent variable of interest is the dispersion of local banks' NIM betas, calculated as the standard deviation of local banks' NIM betas, interacting with the absolute magnitude of changes in the short rate, and the average local banks' NIM betas interacting with the magnitude of changes in the short rate. Column 1 shows changes in total loan volume; and columns 2-5 show changes in loan volume in each loan size bucket. In Panel C, we divide the time series into years when the short rate rises and years when the short rate declines and show the loan counts and dollar volume results. The observations are at county-year level from 1999 to 2016, acquired from the Community Reinvestment Act (CRA) database. County controls include local incumbents' lagged average capital ratio, log of population, income per capita, employment rate, county NIM beta, and county NIM beta dispersion. Standard errors are clustered at county level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Panel A: Loan Counts per Thousand Population

	(1) Full Sample	(2) Below 100k	(3) 100k-250k	(4) 250k-1M
Local Beta Dispersion$\times\|\Delta FF\|$	-1580.72***	-1073.56***	-78.36***	-68.41***
	(303.12)	(193.88)	(11.62)	(8.53)
Local Beta $\times\|\Delta FF\|$	-177.11	59.64	-7.32	9.70
	(219.49)	(136.51)	(8.28)	(6.67)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
R2	0.81	0.82	0.67	0.72
Observations	55218	55218	55218	55218

Panel B: Dollar Volume (Million) per Thousand Population

	(1) Full Sample	(2) Below 100k	(3) 100k-250k	(4) 250k-1M
Local Beta Dispersion$\times\|\Delta FF\|$	-102.92***	-14.90***	-13.82***	-35.85***
	(11.06)	(2.82)	(1.96)	(4.28)
Local Beta $\times\|\Delta FF\|$	5.61	-0.20	-0.53	6.85**
	(8.04)	(2.12)	(1.39)	(3.21)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
R2	0.81	0.82	0.67	0.72
Observations	55218	55218	55218	55218

Panel C: Robustness by Positive and Negative ΔFF Years

	Loan Counts per Capita (k)		Dollar Vol(m) per Capita(k)	
	(1) Positive ΔFF	(2) Negative ΔFF	(3) Positive ΔFF	(4) Negative ΔFF
Local Beta Dispersion $\times\|\Delta FF\|$	-6460.84***	40.41	-329.21***	-35.02***
	(712.68)	(298.54)	(27.64)	(11.66)
Local Beta $\times\|\Delta FF\|$	1606.03***	-656.24***	105.64***	-18.15**
	(612.13)	(198.56)	(20.25)	(8.48)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
R2	0.82	0.82	0.76	0.78
Observations	27655	27563	27655	27563

Appendix

A Supplementary material for Section 2

A.1 Proof of proposition 1

To show equilibrium uniqueness, we will show that aggregate loan supply is monotonically increasing, and loan demand is monotonically decreasing, in the price index R.

Loan demand. From (2.9) in the main text, loan demand is:

$$D(R) = \left(\frac{A}{R}\right)^{\eta}$$

Aggregate loan demand is thus strictly decreasing in R.

Loan supply. Incumbents. Consider an incumbent i with wealth w_i, and operating cost c_i. If incumbents are unconstrained, they set

$$r_i = \rho\left(\frac{\sigma}{\sigma-1}\right)$$

And thus supply a quantity:

$$l_i = \frac{A^{\eta} R^{\sigma-\eta}}{\left(\rho\left(\frac{\sigma}{\sigma-1}\right)\right)^{\sigma}}$$

of loans. If

$$l_i > \Phi w_i$$

then incumbent i is constrained; this occurs if:

$$R \geq \left(\frac{\Phi w_i \left(\rho\left(\frac{\sigma}{\sigma-1}\right)\right)^{\sigma}}{A^{\eta}}\right)^{\frac{1}{\sigma-\eta}} \tag{A.1}$$

Define the RHS of (A.1) as R_i^{cons}. If $R > R_i^{cons}$, the incumbent supplies $l_i = \Phi w_i$ of loans, setting price:

$$r_i = \left(\frac{A^\eta R^{\sigma-\eta}}{\Phi w_i}\right)^{\frac{1}{\sigma}}$$

Now, banks' profits are:

$$\pi_i = l_i\left(r_i - \rho\right)$$

Both r_i and l_i are weakly increasing in R, meaning that profits are also weakly increasing in R. Bank i operate if profits are higher than c_i, otherwise they shut down and supply no loans. Thus, there is some cutoff R_i^{exit}, below which i does not lend, setting $l_i = 0$. Bank i's loan supply, as a function of R, is thus:

$$s_i\left(R\right) = \begin{cases} \Phi w_i & R > R_i^{cons} \\ \frac{A^\eta R^{\sigma-\eta}}{\left(\rho\left(\frac{\sigma}{\sigma-1}\right)\right)^\sigma} & R_i^{exit} \leq R \leq R_i^{cons} \\ 0 & R \leq R_i^{exit} \end{cases} \tag{A.2}$$

The function (A.2) is weakly increasing in R, so individual banks' loan supply is increasing in R. Note in particular that we may have $R_i^{cons} \leq R_i^{exit}$, in which case the region $R_i^{exit} \leq R \leq R_i^{cons}$ will be empty. Also, note that $s_i\left(R\right)$ is a correspondence, not a function: when $R = R_i^{exit}$, type i banks are indifferent between producing and exiting.

Aggregate loan supply. Aggregate loan quantity is:

$$\Lambda = \left(\int_0^n \left(l_{i,t}^Y\right)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}$$

With slight abuse of notation, index incumbent types by i, and we have:

$$S\left(R\right) = \left(\sum_{i=1}^{N} n_i\left(s_i\left(R\right)\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{A.3}$$

Since s_i is increasing in R, and $S\left(R\right)$ is increasing in each s_i, $S\left(R\right)$ is weakly increasing in R. Also, note that $S\left(R\right)$, like $s_i\left(R\right)$, is a correspondence rather than a function: when $R = R_i^{exit}$, a positive measure of banks is indifferent between lending and exiting, so $S\left(R\right)$ can take on multiple values. However, $S\left(R\right)$ is an increasing correspondence, in the sense that the graph of $S(R)$ defines a monotone curve in (R, S) space.

Entrants. An entrant will enter if she expected profits higher than c_i^{ent}. We have assumed entrants have sufficient wealth that they are not constrained (though this can be relaxed). Hence, entry is profitable if:

$$l_i (r_i - \rho) \geq c_{ent}$$

$$\implies \frac{A^\eta R^{\sigma-\eta}}{\left(\rho\left(\frac{\sigma}{\sigma-1}\right)\right)^\sigma}\left(\rho\left(\frac{\sigma}{\sigma-1}\right)-1\right) \geq c_{ent} \tag{A.4}$$

Expression (A.4) defines a cutoff R^{entry}, above which entry is profitable. Since there are an infinite mass of potential entrants, the supply of loans is infinitely elastic at R^{entry} – the graph of $S(R)$ is vertical at R^{entry}. Thus, R^{entry} is an upper bound for equilibrium prices.

Supply and demand. We have shown that the function $D(R)$ is strictly decreasing from ∞ towards 0, and $S(R)$ is strictly increasing, from 0 towards ∞. Thus, these two curves cross at exactly one value of R, which is the unique equilibrium price. The price fully pins down all individual banks' prices and quantities, as well as the measure of each kind of bank that operates in equilibrium.

For intuition, figure A1 shows the supply and demand curves $D(R)$ and $S(R)$ for some parameter choices. Loan demand (blue) is monotonically and smoothly decreasing. Loan supply (red) is increasing, but has vertical segments, which correspond to banks' exit boundaries R_i^{exit}. Loan supply may also have horizontal segments, if all banks are constrained and thus cannot respond to prices. The vertical line at approximately $R = 0.75$ corresponds to the R^{entry}; aggregate loan supply is perfectly elastic at this point, so in equilibrium R will never be greater than R^{entry}.

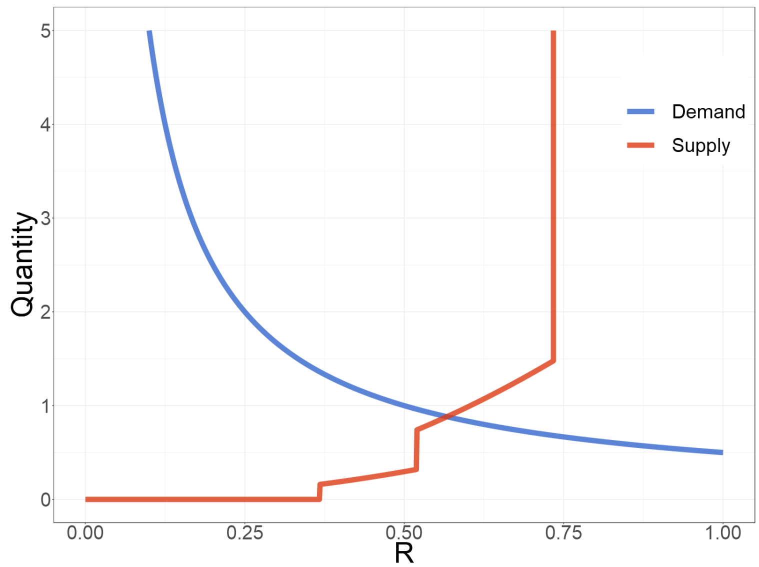
A.2 NIM beta heterogeneity and interest rate pass-through

Figure A2 formally demonstrates the effect we test for in section 5: when NIM betas are more heterogeneous, interest rate changes have a more negative effect on total lending. We simulate the effects of interest rate shocks on total lending, varying the extent of heterogeneity in incumbents' interest rate exposures. In each simulation, there are two kinds of incumbents, with opposite NIM betas of K and $-K$. Thus, the average NIM beta is always 0, but heterogeneity in NIM betas increases with the parameter K. The top panel shows the effect of interest rate shocks on total lending: colors represent different values of K. When K is higher and incumbents' NIM betas are more heterogeneous, interest rate shocks tend to have a more negative effect on total lending.

To show why this happens, the second and third panels of figure A2 show how total lending by incumbents with positive and negative NIM betas responds to rate shocks. When rates decrease, incumbents with positive NIM betas scale down lending, and eventually exit. Negatively exposed incumbents scale up, but not by as much as positively exposed incumbents scale down. When rates increase, negatively exposed incumbents scale down, more than positively exposed incumbents scale up.

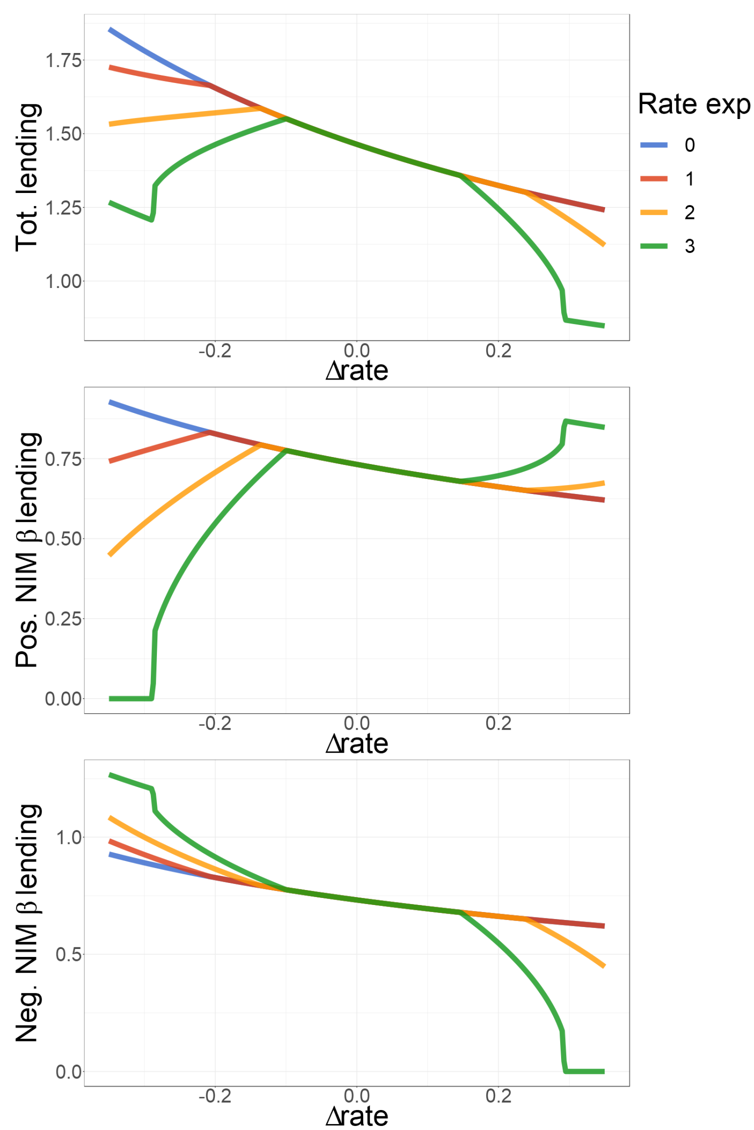
Technically, there are two reasons why this effect occurs. The first is that lending responds in a concave manner to wealth. When a bank receives negative wealth shocks, her constraint becomes more binding, and she is forced to scale down. When she receives positive wealth shocks, her constraint becomes less binding; she scales up if the constraint is binding, but past the point where she is constrained, wealth shocks no matter affect lending. The second is that bank loans are imperfect substitutes. When one set of incumbent banks scale down and exit, this increases loan prices R and encourages scale-up and entry from competitors, but the competitors will never expand to the point where total lending actually increases, even if they are unconstrained.

Figure A1. Loan supply and demand intuition



Notes. Illustration of loan aggregate supply and demand curves.

Figure A2. NIM Beta Heterogeneity and lending



Notes. Interest rate effects on lending, as heterogeneity in NIM betas across banks varies. There are two types of incumbents, who have $n_i = 1, w_i = 0.9, c_i = 0.3$. Incumbent have opposite NIM betas: $\nu_1 = K, \nu_2 = -K$. We vary the extent of NIM beta heterogeneity by varying $K \in \{0, 1, 2, 3\}$. Different colored lines show different values of K. The middle and bottom plots show total loans, $nl_i^{\frac{\sigma-1}{\sigma}}$, from positive and negative NIM beta banks respectively. The top plot shows total loans from both kinds of banks, $n_1 l_1^{\frac{\sigma-1}{\sigma}} + n_2 l_2^{\frac{\sigma-1}{\sigma}}$. We set $A = 2, \eta = 1.1, \sigma = 2, \Phi = 1$.The initial measure of both kinds of incumbents is 1, and the initial value of ρ is 1.

B Supplementary material for Section 3

We estimate the sensitivity of interest income and interest expense to short rate changes, β_{IIM} and β_{IEM}, respectively. As shown in Table 1, interest expense betas have much less variability than interest income betas. For every 100-basis point increase in the short rate, the interest income margins, i.e., interest income divided by assets, of banks in the most positive NIM beta quintile increase by 30 basis points more than that of banks in the most negative NIM beta quintile. On the contrary, the difference in the interest expense margin is only 2 basis points. Banks in the negative NIM beta quintiles are closer to the textbook view of traditional banks that borrow short-term and lend long-term. Thus, when the short rate increases, interest expense responds more quickly than interest income, leading to a reduction in the net interest margin. Thus, the majority of variation in NIM betas across banks is driven by differences in the sensitivity of interest income to interest rates; interest expenses play a relatively minor role.

To understand the fundamental differences across banks with positive and negative interest rate exposures, we project banks' NIM betas onto their balance sheet characteristics in Table A1. We estimate the NIM betas and find their average balance sheet compositions from 1984 to 2019 for every bank. From columns 1 to 5, we gradually add bank characteristics as explanatory variables for banks' NIM betas, with the specification in column 5 being most saturated.

The results confirm our findings in Table 1 and Figure 8. Firstly, older banks tend to have lower NIM betas. Across all specifications, bank age is a strong negatively associated with NIM beta. Secondly, banks with higher NIM betas specialize different loan types than banks with lower NIM betas. Banks with lower NIM betas tend to hold more residential mortgage loans, consumer loans, agricultural loans, and securities, which are typically long term. Banks with higher NIM betas hold more cash and reserves as well as more commercial and industrial loans. Thirdly, banks with lower NIM betas have different financing structure from banks with higher NIM betas. Banks with lower NIM betas tend to be financed with less equity and deposits and with more wholesale funding.

Table A1: Determinants of NIM Beta

This table presents the determinants of NIM beta. NIM betas are estimated using full sample from 1984 to 2019. Standard errors are clustered at bank level. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	NIM Beta				
	(1)	(2)	(3)	(4)	(5)
Bank Age	-0.45***	-0.45***	-0.08**	-0.52***	-0.16***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Ln(Asset)		-0.09	0.07	0.53***	0.61***
		(0.10)	(0.12)	(0.12)	(0.14)
Cash and Reserve/Assets			48.69***		46.69***
			(2.41)		(2.41)
Security/Assets			-9.70***		-11.57***
			(1.28)		(1.28)
C&I Loan/Assets			13.63***		16.10***
			(2.33)		(2.33)
Consumer Loan/Assets			-20.70***		-18.33***
			(2.58)		(2.56)
Agricultural Loan/Assets			-19.72***		-20.17***
			(2.11)		(2.11)
Residential Mortgage/Assets			-12.63***		-12.57***
			(1.72)		(1.71)
Equity/Assets				46.56***	44.69***
				(4.98)	(5.20)
Deposit/Assets				12.89***	13.53***
				(2.66)	(2.98)
Wholesale Funding/Assets				-14.28***	-18.34***
				(2.24)	(2.30)
R2	0.02	0.02	0.15	0.04	0.17
Observations	8099	8099	6060	8099	6060