Welfare Costs of Credit Card Oligopoly[*]

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Abstract

How do large, national credit card lenders affect interest rates, the size of the credit card market, and household welfare? We answer this question by developing a novel theory in which national lenders strategically influence market-level and economy-wide interest rates. Our theory predicts that pass-through rates from bank funding costs to credit card spreads depend on market- and national-level shares, unlike perfect or monopolistic competition. These predictions are borne out in bank regulatory data: pass-through rates are 10% lower in markets where a bank is large (top 30% share) compared to all other markets in which the bank operates. We find similar results for banks with large national shares, and our results are robust to the exclusion of geography in the market definition. We then use these moments to discipline market power in our model and measure its costs. Moving from national oligopoly to perfect competition reduces credit card interest rates by 2pp, increases credit-to-GDP by 3.6pp, and yields a consumption equivalent gain between 0.03% and 0.15%.

JEL codes: D14, D43, D60, E21, E44, G21

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1 Introduction

As the credit card industry grew from its infancy in the 1950s into a multi-trillion dollar market, its competitiveness has been the subject of intense scrutiny.[1] While pass-through rates have risen as technological advances enabled credit card companies to index the majority of credit cards to the federal funds rate (Ausubel (1991) and Grodzicki (2023a)), credit card interest rate spreads – defined to be the credit card interest rate minus the base rate, fees and default costs – are far from competitive levels (Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015) and Dempsey and Ionescu (2021)). Over time, credit card issuing banks have grown more concentrated, and they continue to generate excess returns on assets and wide profit margins.[2] Regulation, innovation, and fixed costs confound the interpretation of these indicators, and so the literature continues to debate the presence, implications, and potential welfare losses of imperfect competition in the credit card market (Nelson (2018), Herkenhoff and Raveendranathan (2020), Whited, Wu, and Xiao (2021), Galenianos, Law, and Nosal (2021), and Galenianos and Gavazza (2022)).

We contribute to this debate by (i) developing a novel theory in which large, national credit card lenders strategically influence market-level and economy-wide interest rates, (ii) using the insights from our theory to derive clean tests of lender market power that circumvent the critiques of existing empirical work, and (iii) estimating our model from our identified elasticities and using it to measure the welfare costs of lender market power.

Our theory allows lenders to operate in multiple markets and internalize their influence on market-level and national-level quantities and prices. This market structure extends the "local" strategic interactions in Atkeson and Burstein (2008) to the national level, and our characterization is, to our knowledge, novel.[3] We de-

[1]See, among others, Ausubel (1991), Knittel and Stango (2003), Evans and Schmalensee (2005), Wildfang and Marth (2005), Stearns (2007), Dick and Lehnert (2010), Herkenhoff and Raveendranathan (2020) and Grodzicki (2023b).

[2]Herkenhoff and Raveendranathan (2020) and Grodzicki (2023b).

[3]In Appendix A.8, contemporaneous work by Burstein, Carvalho, and Grassi (2023) derives markups at a single-plant firm that internalizes its effects on aggregates. They derive first order conditions, but stop short of characterizing pass-through, estimating the model, or considering multi-plant firms. Other contemporaneous work by Chan, Kroft, Mattana, and Mourifié (2024) con-

rive closed-form solutions for optimal pricing strategies under market- and national-level competition, yielding sharp testable implications.

Our model predicts that the responsiveness of interest rate spreads to changes in the federal funds rate depends non-linearly on market- and national-level shares, where (1) *market-level shares* summarize a bank's size (in terms of credit card revenues or balances) in a given market relative to all other competitors in the same market, and (2) *national-level shares* summarize a bank's size in a given market relative to all other economy-wide competitors.[4] When banks have larger market-level shares, they cut spreads less (and may even raise spreads) in response to a rate cut compared to other markets in which that bank has small market-level shares. Banks also dampen pass-through in markets with large national-level shares. In the presence of perfect competition or monopolistic competition, there is no differential pass-through by either market- or national-level shares.

Using our theoretic characterization to guide our empirical analysis, we test for within-bank, across-market differences in pass-through rates from unexpected rate cuts into interest rate spreads. Our within-bank, across-market comparisons extend existing work in "local" deposit markets (e.g. Drechsler, Savov, and Schnabl (2017) among others) to measure market- and national-level oligopoly in the credit card industry. Unlike Drechsler et al. (2017), we show that both market- and national-level shares matter for rate setting, rather than just the market-level Herfindahl studied in Drechsler et al. (2017). Importantly, our identification strategy sidesteps the issues associated with time-series identification of credit card pass-through rates that limited the early literature (see for instance the discussion of time series identification of pass-through rates in Ausubel (1991), Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018), Herkenhoff and Raveendranathan (2020), and Grodzicki (2023b)). By comparing responses within the same bank, we remove heterogeneity in pass-through rates that can be ascribed to differences in capital structure, exposure to federal funds changes, or exposure

sider oligopsonists who affect national wage levels at single-plant firms. In related work, Morelli, Moretti, and Venkateswaran (2024) apply the Atkeson and Burstein (2008) framework to study the trade-offs between market power, idiosyncratic risk and diversification in deposit markets resulting from banks' geographical expansion.

[4]Note that despite the "national" moniker, both market- and national-level shares vary from lender-to-lender and from market-to-market.

to other co-moving macroeconomic factors.

We implement our tests in two stages using the Office of the Comptroller of the Currency (OCC) Credit Card Metrics (CCM) database. This data includes the near-universe of credit card accounts and allows us to build a panel of daily credit card issuances in every market and every bank in the United States (see the OCC data description in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2013)). In the first stage, we use individual account-level data on FICO scores, individual incomes, borrowing history, and product characteristics to remove any composition differences that may drive the time-series response of interest rates in any given market. Unlike other loan-market studies that rely on aggregated (non-borrower-level) interest rate information (Heckmann-Draisbach and Moertel (2020) and Gödl-Hanisch (2022)), our individual panel data allow us to remove high-dimensional fixed effects to correct for compositional changes, fluctuating default premia, and other individual and market-specific factors that may comove with the business cycle. We refer to the residualized first-stage interest rates as spreads.

In the second stage, we aggregate the spreads into a bank-market-week panel, and then we project the spreads onto bank-time fixed effects as well as market- and national-level credit card shares. We define a market to be the intersection of broad FICO bands (subprime/prime), card type (general purpose/non-general purpose cards), product type (co-branded/non-co-branded) and geography. Our baseline measure of geography is a two-digit zip code, but we also consider market definitions that cluster regions by their income, allowing markets to span all 50 U.S. states (see the McKinsey industry report, Fiorio, Mau, Steitz, and Welander (2014)). Our local projections approach allows us to establish that there are no pre-existing trends within-bank, across-markets, lending credibility to our identification approach (e.g. Jordà (2005)).

Following the large, unexpected rate cuts in 2008, we find that when a bank's market-level share exceeds the 70$^{\text{th}}$ percentile, pass through rates are 10% lower than in markets where that bank's market-level share is less than the 70$^{\text{th}}$ percentile. The effect is persistent over the 8 week window following the rate cut, and the effects are present in pooled and event-level analyses. The data also suggests strong non-linearities, with significantly smaller effects arising when comparing markets below and above median shares. We then test the importance of national-level shares for rate setting. We find that when a bank's national-level shares exceed the 90th percentile, pass through rates are 15%-20% lower than in markets where that bank's national-level share is less than the 90th percentile.

To gauge the magnitude of these effects and the potential losses from non-competitive lender behavior, we estimate our model using our identified empirical elasticities. We calibrate the model to 2008, and we treat each model period as a 1-year interval in which mobility across FICO bands, product types, and geography is possible. We simulate a 20bps rate cut, matching the typical surprise rate cut during 2008, and then we estimate an identical two-stage regression used in our empirical work. This approach allows us to credibly estimate the parameters governing market power in the model, while also correcting for general equilibrium effects across markets that are not possible to control for in the data.

Our estimates imply widely varying degrees of market power. Credit card spreads are roughly 1 percentage point in the most competitive markets and 4 percentage points in the least competitive markets. These estimates are in line with our regulatory data, and they are also in line with Herkenhoff and Raveendranathan (2020) who estimate average spreads to be 3.4 percentage points between 1970 and 2020 after factoring in operational costs, fee income, and interchange income.

We then measure the effects of lender market power on interest rates, the size of the credit market, and household welfare. We find that moving from an economy with national market power to a perfectly competitive economy reduces credit card interest rates by 2 percentage points (pp). The gains are driven by reallocation of credit card balances to low-cost lenders who disproportionately cut their markups. The lowest cost lender nearly doubles in size, at the expense of their less productive competitors. With lower interest rates, credit-to-GDP expands by 3.6pp, implying a 1 trillion dollar expansion in the size of the credit card market.

Despite the large expansion of credit induced by perfect competition, credit *services* are a relatively small share of the consumption bundle, and lender profits – which are rebated to households – fall. We estimate welfare gains worth 0.03% of lifetime consumption from perfect competition, allowing lender profits to adjust. When we shut down changes in rebated lender profits, the consumption equivalent welfare gain to the representative household increases to 0.15%.

We also conduct a number of intermediate experiments, removing the components of markups attributable to (1) national-level rate setting power, and (2) market-level rate setting power. These experiments reduce interest rate by 9 basis points and 51 basis points, respectively, indicating that strategic rate setting at the market-level is a more important driver of spreads than strategic rate setting at the national-level.

2 Literature

In terms of theory, a number of studies have approached market power in credit markets via search-and-matching, which yields a highly localized, match-specific notion of market power (e.g. Wasmer and Weil (2000), Drozd and Nosal (2008), Bauducco and Janiak (2015), Petrosky-Nadeau and Wasmer (2017), Herkenhoff (2019), Braxton, Phillips, and Herkenhoff (2019), Raveendranathan (2020), and Galenianos et al. (2021)). Others in the literature have used discrete choice frameworks, but they maintain assumptions that rule out either market or national interactions among lenders (Grodzicki (2014), Nelson (2018), and Galenianos and Gavazza (2022)).[5] There are far fewer papers that consider dynamic, oligopolistic banks (e.g. Corbae and D'Erasmo (2021), Whited et al. (2021) and Herkenhoff and Raveendranathan (2020)). These papers have led to important positive and normative advances in the literature, but they must place strong restrictions on strategic interactions to make progress computationally, preventing those papers from more deeply exploring the nature of competition in the credit card market. We contribute to this literature by proposing a tractable model in which lenders strategically interact at the market and national levels. While our next-CES preference structure is widely known and has been micro-founded via discrete choice in a number of studies (e.g., Verboven (1996) and Berger, Herkenhoff, and Mon-

[5]Papers with global banks also often only consider competitive pricing, e.g. Morelli, Ottonello, and Perez (2022) and Clayton and Schaab (2022).

gey (2022)), we deviate from existing work by relaxing assumptions related to the *boundaries of competition*. By relaxing these assumptions, our theory yields novel tests of non-competitive behavior at the market- and national-level.

In terms of empirics, a handful of papers have used regulatory account-level data to document large spreads in the credit market (Dempsey and Ionescu (2021) and Agarwal et al. (2015)), but they stop short of ascribing the deviations in spreads to market power. Early work by Ausubel (1991) attributed the lack pass-through from the cost of funds to market power. However, recent work by Grodzicki (2023b) and Grodzicki (2023a) documents a much higher rate of pass-through in recent years and the growing prevalence on indexed cards. We contribute to this literature by combining our theory with the identification approach of Drechsler et al. (2017) to test for market- and national-level rate setting power. A few other researchers have adopted the approach of Drechsler et al. (2017) on loan-level data in Germany (Heckmann-Draisbach and Moertel (2020)) and the U.S. (Gödl-Hanisch (2022)). Their focus in on the way local Herfindahls affect the pass-through from rate cuts to branch-level rates. We differ from these studies in our conceptual and empirical approach. First, our model implies that the right proxy for rate setting power is the bank's market-level share of credit card interest income, not the market-wide Herfindahl, and that national-level rate setting power is a potentially important determinant of pass-through. Second, unlike Heckmann-Draisbach and Moertel (2020) and Gödl-Hanisch (2022) who rely on aggregated (non-borrower-level) interest rate information, our individual panel data allow us to remove compositional changes of borrowers that may affect spreads and market-level responses to rate cuts. Our two-stage approach isolates spreads and lets us credibly measure across-market differences in pass-through rates.

3 Institutional features of credit card offers

Despite the end of redlining, the credit card industry continues to target offers toward specific behavioral groups, demographic groups (excluding race) and geographic locations. A report by McKinsey (Fiorio et al. (2014)) summarizes these practices (underlining added):

Credit card issuers have traditionally targeted consumers by using information about their behaviors and demographics. Behaviors are often based on credit bureau reports on how a person spends and pays over time; customers are typically categorized as transactors, revolvers or subprime. Demographics are derived from census reports and other non-financial databases and cover facts such as income, age and geography. This model has served the industry well for decades, enabling it to offer three main card types—rewards, low-rate and subprime—to cater to different users.

This type of market segmentation is common practice in credit card marketing, and many credit card marketing consultancy firms provide demographic and geographic customer segmentation services (Pellandini-Simányi (2023)). In particular, Pellandini-Simányi (2023) discuss the way market segmentation is used to develop, design, and distribute new credit card products. Beyond academic evidence, industry professionals discuss how these segmentation practices have evolved and continue to be employed in the industry. An article by Janine Pollack, the Integrated Marketing Director at MNI Targeted media, explains how targeting is implemented with modern clustering algorithms: "Credit card customer segmentation groups clients according to demographic, behavioral, psychographic, and geographic attributes. It uses AI and machine learning (ML) to identify marketable consumer segments. For instance, the ML clustering method looks at a dataset and may find a correlation between different segments humans may miss. Marketers better understand consumer intent and can create personalized credit card marketing strategies and campaigns."[6]

Chapter V of the "Credit Card Activities Manual" (FDIC, 2007) describes the marketing and acquisition process for credit card issuing banks. The FDIC manual describes the way banks segment customers by credit scores[7], product lines and geographic locations (p. 31):

Product Line

[6] https://www.mni.com/blog/credit-card-marketing?hs_amp=true

[7] Quoting from the FDIC section on targeted offers: *"It is segmented into various levels based on credit criteria, often including credit bureau scores. For example, the levels may be designated as "A," "B," and "C" with level "A" consumers exhibiting higher credit scores and lower credit risk while level "B" and "C" consumers would have lower credit scores and exhibit higher credit risk"* (p.27).

Segmentation by product line focuses on the type of card product offered. Product types such as affinity, co-branded, premium, and standard cards are targeted at different populations and use different selection criteria. Management may segment on this basis to help monitor historical and current trends, adjust marketing strategies, and set interest rates and fees on future products.

Geographic Location

Segmentation by geographic location captures regional differences in card usage and monitors local economic conditions. Not only does geographic segmentation better enable management to concentrate collection efforts on particular hot spots across the country, but it also allows management to adjust marketing strategies for areas with deteriorating economic trends. The importance of geographic segmentation was emphasized when banks across the country had to deal with the impacts of Hurricane Katrina on their cardholders and card portfolios." (p. 31)

While credit scores are independent of geography,[8] we use OCC data to establish a strong geographic dependence of interest rates on new credit accounts, controlling for FICO, credit attributes, income, and all available household demographic information. Analysis is in section 5.

4 Theory

To guide our empirical approach, we develop a theory in which lenders (credit card issuing banks) are large within a market and economy-wide. They operate across many markets and set interest rates internalizing their effects not just on the market-level quantities and prices but also on aggregate quantities and prices. This market structure extends the market-level competition in Atkeson and Burstein (2008) to a national setting. Our characterization of this model economy yields predictions that we test in Section 5. All derivations are included in the online appendix.

[8] https://www.experian.com/blogs/ask-experian/address-information-does-not-impact-credit-scores/

Environment. The economy is populated by a stand-in household and a finite number N of credit card issuing banks $i \in \{1, \dots, N\}$. Those lenders are distributed across a finite number of markets indexed by $j \in \{1, \dots, J\}$. There are $N_j \in \{1, \dots, N\}$ lenders in market j. N_j is exogenously given.

Household. The stand-in household is endowed with y units of the final good and values consumption of the final good, C_1, as well as credit services, C_2. Credit services are proportional to credit card balances l_{ij}, which must be repaid intra-period at interest rate r_{ij}. The proportionality of credit services to credit card balances is designed to proxy the convenience and non-monetary benefits associated with having access to – and utilizing – a particular lender's credit card (e.g. non-cash convenience, merchant coverage, non-monetary benefits, market access, etc.).

We assume that aggregate credit services are produced using a CES aggregator L over market-level credit services l_j, and that market-level credit services are themselves a CES- aggregator over lender-level credit balances l_{ij}. The household's willingness to substitute across lenders within a market is governed by η, and their willingness to substitute across markets is governed by θ. These preferences can be micro-founded in a discrete choice problem over bank loans if the non-monetary value of each bank loan is drawn from a correlated Gumbel in which θ governs the similarity of draws across markets and η governs the similarity of draws within markets (see Verboven (1996) and Berger et al. (2022)).

To provide a concrete interpretation, suppose (as we will in the empirics) a market is the intersection of an individual's broad FICO band (prime/subprime), card type (general purpose/non-general purpose), product type (co-branded/non-co-branded) and geography (2-digit zipcode). η stands in for non-monetary benefits, loyalty, and any other factor limiting intra-market willingness to switch lenders. θ stands in for factors that limit across-market immobility, which may stem from the time costs of altering repayment behavior to change one's FICO, applying for a new product class of credit card, or moving across regions. Consistent with this interpretation, we restrict $\eta \geq \theta > 1$ henceforth, implying that it is easier to substitute across banks within a market than across markets.

We assume that aggregate bank profits, $\Pi = \sum_{i=1}^{N} \Pi_i$, are rebated back to the household. The resulting household problem is given by[9]

$$\max_{\{l_{ij}\},C_1,C_2} \; u\left(C_1, C_2\right) \tag{1}$$

$$C_1 \leq y - \sum_{i,j} r_{ij} l_{ij} + \Pi, \quad C_2 \leq L \tag{2}$$

$$L = \left[\sum_{j=1}^{J} l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \quad l_j = \left[\sum_{i=1}^{N_j} l_{ij}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \tag{3}$$

Under the assumption that the utility function is strictly increasing in both arguments, $C_2 = L$, and the household first order conditions yield the following bank, market, and aggregate demand curves

$$l_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L, \quad l_j = \left(\frac{r_j}{R}\right)^{-\theta} L, \quad R = \frac{u_2(C_1, L)}{u_1(C_1, L)}, \tag{4}$$

where the market-level and national interest rate indexes are given by r_j and R:

$$R = \left[\sum_{j=1}^{J} r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}, \quad r_j = \left[\sum_{i=1}^{N_j} r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \quad RL \equiv \sum_{j=1}^{J} r_j l_j, \quad r_j l_j \equiv \sum_{i=1}^{N_j} r_{ij} l_{ij} \tag{5}$$

Ceteris paribus, higher lender-level interest rates r_{ij} lead to less borrowing. The elasticity of borrowing with respect to r_{ij} is governed by η. Likewise, the elasticity of borrowing with respect to market-level interest rates r_j is given by $\eta - \theta$. The responsiveness of borrowing to national rates R depends on the functional form for $u(\cdot, \cdot)$.

Banks. Bank i is characterized by a marginal cost of lending $c_i + r_f$. c_i reflects bank i's idiosyncratic costs (e.g. differences in capital structure etc.), and the risk free rates r_f is presumed to be set outside of the credit card market. We assume the marginal cost of funds is bank-specific, not market specific.[10] Banks operate in an

[9]We denote $\sum_{j=1}^{J}\sum_{i=1}^{N_j}$ as $\sum_{i,j}$ in the household problem.

[10]This assumption is consistent with previous literature. Campello (2002) finds that upon tightening in the monetary policy rate, funding of loans by bank holding companies (BHCs) is less

exogenously given, positive measure number of markets, $J(i)$.

Competitive structure. We consider two competitive structures. The first assumes that banks are market-level oligopolists and therefore do not internalize their impact on aggregates. This case allows us to explain the model mechanisms and key testable implications of market-level oligopoly. The second formulation assumes banks internalize their impact on both market-level and national aggregates. A special case of the national oligopoly economy yields sharp testable implications. The more general case of national competition is characterized by simulations. We proceed in the aforementioned order.

4.1 Competitive Structure I: Market-Level Oligopoly

In this setting, we assume the number of markets J is large and so banks internalize their impact on market-level prices and quantities, r_j and l_j, but ignore their impact on national-level prices and quantities, R and L. The bank problem is thus separable into market-j specific profit maximization problems. Let $X = (R, L)$ denote national aggregate variables. Banks take X and competitors' behavior as given but understand that they alter all terms in blue:

$$\max_{r_{ij}} r_{ij} l_{ij}(r_{ij}, r_j, X) - \left[c_i + r_f\right] l_{ij}(r_{ij}, r_j, X)$$

subject to the bank-level demand curve and aggregate price index definition,

$$l_{ij}(r_{ij}, r_j, X) = \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L, \qquad r_j = \left[{r_{ij}}^{1-\eta} + \sum_{k \neq i} r_{kj}^{1-\eta} \right]^{\frac{1}{1-\eta}}.$$

dependent on affiliate-level cash flows compared with funding of loans by independent banks. Cremers, Huang, and Sautner (2011) find empirical evidence suggesting that headquarters smooth out deposit fluctuations from their member banks. Furthermore, Drechsler et al. (2017) empirical analysis for the deposit channel of monetary policy relies on the identification assumption that banks pool deposits to finance loans across their branches. They provide supportive evidence by showing that a bank's lending is uncorrelated with local deposit-market concentration.

An important determinant of optimal behavior will be the bank's market-level share:[11]

$$s_{ij} \equiv \frac{r_{ij} l_{ij}}{\sum_{i \in j} r_{ij} l_{ij}} \in [0,1]. \tag{6}$$

Combining the market-level share definition and the bank's first order conditions, we can write the optimal interest rate as a share-dependent markup $\mu(s_{ij})$ over the bank's marginal cost of funds:[12]

$$r_{ij} = \left[c_i + r_f\right] \mu(s_{ij}), \quad \mu(s_{ij}) \equiv \frac{\left[\eta\left(1 - s_{ij}\right) + \theta s_{ij}\right]}{\left[\eta\left(1 - s_{ij}\right) + \theta s_{ij} - 1\right]}. \tag{7}$$

When a bank controls the entire market $s_{ij} = 1$, the markup attains its maximal value, $\frac{\theta}{\theta - 1}$. Lower values of θ imply lower substitution elasticities and greater markups. When credit card borrowers cannot substitute across markets, banks charge larger markups. When a bank is atomistic, $s_{ij} = 0$, the markup attains its minimal value $\frac{\eta}{\eta-1} < \frac{\theta}{\theta-1}$. Greater substitutability of credit card borrowers across lenders within a market (i.e. higher η), yields lower markups.

Market-level Nash equilibrium. Taking competitor actions as given, the market-j equilibrium is defined by a fixed point in bank market-level shares:

$$s_{ij} = \left(\frac{\left[c_i + r_f\right] \frac{\left[\eta\left(1-s_{ij}\right)+\theta s_{ij}\right]}{\left[\eta\left(1-s_{ij}\right)+\theta s_{ij}-1\right]}}{\left[\sum_{i\in j}\left(\left[c_i + r_f\right] \frac{\left[\eta\left(1-s_{ij}\right)+\theta s_{ij}\right]}{\left[\eta\left(1-s_{ij}\right)+\theta s_{ij}-1\right]}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}} \right)^{1-\eta} \quad \forall i \in j. \tag{8}$$

Many models with multiplicative aggregate shocks are block-recursive (Berger et al. (2022)). In our setting, however, the additive nature of the risk free rate r_f ensures that the model is *not* block recursive with respect to the risk-free rate. Namely, $\frac{ds_{ij}}{dr_f} \neq 0$, thus allowing us to study how changes in national interest rates affect market-level rate-setting behavior. The model *is* block recursive with respect

[11] Henceforth, we use the short-hand $\sum_{i \in j} x_i = \sum_{i=1}^{N_j} x_i$

[12] We use the property that $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$.

to L, R, and other multiplicative aggregates.

Competitive and monopolistic competition benchmarks. In the competitive model the interest rate is given by marginal cost pricing:

$$r_{ij} = c_i + r_f. \tag{9}$$

Profits are zero, and interest rates move one-for-one with the cost of funds. In atomistic, monopolistic competition, the interest rate is given by a constant markup over marginal costs:

$$r_{ij} = \frac{\eta}{\eta - 1}[c_i + r_f] \tag{10}$$

Profits are non-zero, and interest rates and the cost of funds co-move in the same proportion at every bank. We use both of these competitive benchmarks as null hypotheses in the testable implications that follow.

Pass-through with market-level oligopoly. We use the results from Amiti, Itskhoki, and Konings (2016) and Berger et al. (2022) to compute pass-through rates when strategic interactions are at the market-level. Our primary object of interest is the semi-elasticity of interest rates with respect to the risk-free rate, $\frac{d \ln r_{ij}}{d r_f}$.

Our central objects of interest are the derivatives of lender i's markups with respect to their (and their competitors') interest rate m_{iij} (m_{ikj}):

$$m_{iij} \equiv \frac{\partial \ln \mu \left(r_{ij}, r_{-ij}\right)}{\partial \ln r_{ij}}, \quad m_{ikj} \equiv \frac{\partial \ln \mu \left(r_{ij}, r_{-ij}\right)}{\partial \ln r_{kj}}.$$

In proposition 1, which follows directly from Amiti et al. (2016) and Berger et al. (2022), we show the semi-elasticity of interest rates with respect to the risk-free rate can be decomposed into two components, the direct effect of the rate cut and the indirect effect of the rate cut through competitor responses (and thus strategic interactions).

Proposition 1: *The semi-elasticity of interest rates with respect to the risk-free rate is* *given by*

$$\frac{d\ln r_{ij}}{dr_f} = \underbrace{\frac{1}{(1-m_{iij})}\frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f}}_{\text{Direct effect}} + \underbrace{\frac{1}{(1-m_{iij})}\sum_{k\neq i} m_{ikj}\frac{d\ln r_{kj}}{dr_f}}_{\text{Indirect effect}} \tag{11}$$

where the own- and competitor-markup responses are given by:

$$m_{iij} = -\frac{(\theta-\eta)(1-\eta)\, s_{ij}\left(1-s_{ij}\right)}{\epsilon_{ij}\left[\epsilon_{ij}-1\right]} < 0, \quad m_{ikj} = \frac{(\theta-\eta)(1-\eta)\, s_{kj}s_{ij}}{\epsilon_{ij}\left[\epsilon_{ij}-1\right]} > 0$$

The *pass-through factor*, $\frac{1}{1-m_{iij}}$, governs the rate at which cost shocks and competitor responses translate into price responses for the focal bank i. Proposition 1 illustrates that the own-markup response is negative, $m_{iij} < 0$, and attains a value of zero at atomistic $s_{ij} = 0$ and pure monopolist $s_{ij} = 1$ banks. As a result, the pass-through factor, $\frac{1}{1-m_{iij}}$, is unity at atomistic $s_{ij} = 0$ and pure monopolist $s_{ij} = 1$ banks, but strictly less than one for any intermediate bank market-level share.

We plot pass-through in Figure 1 using parameter values from our later estimation in Table 4. Pass-through is complete for atomistic firms and declines as the market-level share grows. Pass-through rises beyond a market-level share of 80%. The majority of our data yields shares well below 80% ($s_{ij} < 0.8$), and in our national model, pass-through is not unity even in the extreme case that $s_{ij} = 1$.

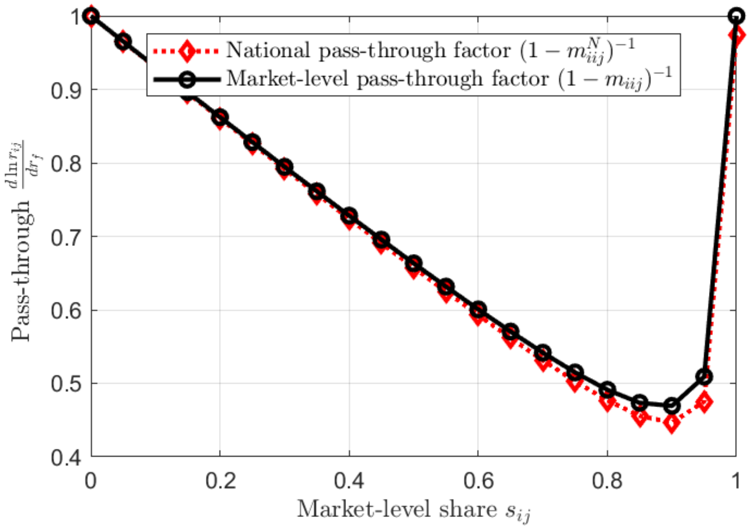
4.1.1 Market-Level Oligopoly Testable implications.

We exploit the model's structure and lack of block recursivity to derive testable implications. In particular, we focus on the way lender interest rates respond to changes in the risk free rate $r_{f,t}$ (or any other national component of bank funding costs), and how those responses vary with their market-level shares. The model is static, but given the time-dependent nature of the experiments we are interested in, we add time subscripts to each variable.

We first express equation (7) in logs which reveals the additive separability of bank funding costs and markups:

$$\ln r_{i,j,t} = \ln\left[c_{i,t} + r_{f,t}\right] + \ln\mu\left(s_{i,j,t}\right)$$

Figure 1: Pass-through comparison, market v. national oligopoly



Notes. The pass-through factor, $\frac{1}{1-m_{iij}}$, in the market-oligopoly model is given by the black-circle line. The pass-through factor, $\frac{1}{1-m_{iij}}$, in the national-oligopoly model is given by the red-diamond line. Parameters are from Table 4. We assume an (extreme) national share of 10% and that the bank is in 50% of markets.

Consider two markets $j = H$ and $j = L$ where bank i has a high market-level share and low market-level share. Define the difference in log interest rate between market H and market L as

$$\Delta_{HL} \ln r_{i,j,t} \equiv \ln r_{i,H,t} - \ln r_{i,L,t} = \ln \mu \left(s_{i,H,t}\right) - \ln \mu \left(s_{i,L,t}\right).$$

Consider two time periods t and $t+1$ in which $r_{f,t+1} \neq r_{f,t}$. We define the double difference of log interest rates across markets and time as

$$\Delta_{H,t} \ln r_{i,j,t} \equiv \Delta_{HL} \ln r_{i,j,t+1} - \Delta_{HL} \ln r_{i,j,t}. \tag{12}$$

With this notation in hand, our main testable implications of the theory – i.e., the share dependence of pass-through rates – are made explicit in Lemma 1.

Lemma 1: *Under perfect competition or monopolistic competition $\Delta_{H,t} \ln r_{i,j,t} = 0$ and therefore the within-bank, across-market response of interest rates to the cost of funds is* *independent of market-level shares. Under market-level oligopoly $\Delta_{H,t} \ln r_{i,j,t}$ depends on market-level shares and is not necessarily equal to zero.*

In perfect competition and monopolistic competition $\mu = \overline{\mu} = 1$ and $\mu = \overline{\mu} = \frac{\eta}{\eta-1}$ are both constant, respectively. This implies $\Delta_{H,t} \ln r_{i,j,t} = 0$. With oligopolistic competition, equation (8) implies $ds_{ij}/dr_f \neq 0$ for finite N and $s_{ij} \in (0,1)$, implying $\Delta_{H,t} \ln r_{i,j,t}$ is not necessarily zero. In the extreme case that $s_{i,H} = 1$ and $s_{i,L} = 0$, $\Delta_{H,t} \ln r_{i,j,t} = 0$ even in the case of oligopoly.

We numerically illustrate the share-dependence of pass-through rates in Figure 2. We assume rates are cut by 1%, with banks' costs c_i evenly spaced over the interval $[\underline{c}, \overline{c}] = [.02, .04]$.

Panel A of Figure 2 shows that large (low cost) bank market-level shares expand. Since market-level shares must sum to one, this comes at the expense of small banks. Panel B plots the change in spreads of each bank. In terms of spreads, $\mu(s_{ij})$ is strictly increasing in s_{ij}, implying that large banks increase spreads in response to the reduction in rates. Small banks do the opposite and partially pass-through the rate cuts to borrowers. Our subsequent empiric strategy is designed to recover the markup dynamics in Panel B, i.e. large firms pass-through less.

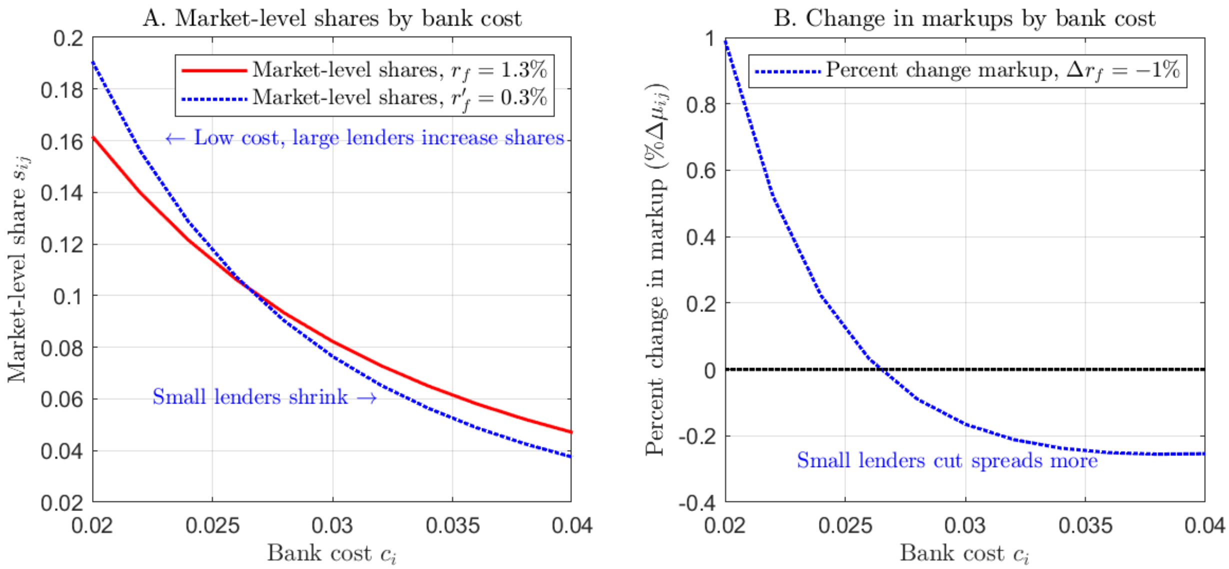
4.2 Competitive Structure II: National Oligopoly

We assume lender i operates in an exogenously given set of markets, $J(i)$. Lenders understand that they affect market-level and national-level prices, r_j and R respectively. Let c_i denote the lender's national cost of funds. We maintain the assumption that the risk-free rate r_f is set outside of the credit card market, despite the lender's national market power in the credit market market.

To make progress on the national lender problem, we assume households have linear preferences over final goods and separable CRRA preferences over credit services:

$$u(C_1, C_2) = C_1 + A\frac{C_2^{1-\gamma}}{1-\gamma}.$$

Figure 2: Pass-through from risk free rate to markups in the market-level oligopoly model



Notes. This is a numeric example market with 11 banks, where costs are uniformly distributed across 0.02 to 0.04. All other parameters are from Table 4.

This yields the following isoelastic aggregate demand curve:

$$L = \left(\frac{A}{R}\right)^{\frac{1}{\gamma}} \tag{13}$$

The lenders maximize national profits Π_i, summing over all markets in which they operate, $j \in J(i)$, internalizing their effects on all terms in blue:

$$\Pi_i = \max_{\{r_{ij}\}} \sum_{j \in J(i)} \Big\{ r_{ij} l_{ij}(r_{ij}, r_j, R) - \left[c_i + r_f\right] l_{ij}(r_{ij}, r_j, R) \Big\}. \tag{14}$$

subject to each of the relevant firm-level demand curves for every $j \in J(i)$:

$$l_{ij}(r_{ij}, r_j, R) = \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} \left(\frac{A}{R}\right)^{\frac{1}{\gamma}}, \quad R = \left[\sum_j r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}, \quad r_j = \left[r_{ij}^{1-\eta} + \sum_{k \neq i} r_{kj}^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

A central component of optimal pricing is a lender's <u>national-level share</u> s_{ij}^N:[13]

$$s_{ij}^N \equiv s_j s_{ij} = \frac{r_{ij} l_{ij}}{\sum_{i,j} r_{ij} l_{ij}}, \quad s_j = \frac{\sum_i r_{ij} l_{ij}}{\sum_{i,j} r_{ij} l_{ij}} \quad s_{ij} = \frac{r_{ij} l_{ij}}{\sum_i r_{ij} l_{ij}}$$

The national-level share is the size of the lenders' position in the market relative to the national or aggregate market. The numerator is still market specific. Market- and national-level shares are only imperfectly correlated. Banks may be large within a market $s_{ij} = 1$, but the market is small nationally, $s_j \approx 0$, yielding a small national share. Notice that our notion of national-level share exists even in absence of a geographic dimension for a market.

Under these functional form assumptions, the implicit function that defines the optimal interest rate is given by

$$\begin{aligned} r_{ij} &= \frac{\left[\eta(1-s_{ij}) + \theta s_{ij}\right]\left[r_f + c_i\right] + \left(\theta - \frac{1}{\gamma}\right) s_{ij}^N \frac{\Pi_i}{l_{ij}}}{\left[\eta(1-s_{ij}) + \theta s_{ij} - 1\right]}, \\ &= \mu(s_{ij})(r_f + c_i) + \frac{\mu(s_{ij})}{\mu(s_{ij}) - 1}\left(\theta - \frac{1}{\gamma}\right) s_{ij}^N \frac{\Pi_i}{l_{ij}}. \end{aligned} \tag{15}$$

When $s_{ij}^N = 0$, this expression simplifies to the market-level oligopoly expression. Outside of this corner case, we make progress on the characterization of this implicit function by imposing additional assumptions on the problem.[14]

Symmetric market characterization. Suppose the same set of lenders compete in every market. Since bank costs are common across markets, markets are symmetric. Lenders have heterogeneous costs c_i, and so lenders control asymmetric shares of the market. However, allocations are mirrored across all markets $r_i = r_{ij}$, $l_{ij} = l_i \; \forall j$.

Then we can characterize the interest rate in a similar fashion to our market-

[13] We use $\sum_{i,j} x_{ij}$ to denote the double sum $\sum_i \sum_j x_{ij}$.

[14] In Appendix A, we consider an alternative version of the national oligopoly model that accounts for uniform pricing along the geographic dimension of a market. This is motivated by recent work suggesting that banks often set similar deposit rates across geographical markets (Granja and Paixao, 2021; Begenau and Stafford, 2022). Appendix equation (A3) is similar to equation (15), with modified notions of market-level shares that are weighted averages of market-level revenue-based shares across all locations the lender operates.

level oligopoly economy:

$$r_{ij} = \mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right], \quad \mu\left(s_{ij}, s_{ij}^N, J_i\right) \equiv \frac{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - J_i\left(\theta - \frac{1}{\gamma}\right)s_{ij}^N}{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - J_i\left(\theta - \frac{1}{\gamma}\right)s_{ij}^N - 1} \quad (16)$$

Assume that the aggregate demand elasticity $\frac{1}{\gamma}$ is lower than the market-level demand elasticity $\frac{1}{\gamma} < \theta$, markups and interest rates are increasing in the measure of markets J_i. Likewise, markups are increasing the national share s_{ij}^N, ceteris paribus. When a bank's position in a market is large in relation to the nation, the bank charges greater markups.

However, if the aggregate demand elasticity is greater than the cross-market elasticity, $\frac{1}{\gamma} > \theta$, then as the banks get larger, they place more weight on the aggregate demand elasticity and lower their markups. They understand that at a national level, the household is more sensitive to aggregate rate changes. When the bank is large, they care disproportionately about the national responsiveness to their rate changes. On the other hand, as $J_i \to 0$, the markup expression coincides with the market-level oligopoly markup expression in equation (7).

The symmetric-market Nash equilibrium is a fixed point in national $\{s_{ij}^N\}$ and market-level shares $\{s_{ij}\}$,

$$s_{ij} = \left(\frac{\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]}{\left[\sum_i\left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}}\right)^{1-\eta}, \quad s_j = \left(\frac{\left[\sum\left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}}{\left[\sum_j\left[\sum_i\left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1-\theta}{1-\eta}}\right]^{\frac{1}{1-\theta}}}\right)^{1-\theta}, \quad s_{ij}^N = s_j s_{ij} \quad \forall ij, \quad (17)$$

where we have used $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$ and $s_j = \left(\frac{r_j}{R}\right)^{1-\theta}$. As before, the system is *not* block recursive with respect to r_f in either market-level or national shares. In other words, $ds_{ij}^N / dr_f \neq 0$.

Pass-through with national oligopoly. We now depart from Amiti et al. (2016) and Berger et al. (2022), and develop new formulas for pass-through rates when competition is national. Our primary object of interest remains the semi-elasticity of interest rates with respect to the risk-free rate, $\frac{d \ln r_{ij}}{dr_f}$. As before, we define the own, competitor, and national responses of markups:

$$m_{iij}^N \equiv \frac{\partial \ln \mu\left(s_{ij}, s_{ij}^N, J_i\right)}{\partial \ln r_{ij}}, \quad m_{ikj}^N \equiv \frac{\partial \ln \mu\left(s_{ij}, s_{ij}^N, J_i\right)}{\partial \ln r_{kj}}, \quad m_{ikj'}^N \equiv \frac{\partial \ln \mu\left(s_{ij}, s_{ij}^N, J_i\right)}{\partial \ln r_{kj'}}$$

Proposition 2 shows that the semi-elasticity of interest rates with respect to the risk-free rate now includes three components: the market-level direct effect, the market-level indirect effect (through market-level strategic interactions), and the national indirect effect (through national strategic interactions).

Proposition 2: *The semi-elasticity of interest rates with respect to the risk-free rate is given by*

$$\frac{d \ln r_{ij}}{d r_f} = \underbrace{\frac{1}{\left(1 - m_{iij}^N\right)} \frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f}}_{\text{Market direct}} + \underbrace{\frac{1}{\left(1 - m_{iij}^N\right)} \sum_{k \neq i} m_{ikj}^N \frac{d \ln r_{kj}}{d r_f}}_{\text{Market indirect (MI)}} + \underbrace{\frac{1}{\left(1 - m_{iij}^N\right)} \sum_{j' \neq j} \sum_k m_{ikj'}^N \frac{d \ln r_{kj'}}{d r_f} dj'}_{\text{National indirect (NI)}} \tag{18}$$

where the own- markup response is given by:

$$m_{iij}^N = \frac{\left(\epsilon_{ij} - \eta\right)\left(\eta - 1\right)\left(1 - s_{ij}\right) + \left(\epsilon_{ij} - \epsilon_{ij}^M\right)\left(\theta - 1\right) s_{ij}^N s_{ij}\left(1 - s_j\right)}{\epsilon_{ij}\left(\epsilon_{ij} - 1\right)}$$

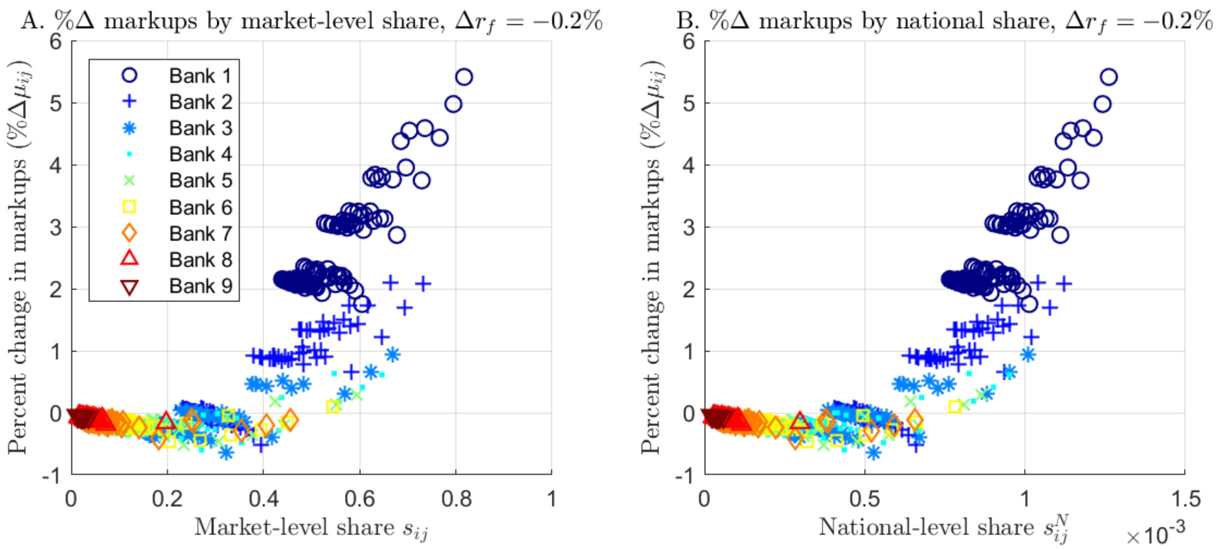
$$\epsilon_{ij} = \eta\left(1 - s_{ij}\right) + \theta s_{ij} - J_i\left(\theta - \frac{1}{\gamma}\right) s_{ij}^N, \quad \epsilon_{ij}^M = \eta\left(1 - s_{ij}\right) + \theta s_{ij}$$

And the market-level indirect (MI) and national indirect (NI) effects are given by:

$$MI + NI = \frac{-1}{\left(1 - m_{iij}^N\right)\epsilon_{ij}\left(1 - \epsilon_{ij}\right)}\Big\{\left[-\left(1 - \eta\right)\left(\epsilon_{ij} - \eta\right) + \left(1 - \theta\right)\left(\epsilon_{ij} - \epsilon_{ij}^M\right)\left(1 - s_j\right)\right] \sum_{k \neq i} s_{kj} \frac{d \ln r_{kj}}{d r_f} - \left(1 - \theta\right)\left(\epsilon_{ij} - \epsilon_{ij}^M\right) \sum_{j' \neq j} \sum_k \left(s_{kj'} s_{j'}\right) \frac{d \ln r_{kj'}}{d r_f}\Big\}$$

The *national pass-through factor*, $\frac{1}{1 - m_{iij}^N}$, is illustrated in Figure 1 with the red-diamond line. When $J_i\left(\theta - \frac{1}{\gamma}\right) > 0$, as is the case in our subsequent estimation, the national pass-through factor lies everywhere below the market-level pass-through factor. It is worth noting that the pass-through rate is no longer unity for pure monopolist $s_{ij} = 1$ banks. Their presence across multiple markets makes it optimal for them to pass-through rate cuts less than one-for-one even when they face no market-level competitor.

Figure 3: Pass-through from risk free rate to markups under national oligopoly



Notes. A 20 basis point reduction in the risk free rate is simulated. Panel A plots the percent change in markups across the high and low interest rate economies stratified by market-level shares. Panel B plots the percent change in markups across the high and low interest rate economies stratified by national-level shares. Parameters are from Table 4.

General characterization. When markets are not symmetric, equation (15) must be solved numerically. A national Nash equilibrium is (1) a set of policy functions $\{r_{ij}\}$ such that in every market j, given competitor behavior $\{r_{-ij}\}$, r_{ij} solves equation (14) and is consistent with r_j and R, and (2) the credit services market clears.

Figure 3 illustrates how lenders adjust their markups in response to a rate cut based on the estimated parameters in Section 6. We simulate a 20 basis point reduction in r_f. The x-axis is the lenders national-level share s_{ij}^N and the y-axis is the percent change in markups. Each color is one of the nine distinct lenders in the U.S. economy.

Figure 3 clearly illustrates national-share-dependent pass-through rates. Fixing a bank (e.g. the purple dots), we see that within that bank, spreads are only cut at very low national shares, and spreads are actually increased at very high national shares. This differential pass-through is the basis of our testable implications in Section 5.

4.3 National- and Market-level Oligopoly Testable Implications

As before, we add back the time dimension to all variables, and work with equation (15) in logs. Instead of market-level shares, we now consider two markets $j = H$ and $j = L$ where bank i has a high and low national-level share (i.e. $s_{iH}^N > s_{iL}^N$), but *identical market-level shares*, $s_{iH} = s_{iL}$.[15] Define the difference in log interest rate between high and low national share as

$$\Delta_{HL}^N \ln r_{i,j,t} = \ln r_{i,H,t} - \ln r_{i,L,t}.$$

As in the market-level oligopoly case, we consider two time periods t and $t+1$ in which $r_{f,t+1} \neq r_{f,t}$. We focus on the double difference of log interest rates across markets and time,

$$\Delta_{H,t}^N \ln r_{i,j,t} = \Delta_{HL}^N \ln r_{i,j,t+1} - \Delta_{HL}^N \ln r_{i,j,t}. \tag{19}$$

The main testable implication of our national oligopoly theory is the the national-level share dependence of pass-through rates stated in Lemma 2.

Lemma 2: *Assuming identical market-level shares, under perfect competition or monopolistic competition $\Delta_{H,t}^N r_{i,j,t} = 0$ and is therefore independent of national-level shares. Under national-level oligopoly, $\Delta_{H,t}^N r_{i,j,t}$ depends on national-level shares and is not necessarily equal to zero. Under market-level oligopoly $\Delta_{H,t}^N r_{i,j,t}$ is independent of national shares.*

The independence of perfect competition and monopolistic competition from national-level shares follows directly from the zero and constant markup in each environment, respectively. The dependence of $\Delta_{H,t}^N r_{i,j,t}$ on national shares is implicit in system (17), and illustrated numerically in Figure 3. Depending on the rel-

[15] This variation exists since market sizes differ; however, in practice, we will control for shares.

ative size of γ and θ, Proposition 2 reveals that a larger national share may dampen *or potentially amplify* pass-through rates.

5 Empirical Analysis

In this section, we test Lemma 1 and Lemma 2 by exploiting a high-frequency account-level panel dataset of interest rates at origination in 2008. We combine this dataset with identified monetary policy shocks to estimate the differential pass-through within-bank, across-market following the large surprise rate cuts in 2008. In what follows, we first describe the data used, provide our baseline definition of a market, and then detail our empirical strategy. Our empirical strategy proceeds in two steps:

Step I: Residualization. Our model assumes that lending costs are bank, not market specific. To map our model to the data, we must purge the interest rate from changes in borrowers' characteristics such as default risk, and also from changes in lender-specific characteristics such as differential funding costs or lending opportunities. We do so using a rich set of bank and market fixed effects as well as flexible controls for individual borrower characteristics, such as FICO, product type, etc. We refer to the residualized rates as *spreads*.

Step II: Tests of differential pass-through. We aggregate the *spreads* into a bank-market-week panel and test for the market- and national-level share dependence of pass-through rates of surprise reductions in the federal funds rates. Through the lens of our theory, Lemma 1 and Lemma 2 establish that competitive and monopolistically competitive models yield common within-bank, across-market pass-through rates. The market- and national-level oligopoly market structures yield within-bank, across-market pass-through rates that depend on market- and national-level shares, respectively.

5.1 Data Description and Market Definition

Data on credit card loans is obtained from the OCC CCM database. The dataset starts in 2008 and contains account-level information for credit card loans originated by the nine largest banks in the US.[16] While the identity of the banks in the OCC is private, in public data, the ten largest lenders control 80% of the credit card market, and the nine largest control more than 75% of the market.[17] The dataset provides unique identifiers for banks and accounts, thus allowing us to link a given credit card loan with the bank that originated it. The dataset also contains information about the date of origination, cycle ending interest rate, cycle ending balances, promotional balances, credit limits, credit score, zip code, interest rate type, product type, and borrower income, among other fields.

Having the origination date as a variable in the dataset is useful for several reasons. First, it allows us to build high-frequency windows around FOMC events. Second, since we are focusing on origination dates, we can consider accounts with either fixed or variable interest rates. This is important since around one-third of accounts in our sample have fixed rates. Furthermore, it circumvents the issue that, by regulation, banks cannot change interest rate spreads unless a significant event occurs (e.g., delinquency).

Next, we define a market. In our baseline analysis, we consider a *market* to be the combination of a 2-digit zip code, credit card type, product type, and FICO group. The 2-digit zip code are the first two digits of a zip code within a US state, and it generally covers an area greater than an MSA, as shown in Figure 4. Credit card type refers to it being general purpose or not, and product type refers to it being co-brand or not. Regarding FICO, we generate two groups: subprime (score less than 680) and prime (score greater or equal to 680). To avoid losing observations in our residualization stage, we also create a third category for missing credit scores but then exclude them in our analysis of differential pass-through. In robustness analysis, we redefine a market by substituting the geographical location for zip code level income.

[16] Agarwal et al. (2015) describe the dataset in detail. They write on p. 113-114: "In 2008, the OCC initiated a request to the nine largest banks that issue credit cards to submit data on general purpose, private label, and small business credit cards. The purpose of the data collection was to have more timely information for bank supervision... Reporting started in January 2008 and continues through the present, although the reporting in the first few months of 2008 is incomplete. Due to mergers and other reporting issues, we observe entry and exit of banks during the time period... To obtain a balanced panel of banks while maintaining a sufficiently wide window around the CARD Act implementation dates, we drop a small bank that enters and exits the sample and restrict our time period to March 2008 to December 2011. "

[17] https://wallester.com/blog/business-insights/list-of-top-10-credit-card-issuers

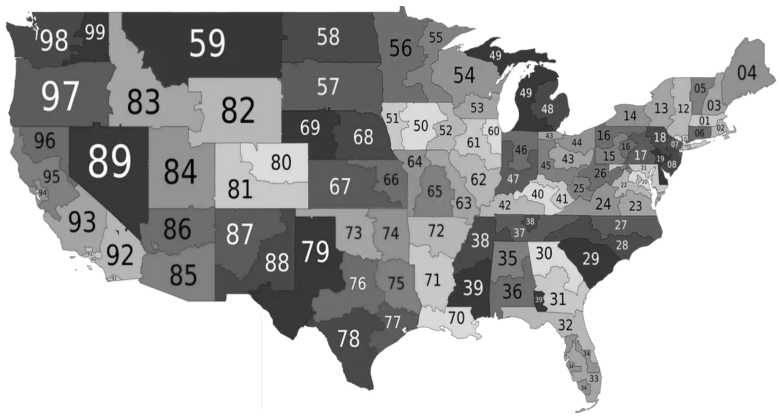


Figure 4: US Map of Two-digit Zip Codes

With this definition of market at hand, we compute a bank's market-level share using balances on all existing accounts,

$$\tilde{s}_{ij} = \frac{l_{ij}}{\sum_i l_{ij}}. \tag{20}$$

Panel (a) of Figure 5 shows the distribution of banks' market-level shares in January 2008, excluding values equal to zero or greater than 95%. The distribution is significantly right-tailed with nontrivial density all up to the upper bound, denoting a significant fraction of markets having lenders with sizeable shares. Panel (b) shows the distribution of the number of markets in which each bank operates on a given week. The distribution is dispersed over a wide range, with the maximum number of markets being around 500. Overall, Figure 5 shows significant variation in market-level shares and in the number of active markets, which is instrumental for our empirical strategy.

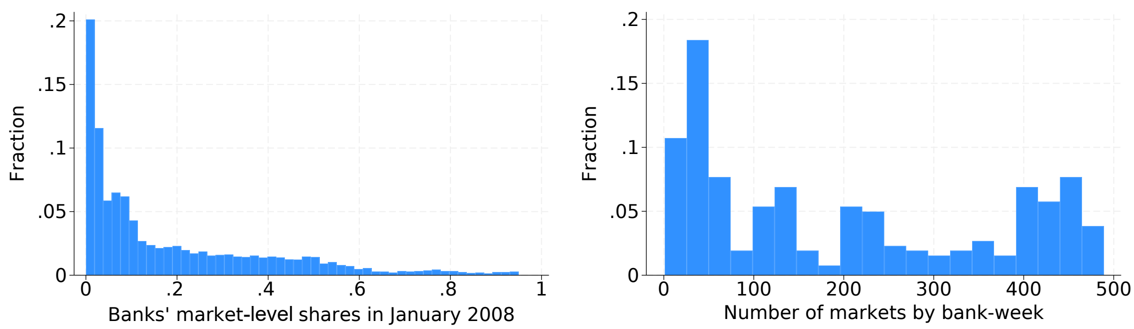
In turn, we define the *national-level* share to be the ratio of a bank's balances in a market over aggregate balances across all banks and markets in a given period,

$$\tilde{s}^N_{ij} = \frac{l_{ij}}{\sum_j \sum_i l_{ij}}. \tag{21}$$

This is a measure of the size or footprint of a bank's balances in a market from a national level perspective. Figure 6 shows the distribution of these shares which is

Figure 5: Distribution of Banks' Market-level Shares and Number of Markets

(a) Bank Market-level Shares (b) Number of Markets by Bank-Week



also significantly right-tailed, although density is now more concentrated towards 0 since l_{ij} values are compared with national aggregates.[18]

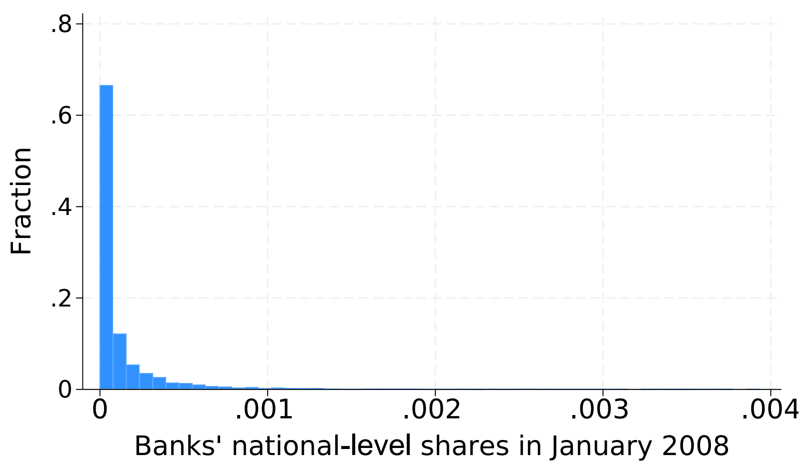


Figure 6: National shares

As mentioned before, our empirical strategy exploits exogenous variation induced by unexpected changes in the monetary policy rate around FOMC events. During the 2008-2019 period, the largest policy rate movements occurred in 2008. Since we are interested in monetary policy shocks, we follow the previous literature to measure the unexpected component of changes in the policy rate. To this end, we use surprises in the current month's (FF1) and 3-month ahead (FF4) Fed

[18]Of note, due to concerns about clearence for public release, the distribution was truncated at 0.004.

Funds futures in a 30-minute window around FOMC announcements (see, for instance, Kuttner (2001); Gurkaynak, Sack, and Swanson (2005); Gertler and Karadi (2015)). We also consider shocks to the policy rate that are stripped from any *news* component, as constructed by Miranda-Agrippino and Ricco (2021). Overall, the largest monetary policy shocks induced by changes in the policy rate during FOMC meetings were in January 22, January 30, April 30, and December 16.

After having identified FOMC events with the largest shocks to the policy rate, we construct windows that start 3 weeks before end 8 weeks after each FOMC meeting. If there are multiple meetings within a window, we do a cumulative sum of the shocks across time within such window. While market- and national-level shares, $\tilde{s}_{ijt}$ and $\tilde{s}^N_{ijt}$, are computed using all outstanding balances in a given month, our econometric analysis is based on data for newly originated accounts across the three FOMC events.[19]

Table 1 presents descriptive statistics of a set of continuous account-level variables from our originations dataset. In particular, it shows the mean, median, dispersion, 10^{th} and 90^{th} percentiles, skewness, and number of nonmissing observations. The table shows rich heterogeneity for each of these variables, with some variables being rather symmetric (e.g., credit score) and others exhibiting significant right-tails (e.g., real income).

In turn, Table 2 shows fractions for categorical (dichotomic) variables. Roughly one-half of our sample consists of general purpose credit cards, and around a fifth are co-branded. In turn, almost one-third of the accounts in our sample exhibit fixed interest rate, while 12% of the accounts have positive promotional balances. Regarding network patterns, one-half of the accounts belong to borrowers with multiple credit cards, while a much lower fraction of 12% of accounts are from borrowers with multiple banking relationships. Lastly, only a small fraction of the sample are securitized or secured credit card accounts (6.8% and 1.1%, respectively).

[19] We consider an account to be newly originated if the month of origination equals the month the data was reported.

Table 1: Descriptive Statistics: Continuous Variables

Variable	Mean	P10	P50	P90	S.D.	Skewness	Observations
Cycle ending balance	271	0	0	500	1,239	14.7	2,784,892
APR	16.5%	2.9%	18.9%	22.9%	7.2%	-1.1%	2,987,413
Credit score	718	611	728	810	79	-0.5	2,680,073
Credit limit	4,358	500	3,000	10,000	4,619	3.2	2,857,029
Real income	31,394	0	20,758	56,416	792,340	394.7	1,805,181
Utilization rate	9.5%	0%	0%	32.7%	41.1%	358.0	2,654,605

Table 2: Descriptive Statistics: Categorical Variables

Variable	Fraction	Observations
General purpose	54.7%	2,987,413
Co-brand	21.8%	2,987,413
Fixed interest rate	34.1%	2,962,753
Promo balances	12.7%	2,714,378
Multiple credit cards	50.8%	2,912,744
Multiple banking rels	12.3%	2,731,563
Securitized credit card	6.8%	2,987,413
Secured credit card	1.1%	2,967,527

5.2 Residualization

In order to properly exploit within-bank across-market variation, we first need to residualize the observed interest rates from common borrower and lender characteristics. In words, our goal is to compare the pass-through of two loan contracts that differ only by the share that the lender has in the market that the loan was originated. That way, we purge the interest rate from changes in borrowers' characteristics such as default risk, and also from changes in lender-specific characteristics such as differential funding costs or lending opportunities.

Before specifying the residualization regression, we introduce some notation that is consistent with that from the quantitative section. Let n be individual, $i(n)$ bank, $j(n)$ market, t date, τ_t week FE, dow_t day-of-week FE, α_j market FE, α_i bank FE, and $\tilde{sh}_{ij}$ and $\tilde{sh}_{ij}^N$ sets of quantiles on banks' market- ($\tilde{s}_{ij}$) and national-level shares ($\tilde{s}_{ij}^N$) , respectively. Let X_n be a vector of borrower-level controls, which includes fine quantiles on the following variables: credit score, credit limit, cycle ending balances, utilization rate, and borrowers' real income.[20] The vector X_n also includes dummies on interest rate type, secured credit card, securitized credit card, promotional balances, borrower with multiple banking relations, borrower with multiple credit cards.

With these definitions for variables and controls at hand, the regression specification for the residualization step is given by

$$\begin{aligned} \ln APR_{nt} =& \beta_0 + \tau_t + \alpha_j + \alpha_i + \tilde{sh}_{ij} + \tilde{sh}_{ij}^N + dow_t + \Gamma_1' X_n + ... \\ & \alpha_j \cdot \tau_t + \alpha_i \cdot \tau_t + \tilde{sh}_{ij} \cdot \tau_t + \tilde{sh}_{ij}^N \cdot \tau_t + \Gamma_2' X_n \cdot \tau_t + \epsilon_{nt}, \end{aligned} \tag{22}$$

where the treatment of the interest rate in logs follows arguments put forward in the quantitative section. This panel regression is estimated separately for each window, and residualized spreads are computed as

$$Y_{nt} = \hat{\epsilon}_{nt} + \widehat{\alpha_j \cdot \tau_t} + \widehat{\tilde{sh}_{ij} \cdot \tau_t} + \widehat{\tilde{sh}_{ij}^N \cdot \tau_t}, \tag{23}$$

where variables in *hat* notation denote projected values. Since our goal of residualizing the data is to isolate a markup, our residualized spreads Y_{nt} include (1) market-time variation, which captures changing non-share factors such as lending quantities l_{ij} in the non-symmetric national markup formula (15), (2) market-level share-time variation, and (3) national-level share-time variation.

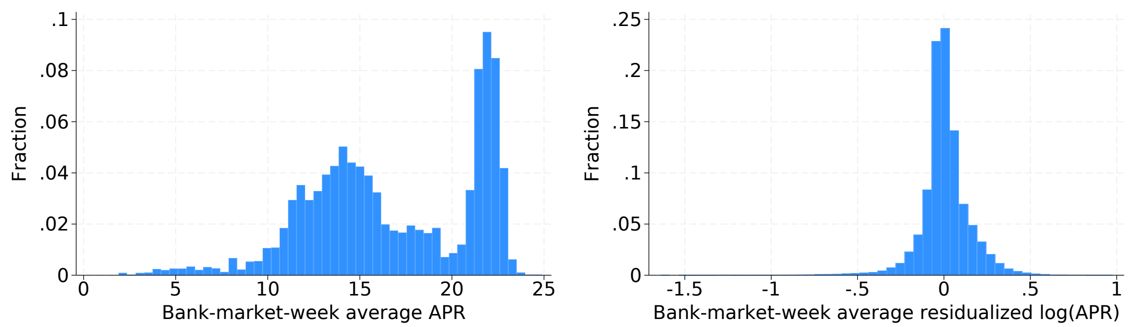
Of note, we exclude volatile markets by computing the average cross-sectional dispersion of weekly changes in interest rates and dropping markets that lie above the top 1%. We also drop markets whose maximum (minimum) change in interest rates lie above the top 1% (bottom 1%).

Panel (a) of Figure 7 shows the distribution of interest rates from our sample, and panel (b) shows the distribution of spreads (i.e., residuals Y_{nt}). Despite the residualization procedure purging various dimensions of variation, the resulting spreads still exhibit nontrivial dispersion to be exploited in the regressions aimed at measuring the differential pass-through within-bank across markets.

[20] In particular, it includes 40 quantiles on credit score, 20 quantiles on credit limit and on cycle ending balance, and deciles on utilization rate and borrowers' real income.

Figure 7: Distribution of Interest Rates and Spreads

(a) Distribution of APR (Levels) (b) Distribution of Residualized log(APR)



5.3 Estimation of Differential Pass-through

In what follows, we estimate the differential response of spreads (i.e., residualized log(APR)) to exogenous movements in the policy rate for high versus low market- and national-level shares. To this end, we first collapse account-level data to bank (i), market (j), and week (t) level, and then stack data across events defined in Section 5.1.

Let τ denote an FOMC event, FF_τ the monetary policy shock, $\mathbb{I}_{i,j}^{M,high}$ a dummy for a high market-level share, $\mathbb{I}_{i,j}^{N,high}$ a dummy for high national-level share. For each horizon $h \in \{-2, ..., 8\}$, the local projections specification is given by

$$\begin{aligned} Y_{i,j,\tau+h} =& \beta_{0h} + \beta_{M,h}\left(FF_\tau \times \mathbb{I}_{i,j}^{M,high}\right) + \beta_{N,h}\left(FF_\tau \times \mathbb{I}_{i,j}^{N,high}\right) + ... \\ & \sum_{p=1}^{3} \rho_{p,h} Y_{i,j,\tau-p} + \alpha_{\tau h} + \alpha_{jh} + \Omega_1' X_{ij} + \Omega_2'(X_{ij} \cdot \tau) + \epsilon_{i,j,\tau+h}, \end{aligned} \tag{24}$$

where $\alpha_{\tau h}$ is event FE, α_{jh} market FE, and X_{ij} a vector of controls.[21] The vector X_{ij} contains bank FE, and quantiles on the following variables: fraction of accounts that have fixed rates, number of originated loans, fraction of accounts with multiple credit cards, and fraction of accounts with multiple banking relations. Such quantiles are computed for data at the bank-market level.[22] If $\beta_{Mh} < 0$,

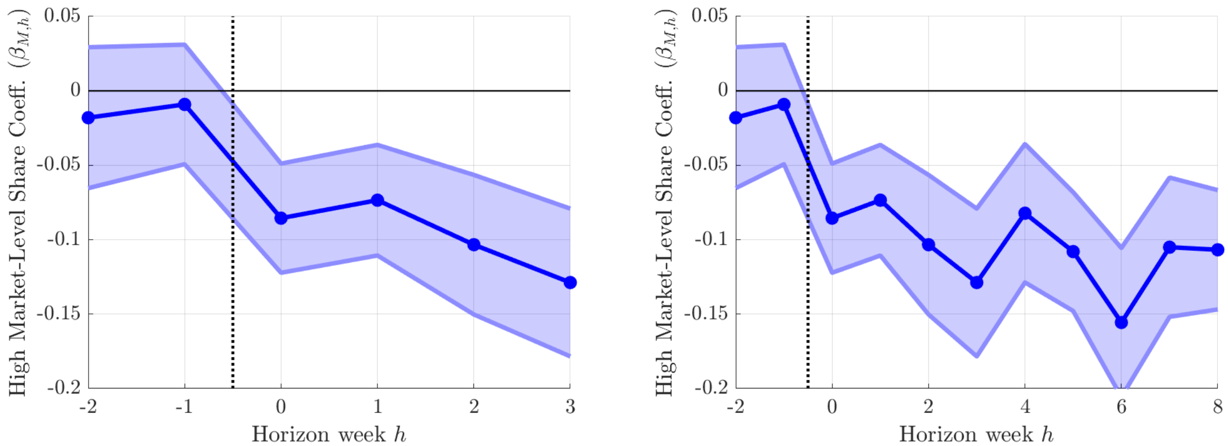
[21] Once again, we exclude volatile markets by following the same procedure as described in the previous section.

[22] Pre-trend regressions for $h = -2$ include only one lag, $Y_{i,j,\tau-1}$, due to data availability for the January event. Regressions for $h = -1$ include two lags. In all cases, observations are included

then lenders with large market-level shares have lower pass-through. Similarly, $\beta_{Nh} < 0$ implies that if the market is large at the national level then there is a lower pass-through.

Figure 8: Differential pass-through estimates based on market-level shares only

(a) Pass-through by market-level $\tilde{s}_{ij}$ only, short window **(b) Pass-through by market-level $\tilde{s}_{ij}$ only, long window**



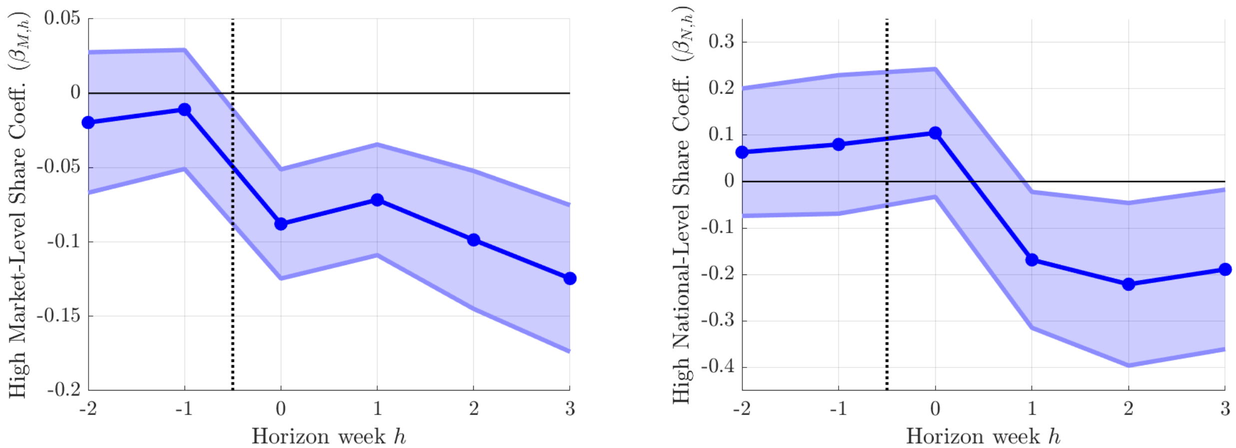
Notes. Figure (a) plots the differential pass-through $\beta_{M,h}$ from FF4 to residualized interest rates across stacked events, where $\beta_{M,h}$ is defined by equation (24) and $\mathbb{I}_{i,j}^{M,high}$ to be the top 30% of market-level shares. We omit the national share controls from this regression. Figure (b) repeats the exercise with a longer window.

We begin by analyzing differential pass-through across markets with differing market-level shares. Figure 8 estimates equation (24) with market-level shares alone, omitting national controls. We define high market-level shares $\mathbb{I}_{i,j}^{M,high}$ to be the top 30% of market-level shares. FF_t to be the surprise in the 3-month ahead Fed Funds futures (FF4) across stacked events. Panel (a) plots a 1 month window around the FOMC surprise. On impact, the differential pass-through coefficient is significant and large, $\beta_{M,h} = -0.086$. The average $\beta_{M,h}$ from t=0 to t=3 is -0.098.

only if banks operate in at least 100 markets that week and originate at least 5 loans in a given market-week. Results are robust to reasonable variations in these filters.

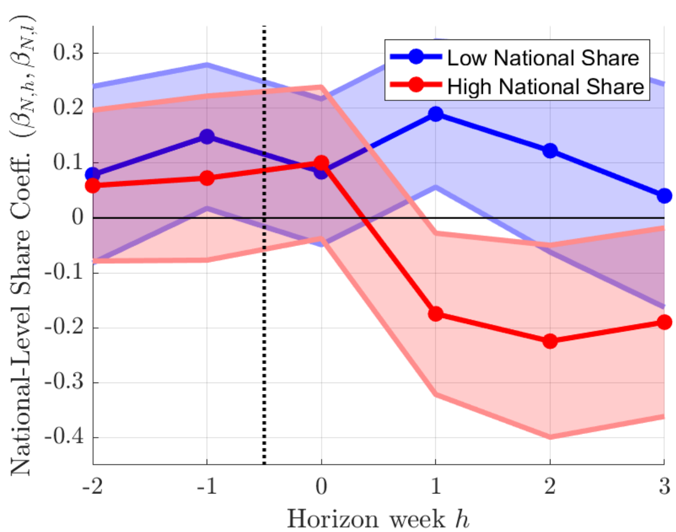
Figure 9: Differential pass-through estimates with market- and national-level shares

(a) Pass-through by market-level share $\tilde{s}_{ij}$, controlling for $\tilde{s}^N_{ij}$ **(b) Pass-through by national share $\tilde{s}^N_{ij}$, controlling for $\tilde{s}_{ij}$**



Notes. Figure (a) plots the differential pass-through $\beta_{M,h}$ from FF4 to residualized interest rates across stacked events, where $\beta_{M,h}$ is defined by equation (24) and $\mathbb{I}^{M,high}_{i,j}$ to be the top 30% of market-level shares and $\mathbb{I}^{N,high}_{i,j}$ to be the top 10% of national shares. Figure (b) plots the corresponding national coefficient $\beta_{N,h}$ from the same regression.

Figure 10: Differential pass-through estimates based on high, moderate, and low national shares



Notes. This figure plots the differential pass-through when include three dummies $\mathbb{I}^{N,high}_{i,j}$ (top 10% of national shares), $\mathbb{I}^{N,moderate}_{i,j}$ (middle 85% of national shows), $\mathbb{I}^{N,low}_{i,j}$ (bottom 5% of national shares). The omitted group is the moderate national share market.

How should we interpret these results? Since the $\beta_{M,h}$ is a semi-elasticity, we have

$$\frac{dln\,(APR)}{dFF} = \frac{1}{APR}\frac{dAPR}{dFF} = \beta_{M,h}\mathbb{I}_{ij}^{M,high} \tag{25}$$

$$\Rightarrow \quad \frac{dAPR^{high}}{dFF} - \frac{dAPR^{low}}{dFF} = \beta_{M,h} \times APR. \tag{26}$$

Thus, if $\beta_{M,h} = -0.098$ and the average residual interest rate (exponentiated) is 1.02pp, a market-level share above the 70th percentile implies a 10% lower pass-through ($= -0.098 \times 1.02$) compared to markets operated by the same bank in which the market-level share is below the 70th percentile.

Panels (a) and (b) of Figure C2 estimate equation (24) including both both national- and market-level shares. The high market-level share dummy $\mathbb{I}_{i,j}^{M,high}$ is defined to be the top 30% of market-level shares, and the high national share dummy $\mathbb{I}_{i,j}^{N,high}$ is defined to be the top 10%. Panel (a) shows that the differential response across markets is unchanged with the inclusion of national-level share controls. Panel (b) shows that the differential national response is of similar magnitude, but less precisely estimated. The average coefficient from t=0 to t=3 is $\beta_{N,h} = -0.12$. Since the average residual interest rate (exponentiated) is 1.02pp, a national-level share above the 90th percentile implies a 12.2% lower pass-through rate ($= -0.12 \times 1.02$) compared to markets operated by the same bank in which the national share is below the 90th percentile. Despite the imprecision, we can reject the null of zero-share dependent pass-through, both at the market and national levels. Appendix C shows similar results for the FF1 and FFMR shocks.

Figure 10 explores the differential response of rates across 'high,' 'moderate,' and 'low' national-level share markets. In this figure, we plot the differential pass-through when the high national share dummy is defined as the top 10% of national shares, and the low national share dummy is defined as the bottom 5% of national shares. The omitted group is moderate national share markets (the remaining 85% of the distribution). Figure 10 shows that relative to moderate share markets, banks that are operating in high national-level share markets have much lower pass-through rates. The high and low share markets parallel each other and then diverge after the FOMC surprise, providing credibility to our identifying assumption of parallel trends.

Table 3 shows statistics for the estimated coefficients as we vary the threshold for $\mathbb{I}_{i,j}^{M,high}$. Different rows depict changing the threshold from above the median all the way to the top 10%, while columns show averages for the estimated coefficients, standard errors, and lower and upper bounds of 90% confidence intervals, across the first three weeks starting from the FOMC event week. Results are robust to variations in the cutoffs.

Table 3: Differential Pass-through by Cutoff

Cutoff	Mean	Dispersion	C.I. (lb)	C.I. (ub)
Market-level share $\tilde{s}_{ij}$ greater than p40	0.0911	0.0718	-0.0270	0.2092
Market-level share $\tilde{s}_{ij}$ greater than p50	-0.0817	0.0441	-0.1543	-0.0091
Market-level share $\tilde{s}_{ij}$ greater than p60	-0.0912	0.0276	-0.1366	-0.0458
Market-level share $\tilde{s}_{ij}$ greater than p70	-0.0978	0.0259	-0.1403	-0.0552
Market-level share $\tilde{s}_{ij}$ greater than p80	-0.1167	0.0356	-0.1753	-0.0581
Market-level share $\tilde{s}_{ij}$ greater than p90	-0.0660	0.0542	-0.1552	0.0233

Notes. Differential pass-through rate $\beta_{M,h}$ is reported in this table. Each row varies the definition of the cutoff for "high" market-level shares $\widetilde{s}_{ij}$ in equation (24).

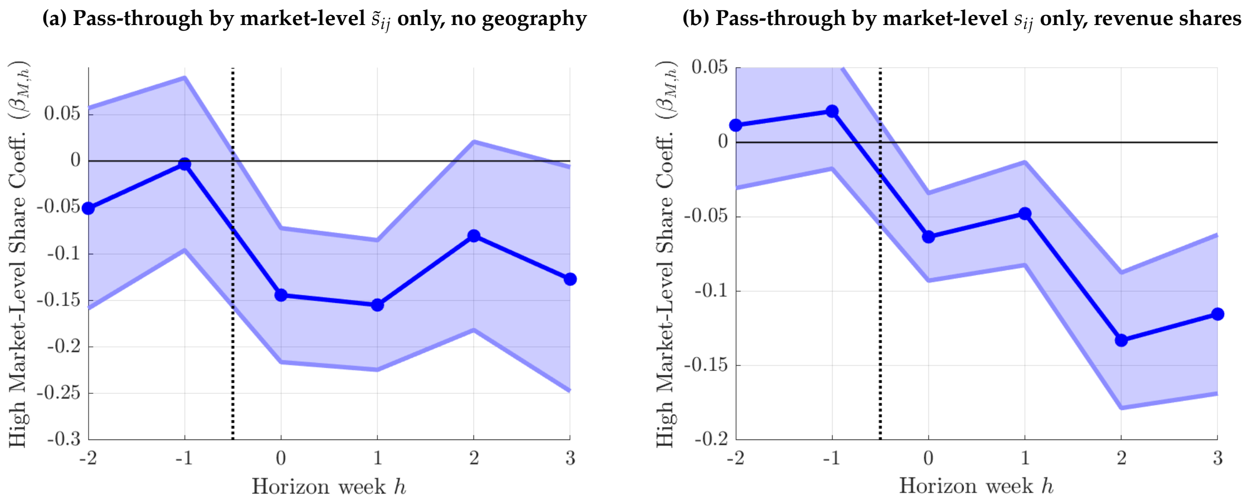
5.4 Robustness: Exclusion of Geography for Market Definition and Alternate Market-level shares

We perform two robustness exercises: (1) we substitute the geographical dimension of the definition of a market for an income-based one, (2) we consider revenue based market-level shares.

Ideally, we would use borrower income from OCC to determine the income dimension of a market. However, as Table 1 shows, that variable is not well-populated. To circumvent this issue, we obtain 5-digit-zip-code-level income from the IRS, and assume that the income of the borrower associated with the account equals the average income of the (5-digit) zip code where the account was originated.[23] Then, we compute 20 quantiles based on the 5-digit-zip-code-level income

[23]Source: https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.

Figure 11: Differential pass-through estimates based on market-level shares only



Notes. Figure (a) uses quantity shares but instead of using 2-digit zipcodes to define geography, we group 5-digit zipcodes into 20 quantiles based on their average regional income. All other non-geography aspects of the market definition are held fixed. Figure (b) plots the differential pass-through based on market-level revenue shares, instead of quantity shares.

distribution, and define the market to be the combination of the income quantile, credit card type, product type, and FICO group. Notice that, despite this variation, all theoretical model analysis and implications remain the same. Furthermore, steps I and II of our empirical approach also remain unchanged. The only difference is how we define a market.

Having redefined a market, we need to recompute new shares, re-run the residualization regression to obtain new spreads, and estimate a new set of local projections. Panel (a) of Figure 11 shows the results, in which our estimated $\tilde{\beta}_{L,h}$ are still negative and mostly statistically significant over the first few weeks after the shock.

Panel (b) of Figure 11 repeats our baseline estimation of (24) with revenue based shares $s_{ij} = \frac{r_{ij} l_{ij}}{\sum_i r_{ij} l_{ij}}$. This alternate definition of share yields very similar results. The differential pass-through coefficient $\beta_{M,h}$ remains bound between -0.1 and -0.2.

6 Macroeconomic effects of lender market power

Our point estimates are consistent with market- and national-level oligopolistic competition among credit card issuing banks. We use a structural model to map our reduced form regressions into estimates of lender market power. Our approach is to follow the literature on "macro-identification" (Nakamura and Steinsson (2018), Berger et al. (2022)) in which we infer the underlying parameters governing market power via simulated method of moments, treating the model and data in an "apples-to-apples" manner. We then quantify how lender market power affects macroeconomic aggregates including interest rates, the size of the credit market, and total welfare.

6.1 Mapping model to data

We set the number of banks to $N = 9$ and the total number of simulated markets to be $J = 600$ based on the OCC CCM database and our baseline market definition. Our model economy requires the specification of seven additional sets of variables: the risk free rate, bank costs, substitutability within and across markets, the set of markets in which banks operate, curvature over credit services, and the preference shifter for credit services: $\left\{r_f, \{c_i\}, \eta, \theta, \{J(i)\}, \gamma, A\right\}$.

We set $r_f = 1.3\%$, which is the average 10-year real interest rate reported by the Cleveland Fed for 2008.[24] We assume that bank lending costs are evenly distributed over the interval $[\underline{c}, \overline{c}]$. We estimate the bounds of bank costs to get the average interest rate and dispersion in interest rates right. We invert A so that the revolving credit to GDP ratio is 6.87%, which corresponds to the level observed in 2008.[25]

We fit the number of banks-per-market to the empirical distribution. We estimate a Gamma distribution over the discrete support $\{1, \ldots, N\}$, yielding a shape parameter of 1.5 and a scale parameter of 2.4. We then estimate $\{J(i)\}$ so that the probability bank i operates in market j is inversely proportional to their costs $P_{ij} \propto -bc_i$.[26] We estimate b to target the variance of ownership shares observed in

[24]See data and notes here: https://fred.stlouisfed.org/series/REAINTRATREARAT10Y

[25]See data and notes here: https://fred.stlouisfed.org/graph/?g=85D8

[26]The probability a bank owns one of the N_j slots is proportional to $P_{ij} = max\left\{a - bc_i, 0\right\}$, where

our data.

Lastly, we infer the parameters that govern market- and national- level oligopolistic behavior, $\{\eta, \theta, \gamma\}$, from the pass-through regressions in equation (24) and the aggregate elasticity of credit-to-GDP with respect to the risk-free rate. We map the regressions to the model in the following steps:

Step 1: First, we simulate a 20 basis point reduction in the risk free rate r_f. This corresponds to the average surprise component of federal funds changes in our sample. We denote the pre-shock period as t and the post-shock period as $t+1$.

Step 2: We take the model simulated interest rate data, $\{r_{ijt}\}$, and we residualize the change in log interest rates $\ln r_{ijt+1} - \ln r_{ijt}$ in an identical manner to equations (22) and (23). Since we estimate our regression in differences, we regress the change in interest rates on a constant, the bank fixed effect ($\widetilde{\alpha}_i$), market fixed effect $\widetilde{\alpha}_j$, market-level share deciles ($sh_{ij}(p)$), and national share deciles ($sh^N_{ij}(p)$) which correspond to bank-time, market-time, and share-time fixed effect in levels. We remove the constant and common bank-time variation as in equation (23):[27]

$$\Delta APR_{nijt} = \widetilde{\beta}_0 + \widetilde{\alpha}_i + \widetilde{\alpha}_j + \sum_p \widetilde{\beta}_p sh_{ij}(p) + \sum_p \widetilde{\beta}_p sh^N_{ij}(p) + \epsilon_{nijt} \tag{27}$$

$$\Delta \widehat{APR}_{nijt} = \Delta APR_{nijt} - \widetilde{\beta}_0 - \widetilde{\alpha}_i. \tag{28}$$

Step 3: We then estimate equation (24) on the residualized data, treating our simulated data as a single event with horizon h. We regress differenced residuals – assuming one h and one event – on a constant, bank fixed effect, market fixed effect, an interaction between the change in the risk free rate and whether that particular bank's market-level share is above a cutoff ($FF_\tau \times \mathbb{I}^{M,high}_{i,j}$), and an interaction between the change in the risk free rate and whether that particular bank's

$a = \frac{1}{2}$. Suppose there are N_j possible lenders in market j. Each one of the $N = 9$ banks draws a random uniform number $u_{ij} \sim U[0,1]$ and then we rank the banks by the product $Rank_{ij} = P_{ij}u_{ij}$. The top N_j lenders in terms of $Rank_{ij}$ are assigned to that market; the tie-breaker is a coin flip.

[27] Our inclusion of bank and market fixed effects in the differenced regression corresponds to bank-time and market-time fixed effects in the non-differenced regression.

national-level share is above a cutoff ($FF_\tau \times \mathbb{I}_{i,j}^{N,high}$):

$$\Delta\widehat{APR}_{nijt} = \widetilde{\beta_0} + \widetilde{\alpha_i} + \widetilde{\alpha_j} + \widetilde{\beta_M}\left(FF_\tau \times \mathbb{I}_{i,j}^{M,high}\right) + \widetilde{\beta_N}\left(FF_\tau \times \mathbb{I}_{i,j}^{N,high}\right) + u_{ij}. \quad (29)$$

$\widetilde{\beta_M}$ and $\widetilde{\beta_N}$ are the model's estimates of differential pass-through which map exactly to $\beta_{M,h}$ and $\beta_{N,h}$ in equation (24).

Lastly, we identify the households' willingness to substitute between credit services and consumption, γ, by targeting the elasticity of credit-to-GDP ($\sum_{i,j} l_{ij}/y$) to r_f instrumented by surprise rate changes.[28] The model's aggregate demand equation (13) implies that the elasticity of credit to interest rates is inversely proportional to γ. We estimate $\frac{d\ln(\sum l_{ij}/y)}{d\ln r_f} = -0.26$.

Estimation results. Table 4 reports our estimated model parameters and the corresponding model/data moment that yields identification. We estimate an intra-market elasticity of substitution of $\eta = 3.81$ and an inter-market elasticity of substitution of $\theta = 1.15$. As we discuss below, these elasticities imply spreads of roughly 1 percentage point in the most competitive markets and 4 percentage points in the least competitive markets. At our estimated η and θ, the model's differential pass-through rate across high/low share market lie within the 95% confidence interval observed in the data. In response to cutting the risk free rate, pass-through is 4% lower in markets where banks have high market-level shares and 3% lower in markets where banks have high national shares.

Our estimate for curvature over credit services of $\gamma = 1.64$ implies that $\theta > \frac{1}{\gamma}$, so that markups expand when a bank's national shares grow (see Proposition 2). This yields an elasticity of credit-to-GDP with respect to the interest rate of 30% in the model versus 26% in the data.

In terms of bank funding costs, we estimate that the lowest bank cost is a 50 basis point spread over the risk free rate, and the highest bank cost is a 700 basis point spread over the risk-free rate. In Appendix B, we follow an alternative procedure to estimate bank-level noninterest marginal costs that renders similar results. Our baseline cost estimates imply that the mean interest rate across banks, adjusted for

[28] We regress quarterly credit-to-GDP on the Cleveland Fed's 10-year real rate instrumented with Romer and Romer (2004) surprises between 1982-I and 2007-IV.

chargeoffs and inflation, is 6.0% in the model and 7.4% in the data and the standard deviation of interest rates across banks is 2.1% in the model and 4.6% in the data.[29] For robustness, in Appendix B we provide some alternative bank-level estimates for marginal costs based on noninterest expenses that are broadly aligned with our baseline ones.

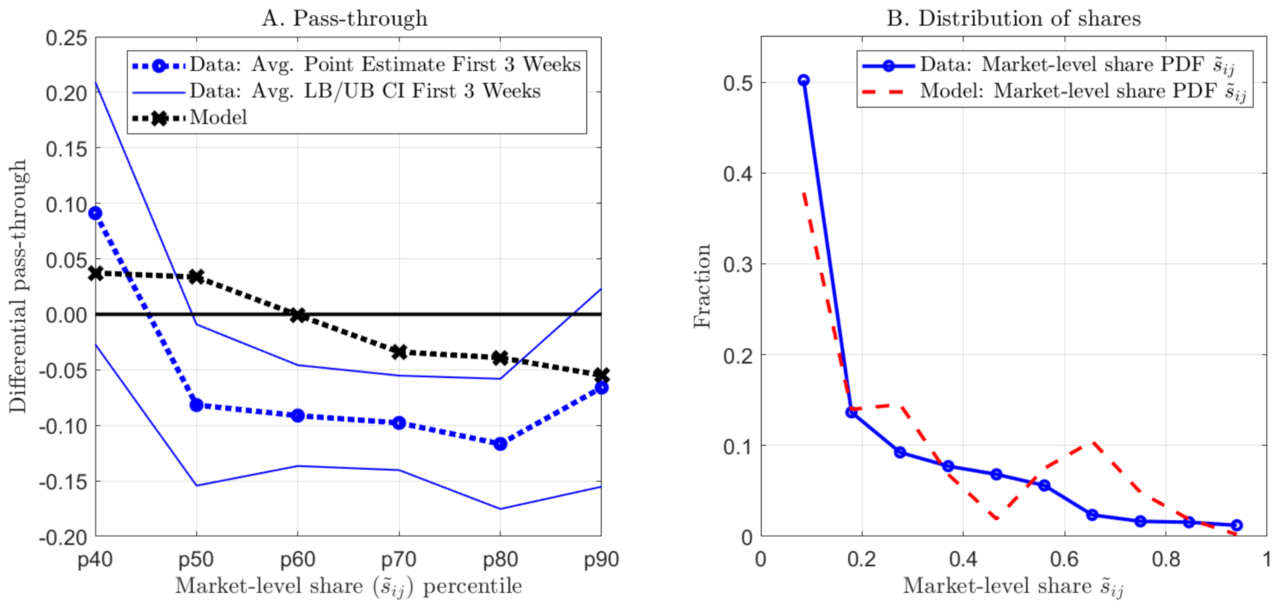
Non-targeted moments. Next, we examine the model's ability to replicate the data profile of pass-through rates, the distribution of shares, and the distribution of residualized interest rates. Panel A of Figure 12 plots the profile of pass-through rates based on equation (29) in the model versus the data. We report point estimates from separate regressions of residualized APR on the high-market-level-share dummy ($\mathbb{I}_{i,j}^{M,high} = 1(\tilde{s}_{i,j} > x)$) as we vary the cutoff of $\tilde{s}_{i,j}$ from 40^{th} to 90^{th} percentile of the distribution. The model is capable of generating positive point estimates for low cutoffs and increasingly negative estimates at higher values of the share distribution.

Panel B of Figure 12 plots the probability distribution function of quantity shares $\tilde{s}_{i,j}$ in the model and data. The model slightly understates the number of low-share competitors, and it exhibits a higher degree of "lumpiness," but it does remarkably well at generating the overall shape of the distribution.

Panel A of Figure 13 plots the model's interest rate spread ($r_{ij} - c_i - r_f$) in percentage points. Given the low base rate $r_f = 1.3\%$, the large percent markups implied by θ translate into very reasonable percentage point markups. The markup distribution rarely exceeds 4.5 percentage points. This estimate falls in line with spread estimates in Herkenhoff and Raveendranathan (2020). They estimate average spreads to be 3.4 percentage points between 1970 and 2020 after factoring in operational costs, fee income, and interchange income.

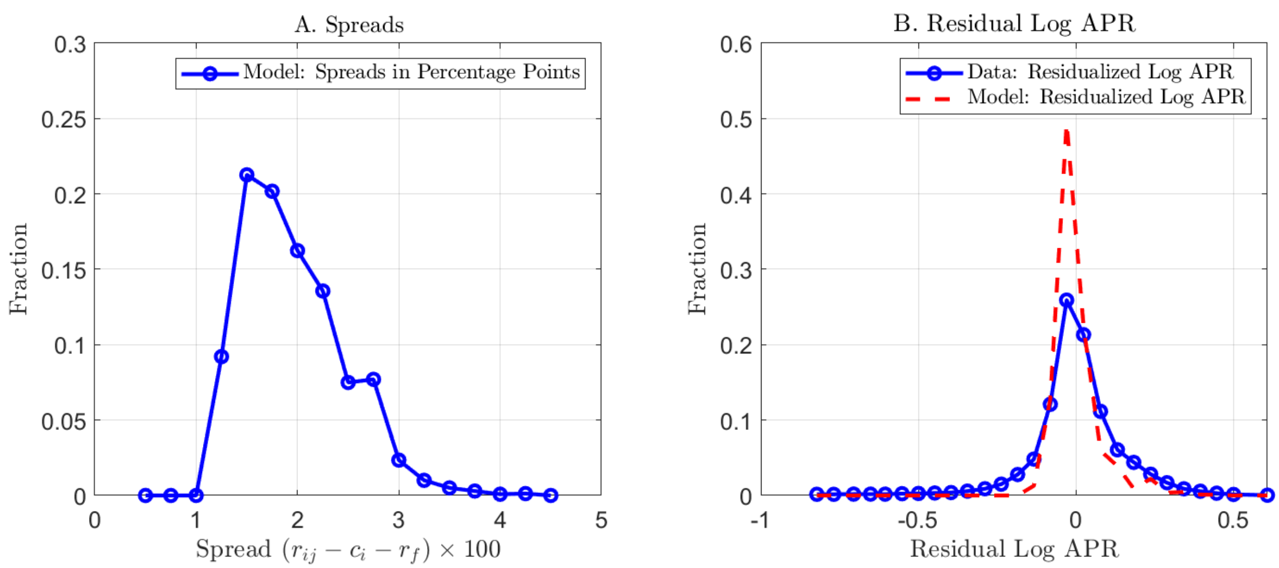
[29] Our sample period is 2008. We subtract the average chargeoff rate in 2008 from each bank's interest rate (`https://fred.stlouisfed.org/series/CORCCACBS`), and we subtract annual inflation in 2008 (`https://fred.stlouisfed.org/series/FPCPITOTLZGUSA`) from each bank's interest rate prior to computing moments.

Figure 12: Pass-through and shares in model versus data



Notes. Panel A plots point estimates from separate regressions of residualized APR on $\mathbb{I}_{i,j}^{M,high} = 1(\tilde{s}_{i,j} > x)$ *where x=40th to 90th percentile of share distribution. Model estimates from equation* (29). *Data estimates from equation* (24). *Panel B plots the probability distribution function of quantity based shares in the model and data,* $\tilde{s}_{i,j}$.

Figure 13: Spread and residualized APR distributions in model versus data



Notes. Panel A plots the model's spread in percentage points $r_{ij} - c_i - r_f$. *Panel B residualizes the model's* r_{ij} *on a constant and bank fixed effects. We compare that to the data residuals obtained via the procedure discussed in Section* 5.

Table 4: Model moments versus data

Var.	Description	Value	Moment	Model	Data
A	Credit Service Utility Shifter	3.3e+08	Revolving Credit (Non-Real Estate) to GDP	0.069	0.069
$\underline{c}$	Lower bound bank cost of funds	0.005	Mean r_{ij} (Net Inflation, Chargeoffs), Unwtd	0.060	0.074
$\bar{c}$	Upper bound bank cost of funds	0.070	SD r_{ij} (Net Inflation, Chargeoffs), Unwtd	0.021	0.046
γ	Curvature over credit services L	1.64	Elast. Credit-to-GDP WRT r_f	-0.29	-0.26
η	Intramarket elasticity of substitution	3.81	Differential pass-through $\tilde{s}_{ij} > p70, t = 1$	-0.04	-0.07
					[-0.11,-0.03]
θ	Intermarket elasticity of substitution	1.15	Differential pass-through $\tilde{s}^N_{ij} > p90, t = 1$	-0.03	-0.17
					[-0.31,-0.02]
			Std. Dev. of $\tilde{s}_{ij}$	0.2406	0.2123
			Std. Dev. of $\tilde{s}^N_{ij}$	0.0004	0.0004
b	Slope ownernship prob. WRT cost	6.36	Std. Dev. No. Markets-Per-Bank	141	165

6.2 Marcoeconomic consequences of bank market power

We measure the welfare losses from market- and national-level oligopolistic competition by comparing three economies: (1) the baseline market- and national-level oligopoly model (r_{ij} is defined by equation 15), (2) the market-level-only oligopoly model (r_{ij} is defined by equation (7)), (3) the competitive economy (r_{ij} is defined by equation (9)).[30]

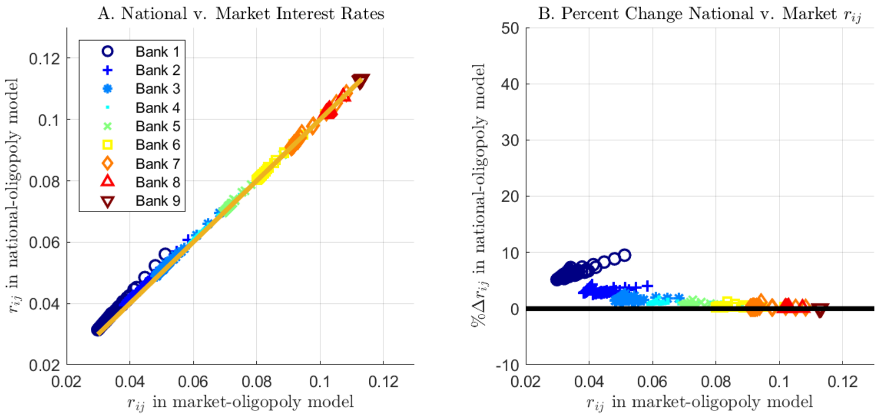
Given national allocations $\{C^N_1, C^N_2\}$ and counterfactual allocations $\{C^{CF}_1, C^{CF}_2\}$, we compute the consumption equivalent welfare gains λ as follows:

$$u(C^N_1(1+\lambda), C^N_2) = u(C^{CF}_1, C^{CF}_2)$$

National- to market-level oligopoly. Table 5 reports the main results from our estimation. In Column (2), we find that moving from national oligopoly to market-level oligopoly yields a consumption equivalent welfare gain of 0.004%. These small quantitative gains are due to the fact that national-level oligopolistic behavior has little influence on markups. Eliminating the national oligopoly component of markups lowers the average interest rate by 9 basis points. Panel A of Figure 14 graphically illustrates the small difference in national versus market-level interest rates. Panel B shows that lower-cost, high national-share lenders lower rates the

[30] In economies (2) and (3), once we solve for r_{ij}, we aggregate to recover r_j and R. We then recover L using the aggregate demand condition, allowing us to back out l_{ij} and compute welfare, profits, etc.

Figure 14: Interest rates in national- versus market-level oligopoly



Notes. Panel A compares the distribution of r_{ij} in the national- versus market-level oligopoly models. Panel B reports the percent difference in interest rates in the national- and market-level oligopoly economies. Parameters are from Table 4.

most, but the welfare costs are muted.

The 9 basis point reduction in interest rates yields a 0.25 percentage point expansion of the credit market. Despite the relatively large expansion of the credit market, the rate cuts translate to small consumption gains. This is due – in part – to the decline in aggregate lender profits which partially offsets the gains to the representative household. Holding bank profits fixed in the household budget constraint, the welfare gains from eliminating national-level oligopolistic behavior more than double but remain quantitatively small.

National-oligopoly to monopolistic competition. Next, we consider monopolistic pricing (i.e. $r_{ij} = \frac{\eta}{\eta-1}[r_f + c_i]$) which eliminates the variable markups generated by strategic behavior. Despite the lack of variable markups, there is still a sizeable constant markup of $1.3\times\left(=\frac{\eta}{\eta-1}\right)$.

We report the results in Column (3) of Table 5. Moving from national oligopoly to monopolistic pricing yields a consumption equivalent gain of 0.021% when allowing profits to adjust, and 0.071% when holding lender profits fixed. Interest rates fall by 51 basis points, generating a large 2 percentage point expansion in the credit-to-GDP ratio. This translates to a 500 billion dollar expansion of the credit

Table 5: Welfare costs of market-level and national-level rate setting power

	(1) National Oligopoly	(2) Market Oligopoly	(3) Monopolistic Competition	(4) Perfect Competition
Welfare gain leaving national eq. (%)	–	0.004	0.021	0.028
Welfare gain leaving national eq., Π fixed (%)	–	0.011	0.072	0.151
Average interest rate (Percent)	5.97	5.88	5.46	4.03
Profit to GDP (Percent)	0.12	0.12	0.07	0.00
Credit to GDP (Percent)	6.87	7.12	8.72	10.49

Notes. Column (1) reports our baseline national oligopoly economy. Column (2) removes national considerations from the lenders rate setting. Column (3) imposes monopolistic competition. Column (4) imposes the competitive solution which is marginal cost pricing. Welfare gain is consumption equivalent as defined in the text. The average interest rate is unweighted. Profit to GDP is Π/y. Credit to GDP is $\sum_{i,j} l_{ij}/y$.

Table 6: Fraction of gains due to reallocation

		No reallocation, l_{ij} fixed at national eq.		
	(1) National Oligopoly	(2) Market Oligopoly	(3) Monopolistic Competition	(4) Perfect Competition
Welfare gain leaving national eq., no reallocation (%)	–	0.001	0.008	0.006
Fraction of Welfare gains due to reallocation (%)	–	75.72	63.90	79.86

Notes. In these experiments, we hold l_{ij} fixed at our baseline national oligopoly economy. We compute welfare gains only allowing r_{ij} to adjust, and thus preventing any reallocation of balances l_{ij} across lenders.

market.

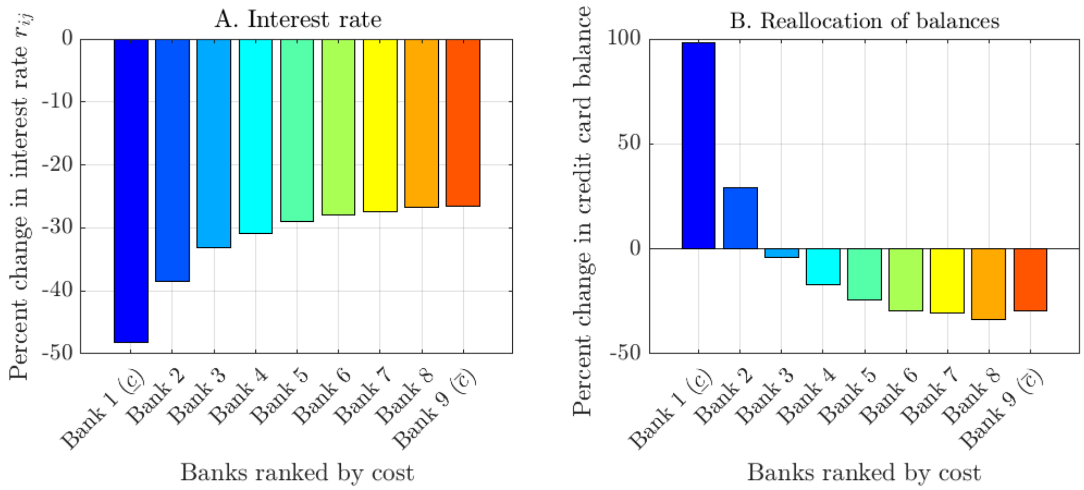
Nationaloligopoly to perfect competition. Lastly, we consider the transition from national oligopoly to competitive pricing ($\mu_{ij} = 1, \forall ij$) in Column (4) of Table 5. Competitive pricing yields a consumption equivalent welfare gain of 0.028% when allowing profits to adjust, and 0.151% when holding lender profits fixed. The competitive allocation lowers interest rates by 2 percentage points. This dwarfs the interest rate reduction in our prior counterfactuals, implying that most of the observed markups (and spreads) in our data are to monopolistic component of markups, $\frac{\eta}{\eta-1}$.

When we eliminate market-level oligopoly power, low-cost lenders expand disproportionately. With lower interest rates in the credit market, household borrow more and credit-to-GDP increases by 52%. This translates to a 1 trillion dollar expansion of the credit market.

Reallocation. What drives the welfare gains and credit expansion? Table 6 recomputes welfare gains assuming that the distribution of balances across lenders, $\{l_{ij}\}$, is held fixed at the national equilibrium values. In other words, we shutdown any associated gains coming from credit balance reallocation across lenders. The welfare gains are effectively zeroed out. A corollary of this results is that more than two-thirds of the welfare gains observed in Table 5 are driven by reallocation from high-cost lenders to low-cost lenders. High-cost lenders begin with the greatest markups and thus cut their interest rates more in the competitive equilibrium. Balances flow towards those lenders, generating welfare gains.

Figure 15 illustrates the reallocation in our model economy as we transition from national oligopoly to competitive pricing. Panel A shows that interest rates fall (in percent terms) most at the largest, lowest-cost lenders. Those lenders had the highest initial markups in the national oligopoly economy. Panel B shows that the lowest-cost lenders expand balances significantly, at the expense of high-cost lenders. The competitive allocation is clearly more concentrated than the original economy with national oligopolists.

Figure 15: Interest rates and balance reallocation



Notes. X-axis is banks' rank in terms of costs. y-axis is percent change in balances between competitive equilibrium and national equilibrium. Parameters are from Table 4.

Policy Discussion. Our results suggest that inefficiencies are generated by market-level (and less so from national) oligopoly in the credit card market. While an optimal policy exercise is beyond the scope of this paper, our framework can be used to analyze the effects of mergers, and the potential benefits of stricter antitrust enforcement in the credit card market. Such analysis would require a theory of mergers, including their efficiency gains, which would entail significant additional empirical and theoretical analysis. We leave these extensions to future work.

7 Conclusion

What are the welfare costs of credit card lenders that influence market and economy-wide interest rates? We answer this question by developing a theory of market- and national-level oligopolistic competition in the credit card market. We use the theory to derive sharp testable implications, namely that pass-through rates depend on market- and national-level shares.

We test this theory using using OCC data which contains the vast majority of credit card issuances in the U.S. We use the date of issuance, which is attached to every credit card in the OCC data, to build a high-frequency panel of spreads for every bank in every market.

We find that pass-through rates vary systematically by market- and national-level shares. When a bank's market-level share exceeds the top 70$^{\text{th}}$ percentile, pass-through rates are 10% lower compared to all other markets in which the bank operates. We similar results when using national shares. Results are robust to the exclusion of geography from our market definition.

We use these moments to discipline market power in our model and measure the costs of national oligopoly in the credit card industry. We find that moving from an economy with national market power to a perfectly competitive economy would lower interest rates by 2 percentage points. The gains are driven by low-cost lenders cutting markups more and expanding disproportionately. With lower interest rates, the consumer credit market expands by 50%. This corresponds to a 1 trillion dollar expansion of the credit card market. Despite the large expansion, credit *services* are a relatively small share of the consumption bundle, and so we estimate welfare gains from perfect competition are worth between 0.03% and 0.15% of lifetime consumption.

In future work, we plan to analyze commercial loans and payment networks. Our theoretic methods and empirical approach can be readily extended to other markets in which large players influence market-level and national-level prices.

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Online Appendix

A Derivations

- We repeat the household problem:

$$\max_{l_{ij},C_1,C_2} u\left(C_1, C_2\right)$$

$$C_1 \leq y - \sum_{i,j} r_{ij} l_{ij} + \Pi, \qquad C_2 \leq L$$

$$l_j = \left[\sum_i l_{ij}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \qquad L = \left[\sum_j l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$$

- **Bank-market demand curve:**
  - We first derive the bank-market level demand curve using the Lagrangian with multiplier λ on the budget constraint and μ on the credit service constraint:

$$\mathcal{L} = u(C_1, C_2) + \lambda\left[y - \sum_{i,j} r_{ij} l_{ij} - C_1 + \Pi\right] + \mu\left[\left[\sum_j \left[\sum_i l_{ij}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} - C_2\right]$$

  - The first order conditions are:

$$u_1(C_1, C_2) = \lambda$$
$$u_2(C_1, C_2) = \mu$$
$$\lambda r_{ij} = \mu \frac{\partial L}{\partial l_j}\frac{\partial l_j}{\partial l_{ij}}$$

  - We can rewrite these

$$\begin{aligned}\lambda r_{ij} &= \mu \frac{L}{L}\frac{\partial L}{\partial l_j}\frac{l_j}{l_j}\frac{\partial l_j}{\partial l_{ij}}\frac{l_{ij}}{l_{ij}} \\ &= \mu \frac{L}{l_{ij}}\frac{\partial \log L}{\partial \log l_j}\frac{\partial \log l_j}{\partial \log l_{ij}}\end{aligned}$$

  - Using the definition of L and l_j

$$\frac{\partial \log L}{\partial \log l_j} = \left[\frac{l_j}{L}\right]^{\frac{\theta-1}{\theta}}, \qquad \frac{\partial \log l_j}{\partial \log l_{ij}} = \left[\frac{l_{ij}}{l_j}\right]^{\frac{\eta-1}{\eta}}$$

- Substituing

$$r_{ij} = \frac{\mu}{\lambda}\left(\frac{l_j}{L}\right)^{-\frac{1}{\theta}}\left(\frac{l_{ij}}{l_j}\right)^{-\frac{1}{\eta}}$$

- *This yields the bank-market inverse demand curve:*

$$r_{ij} = \frac{\mu}{\lambda}\left(\frac{l_j}{L}\right)^{-\frac{1}{\theta}}\left(\frac{l_{ij}}{l_j}\right)^{-\frac{1}{\eta}}$$

- **Aggregate demand curve:**
  - Define R as the number such that $RL \equiv \sum r_j l_j$, redefine the Lagrangian and take FOCs for L, C_1, C_2:

$$\mathcal{L} = u(C_1, C_2) + \lambda\left[y - RL - C_1 + \Pi\right] + \mu\left[L - C_2\right]$$

  - *This yields the aggregate inverse demand curve:*

$$R = \frac{\mu}{\lambda}$$
$$R = \frac{u_2(C_1, C_2)}{u_1(C_1, C_2)}$$

  - The GHH-Linear case, $u(C_1, C_2) = C_1 + A\frac{C_2}{1-\gamma}$, yields the *aggregate demand curve:*

$$L = \left(\frac{A}{R}\right)^{\frac{1}{\gamma}}$$

- **Market demand:**
  - Define r_j as the number such that $r_j l_j \equiv \sum_i r_{ij} l_{ij}$. Take FOCs for l_j to obtain market-level demand curves:

$$\mathcal{L} = u(C_1, C_2) + \lambda\left[y - \sum_j r_j l_j - C_1 + \Pi\right] + \mu\left[\left[\sum_j l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} - C_2\right]$$

  - *This yields the market level demand curve:*

$$l_j = \left(\frac{r_j}{R}\right)^{-\theta} L$$

- **Bank-market level demand:** putting the aggregate, market, and bank-market demand curves together yields:

$$l_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{-\eta}\left(\frac{r_j}{R}\right)^{-\theta} L$$

- **Ideal price indeces:**

– Recover aggregate price indexes using the market level demand curve:

$$RL \equiv \sum_j r_j l_j$$

$$RL = \sum_j r_j \left(\frac{r_j}{R}\right)^{-\theta} L$$

$$R = \left[\sum_j r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}$$

– Recover market level price index using the bank-market level demand curve:

$$r_j l_j \equiv \sum_i r_{ij} l_{ij}$$

$$r_j l_j = \sum_i r_{ij} \left(\frac{r_{ij}}{r_j}\right)^{-\eta} l_j$$

$$r_j = \left[\sum_i r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

- **Bank market shares are given by:**

$$s_{ij} = \frac{r_{ij} l_{ij}}{\sum_i r_{ij} l_{ij}} = \frac{r_{ij} \left(\frac{r_{ij}}{r_j}\right)^{-\eta} l_j}{\sum_i r_{ij} \left(\frac{r_{ij}}{r_j}\right)^{-\eta} l_j} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta} = \frac{\partial \log r_j}{\partial \log r_{ij}}$$

- In words, market shares are proportional to your price-impact on the market.

A.1 Market-oligopoly

- Suppose bank i acts as a market oligopolist (internalizes effects on r_j but not on R or other aggregates) and has funding cost c_i. The bank solves

$$\max_{r_{ij}} r_{ij} l_{ij} - \left[c_i + r_f\right] l_{ij}$$

subject to the firm-level demand curve

$$l_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L$$

- Substituting into the firm's problem and factoring out aggregates (which are positive scalars), the bank maximizes:

$$\max_{r_{ij}} r_{ij}^{1-\eta} r_j^{\eta-\theta} - \left[c_i + r_f\right] r_{ij}^{-\eta} r_j^{\eta-\theta}$$

- Taking first order conditions:

$$
\begin{aligned}
(1-\eta)\, r_{ij}^{-\eta} r_j^{\eta-\theta} + r_{ij}^{1-\eta}\,(\eta-\theta)\, r_j^{\eta-\theta-1}\frac{\partial r_j}{\partial r_{ij}} - \left[c_i + r_f\right](-\eta)\, r_{ij}^{-\eta-1} r_j^{\eta-\theta} - \left[c_i + r_f\right] r_{ij}^{-\eta}\,(\eta-\theta)\, r_j^{\eta-\theta-1}\frac{\partial r_j}{\partial r_{ij}} &= 0\\
(1-\eta)\, r_{ij}^{-\eta} r_j^{\eta-\theta} + r_{ij}^{-\eta}\,(\eta-\theta)\, r_j^{\eta-\theta}\frac{\partial r_j}{\partial r_{ij}}\frac{r_{ij}}{r_j} - \left[c_i + r_f\right](-\eta)\, r_{ij}^{-\eta} r_j^{\eta-\theta}\frac{1}{r_{ij}} - \left[c_i + r_f\right] r_{ij}^{-\eta}\,(\eta-\theta)\, r_j^{\eta-\theta}\frac{\partial r_j}{\partial r_{ij}}\frac{r_{ij}}{r_{ij}}\frac{1}{r_j} &= 0\\
(1-\eta) + (\eta-\theta)\, s_{ij} - \left[c_i + r_f\right](-\eta)\frac{1}{r_{ij}} - \left[c_i + r_f\right](\eta-\theta)\, s_{ij}\frac{1}{r_{ij}} &= 0\\
r_{ij}\left[(1-\eta) + (\eta-\theta)\, s_{ij}\right] + \eta\left[c_i + r_f\right] - \left[c_i + r_f\right](\eta-\theta)\, s_{ij} &= 0
\end{aligned}
$$

$$
\implies r_{ij} = \left[c_i + r_f\right]\frac{\left[\eta\left(1-s_{ij}\right) + \theta s_{ij}\right]}{\left[\eta\left(1-s_{ij}\right) + \theta s_{ij} - 1\right]}
$$

- To prevent negative markups, we must restrict parameters such that $\eta, \theta > 1$.
- The Nash equlibrium is a fixed point in market shares. Use $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$ which implies $s_{ij} = \left(\frac{r_{ij}}{\left[\sum_i r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}}\right)^{1-\eta}$. Substitute for r_{ij} to obtain the fixed point formula:

$$
s_{ij} = \left(\frac{\left[c_i + r_f\right]\frac{\left[(\eta-\theta)s_{ij}-\eta\right]}{\left[(1-\eta)+(\eta-\theta)s_{ij}\right]}}{\left[\sum_i\left(\left[c_i + r_f\right]\frac{\left[(\eta-\theta)s_{ij}-\eta\right]}{\left[(1-\eta)+(\eta-\theta)s_{ij}\right]}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}}\right)^{1-\eta}
$$

A.2 National-oligopoly

- In order to make progress on the national economy, we require several preliminary results:
  - First note that the elasticity of national prices WRT market prices:

$$
\frac{d\log R}{d\log r_j} = \left(\frac{r_j}{R}\right)^{1-\theta}
$$

  - Overall market shares are given by

$$
s_j = \frac{\sum_i r_{ij} l_{ij}}{\sum_{i,j} r_{ij} l_{ij}} = \frac{r_j l_j}{\sum_j r_j l_j} = \frac{r_j\left(\frac{r_j}{R}\right)^{-\theta} L}{\sum_j r_j\left(\frac{r_j}{R}\right)^{-\theta} L} = \left(\frac{r_j}{R}\right)^{1-\theta}
$$

  - Thus we have that the aggregate price impact of a market is equal to the overall share of the market

$$
\frac{d\log R}{d\log r_j} = \left(\frac{r_j}{R}\right)^{1-\theta} = s_j
$$

– Lastly, the national share is defined as follows:

$$s_{ij}^N = s_j s_{ij} = \frac{r_{ij} l_{ij}}{\sum_{i,j} r_{ij} l_{ij}}$$

- **Lender problem with national oligopoly:**
  – Assume lender i operates in $J(i)$ markets and understands that it affects r_j and R. The risk free rate r_f is set outside of the market. The lenders now solve the following problem

$$\max_{\{r_{ij}\}} \sum_{j \in J(i)} r_{ij} l_{ij} - \left[c_i + r_f\right] l_{ij}$$

  subject to each of the relevant firm-level demand curves in every market $J(i)$ in which they operate:

$$l_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L$$

- Substituting and imposing GHH-linear preferences, the objective function becomes

$$\max_{\{r_{ij}\}} R^{\theta - \frac{1}{\gamma}} \left\{ \sum_{j \in J(i)} r_j^{\eta-\theta} r_{ij}^{-\eta} \left(r_{ij} - r_f - c_i\right) \right\}$$

  where we have dropped the positive scalar $A^{\frac{1}{\gamma}}$ from the objective.
- FOC for r_{ij} :

$$R^{\theta-\frac{1}{\gamma}} \left\{ \left[-\eta r_{ij}^{-\eta-1} r_j^{\eta-\theta} + (\eta-\theta) r_{ij}^{-\eta} r_j^{\eta-\theta-1} \frac{\partial r_j}{\partial r_{ij}} \right] \left(r_{ij} - r_f - c_i\right) + r_j^{\eta-\theta} r_{ij}^{-\eta} \right\} + \left\{ \sum_{j \in J(i)} r_j^{\eta-\theta} r_{ij}^{-\eta} \left(r_{ij} - r_f - c_i\right) \right\} \frac{dR^{\theta-\frac{1}{\gamma}}}{dr_{ij}} = 0$$

$$\left\{ \left[-\eta r_{ij}^{-\eta-1} r_j^{\eta-\theta} + (\eta-\theta) r_{ij}^{-\eta} r_j^{\eta-\theta} \frac{\partial r_j}{\partial r_{ij}} \frac{r_{ij}}{r_{ij}} \frac{1}{r_j} \right] \left(r_{ij} - r_f - c_i\right) + r_j^{\eta-\theta} r_{ij}^{-\eta} \right\} + \left\{ \sum r_j^{\eta-\theta} r_{ij}^{-\eta} \left(r_{ij} - r_f - c_i\right) \right\} \frac{dR^{\theta-\frac{1}{\gamma}}}{dr_{ij}} \frac{1}{R^{\theta-\frac{1}{\gamma}}} \frac{r_{ij}}{r_{ij}} = 0$$

$$\left\{ \left[-\eta r_{ij}^{-\eta-1} r_j^{\eta-\theta} + (\eta-\theta) r_{ij}^{-\eta} r_j^{\eta-\theta} \frac{d\log r_j}{d\log r_{ij}} \right] \left(r_{ij} - r_f - c_i\right) + r_j^{\eta-\theta} r_{ij}^{-\eta} \right\} + \left\{ \sum r_j^{\eta-\theta} r_{ij}^{-\eta} \left(r_{ij} - r_f - c_i\right) \right\} \left(\theta - \frac{1}{\gamma}\right) \frac{d\log R}{d\log r_j} \frac{d\log r_j}{d\log r_{ij}} \frac{1}{r_{ij}} = 0$$

$$\left\{ \left[-\eta r_{ij}^{-\eta-1} + (\eta-\theta) r_{ij}^{-\eta-1} s_{ij} \right] \left(r_{ij} - r_f - c_i\right) + r_{ij}^{-\eta} \right\} + \left\{ \sum_{J(i)} r_j^{\eta-\theta} r_{ij}^{-\eta} \left(r_{ij} - r_f - c_i\right) \right\} \left(\theta - \frac{1}{\gamma}\right) s_j s_{ij} \frac{1}{r_j^{\eta-\theta} r_{ij}} = 0$$

$$\left[1 - \eta + (\eta-\theta) s_{ij}\right] r_{ij} - \left[-\eta + (\eta-\theta) s_{ij}\right] \left[r_f + c_i\right] + \left\{ \sum_{J(i)} r_j^{\eta-\theta} r_{ij}^{-\eta} R^{\theta} \left(\frac{A}{R}\right)^{\frac{1}{\gamma}} \left(r_{ij} - r_f - c_i\right) \right\} \left(\theta - \frac{1}{\gamma}\right) s_j s_{ij} \frac{1}{r_j^{\eta-\theta} r_{ij}^{-\eta} R^{\theta} \left(\frac{A}{R}\right)^{\frac{1}{\gamma}}} = 0$$

$$\implies r_{ij} = \frac{\left[\eta \left(1 - s_{ij}\right) + \theta s_{ij}\right] \left[r_f + c_i\right] + \left(\theta - \frac{1}{\gamma}\right) s_{ij}^N \frac{\Pi_i}{l_{ij}}}{\left[\eta \left(1 - s_{ij}\right) + \theta s_{ij} - 1\right]}$$

- Suppose the markets are identical $r_i = r_{ij}, l_{ij} = l_i$, let J_i denote the number of elements in $J(i)$. Then we have,

$$\left[1 - \eta + (\eta-\theta) s_{ij}\right] r_{ij} - \left[-\eta + (\eta-\theta) s_{ij}\right] \left[r_f + c_i\right] + \left(r_{ij} - r_f - c_i\right) J_i \left(\theta - \frac{1}{\gamma}\right) s_{ij}^N = 0$$

- This yields the expression for r_{ij} in the text:

$$r_{ij} = \frac{\eta\left(1-s_{ij}\right)+\theta s_{ij} - J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N}{\eta\left(1-s_{ij}\right)+\theta s_{ij} - J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N - 1}\left[r_f + c_i\right]$$

A.3 Solution method for asymmetric national oligopoly

- **We initialize the national oligopoly economy with guesses from the market oligopoly economy.**
  - Guess an economy-wide vector of prices $\left\{r_{ij}\right\}$.
  - This yields market and aggregate prices: $R = \left[\sum_j r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}$, $\quad r_j = \left[\sum_i r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}$
  - Solve for bank, market, and national shares $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$, $s_j = \left(\frac{r_j}{R}\right)^{1-\theta}$, $s_{ij}^N = s_j s_{ij}$.
  - Use the FOC of the lenders to update the interest rate:

$$r_{ij}^{update} = \frac{1}{\eta\left(1-s_{ij}\right)+\theta s_{ij}-1}\left[\left[\eta\left(1-s_{ij}\right)+\theta s_{ij}\right]\left[r_f+c_i\right] + \left\{\sum_{J(i)} r_j^{\eta-\theta} r_{ij}^{-\eta}\left(r_{ij}-r_f-c_i\right)\right\}\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N \frac{1}{r_j^{\eta-\theta} r_{ij}^{-\eta}}\right]$$

  - Iterate until convergence.

A Pass-through in national oligopoly economy

- Throughout this section, we assume identical markets. Banks may have different costs, but markets are replicas.
- We have $\ln r_{ij} = \ln\left[c_i + r_f\right] + \ln \mu\left(s_{ij}, s_{ij}^N, J_i\right)$, and $\mu\left(s_{ij}, s_{ij}^N, J_i\right) = \frac{\eta\left(1-s_{ij}\right)+\theta s_{ij}-J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N}{\eta\left(1-s_{ij}\right)+\theta s_{ij}-J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N-1}$,
and $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$, $s_{ij}^N = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}\left(\frac{r_j}{R}\right)^{1-\theta}$, $r_j = \left[\sum_i r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}$,
- We define the credit demand elasticity and markup in the national economy as follows:

$$\epsilon_{ij} = \eta\left(1-s_{ij}\right)+\theta s_{ij} - J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N, \qquad \mu\left(s_{ij}, s_{ij}^N, J_i\right) = \frac{\epsilon_{ij}}{\left[\epsilon_{ij}-1\right]}$$

- We assume J_i is fixed, and so can write $s_{ij} = s_{ij}\left(r_{ij}, r_{-ij}\right)$ and $s_{ij}^N = s_{ij}^N\left(r_{ij}, \left\{r_{-ij}\right\}\right)$.
- Thus $\mu\left(s_{ij}, s_{ij}^N, J_i\right) = \mu\left(r_{ij}, \left\{r_{-ij}\right\}\right)$ and $\ln r_{ij} = \ln\left[c_i + r_f\right] + \ln \mu\left(r_{ij}, \left\{r_{-ij}\right\}\right)$.
- Based on our empirics, we are interested in the semi elasticity $\frac{d \ln r_{ij}}{dr_f}$.
- Total differentiation yields:

$$\ln r_{ij} = \ln\left[c_i + r_f\right] + \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)$$

$$d\ln r_{ij} = \frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f} dr_f + \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{ij}} d\ln r_{ij} + \sum_{k\neq i} \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj}} d\ln r_{kj} + \sum_{j'\neq j}\sum_{k} \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj'}} d\ln r_{kj'}$$

$$d\ln r_{ij}\left(1 - \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{ij}}\right) = \frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f} dr_f + \sum_{k\neq i} \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj}} d\ln r_{kj} + \sum_{j'\neq j}\sum_{k} \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj'}} d\ln r_{kj'}$$

$$d\ln r_{ij}\left(1 - m_{iij}\right) = \frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f} dr_f + \sum_{k\neq i} m_{ikj} d\ln r_{kj} + \sum_{j'\neq j}\sum_{k} m_{ikj'} d\ln r_{kj'}$$

$$\frac{d\ln r_{ij}}{dr_f} = \underbrace{\frac{1}{\left(1 - m_{iij}\right)} \frac{\partial \ln\left[c_i + r_f\right]}{\partial r_f}}_{\text{Local direct}} + \underbrace{\frac{1}{\left(1 - m_{iij}\right)} \sum_{k\neq i} m_{ikj} \frac{d\ln r_{kj}}{dr_f}}_{\text{Local indirect (LI)}} + \underbrace{\frac{1}{\left(1 - m_{iij}\right)} \sum_{j'\neq j}\sum_{k} m_{ikj'} \frac{d\ln r_{kj'}}{dr_f}}_{\text{National indirect (NI)}}$$

where $m_{iij} = \frac{\partial \ln\mu\left(r_{ij}, r_{-ij}\right)}{\partial \ln r_{ij}}$, $m_{ikj} = \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj}}$, and $m_{ikj'} = \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{kj'}}$

- Next, note that

$$\frac{\partial \log \epsilon_{ij}\left(s_{ij}, s_j\right)}{\partial \log r_{ij}} = \frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}} \frac{\partial \log s_{ij}}{\partial \log r_{ij}} + \frac{\partial \log \epsilon_{ij}}{\partial \log s_j} \frac{\partial \log s_j}{\partial \log r_{ij}}$$

- We can therefore characterize m_{iij} as follows:

$$\frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \ln r_{ij}} = \frac{\partial \ln\mu\left(r_{ij}, \{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}} \left\{ \frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}} \frac{\partial \log s_{ij}}{\partial \log r_{ij}} + \frac{\partial \log \epsilon_{ij}}{\partial \log s_j} \frac{\partial \log s_j}{\partial \log r_{ij}} \right\}$$

- We characterize first term using the fact that $\mu\left(r_{ij}, \{r_{-ij}\}\right) = \frac{\epsilon_{ij}}{\left[\epsilon_{ij} - 1\right]}$:

$$\frac{\partial \ln\mu\left(r_{ij}, r_{-ij}\right)}{\partial \log \epsilon_{ij}} = -\frac{\mu_{ij}}{\epsilon_{ij}}$$

- The credit demand elasticity varies with market-level shares as follows:

$$\frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}} = \frac{\epsilon_{ij} - \eta}{\epsilon_{ij}}$$

- The credit demand elasticity varies with overall market shares as follows:

$$\begin{aligned}
\frac{\partial \log \epsilon_{ij}}{\partial \log s_j} &= \frac{1}{\epsilon_{ij}}\left(-J_i\left(\theta - \frac{1}{\gamma}\right) s_{ij} s_j\right) \\
&= \frac{\epsilon_{ij} - \epsilon_{ij}^M}{\epsilon_{ij}} \\
\epsilon_{ij}^M &\equiv \eta + \left(\theta - \eta\right) s_{ij}
\end{aligned}$$

- The market-level and overall market share elasticities with respect to interest rates are given by:

$$\frac{\partial \ln s_{ij}}{\partial \ln r_{ij}} = (1-\eta)\left(1-s_{ij}\right)$$
$$\frac{\partial \ln s_j}{\partial \ln r_{ij}} = (1-\theta)\, s_{ij}\left(1-s_j\right)$$

- Put it together

$$\frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \ln r_{ij}} = \frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}}\left\{\frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}}\frac{\partial \log s_{ij}}{\partial \log r_{ij}} + \frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\frac{\partial \log s_j}{\partial \log r_{ij}}\right\}$$
$$\implies m_{iij} = \frac{-\left(\left((\eta-\theta)\, s_{ij} + J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N\right)(\eta-1)\left(1-s_{ij}\right) - J_i\left(\theta-\frac{1}{\gamma}\right)(\theta-1)\, s_{ij}^N s_{ij}\left(1-s_j\right)\right)}{\epsilon_{ij}\left(\epsilon_{ij}-1\right)}$$

- A similar procedure yields m_{ikj}(market indirect)

$$\frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \ln r_{kj}} = \frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}}\left\{\frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}}\frac{\partial \log s_{ij}}{\partial \log r_{kj}} + \frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\frac{\partial \log s_j}{\partial \log r_{kj}}\right\}$$
$$\frac{\partial \ln s_j}{\partial \ln r_{kj}} = (1-\theta)\, s_{kj}\left(1-s_j\right)$$
$$\implies m_{ikj} = \frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}}\left\{\frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}}\left(-(1-\eta)\, s_{kj}\right) + \frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\left((1-\theta)\, s_{kj}\left(1-s_j\right)\right)\right\}$$

- A similar procedure yields $m_{ikj'}$ (national indirect)

$$\frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \ln r_{kj'}} = \frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}}\left\{\frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\frac{\partial \log s_j}{\partial \log r_{kj'}}\right\}$$
$$\frac{\partial \ln s_j}{\partial \ln r_{kj'}} = -(1-\theta)\, s_{kj'}s_{j'}$$
$$\implies m_{ikj'} = \frac{\partial \ln \mu\left(r_{ij},\{r_{-ij}\}\right)}{\partial \log \epsilon_{ij}}\left\{\frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\left\{-(1-\theta)\, s_{kj'}s_{j'}\right\}\right\}$$

- Putting it all together, we obtain the pass-through expression in the text:

$$\frac{d\ln r_{ij}}{dr_f} = \underbrace{\frac{1}{\left(1-m_{iij}\right)}\frac{\partial \ln\left[c_i+r_f\right]}{\partial r_f}}_{\text{Market direct}} + \underbrace{\frac{1}{\left(1-m_{iij}\right)}\sum_{k\neq i} m_{ikj}\frac{d\ln r_{kj}}{dr_f}}_{\text{Market indirect (MI)}} + \underbrace{\frac{1}{\left(1-m_{iij}\right)}\sum_{j'\neq j}\sum_{k} m_{ikj'}\frac{d\ln r_{kj'}}{dr_f}}_{\text{National indirect (NI)}}$$
$$LI+NI = \frac{1}{\left(1-m_{iij}\right)}\left(-\frac{\mu_{ij}}{\epsilon_{ij}}\right)\left\{-(1-\eta)\frac{\partial \log \epsilon_{ij}}{\partial \log s_{ij}}\sum_{k\neq i} s_{kj}d\ln r_{kj} + (1-\theta)\frac{\partial \log \epsilon_{ij}}{\partial \log s_j}\left[\left(1-s_j\right)\sum_{k\neq i} s_{kj}d\ln r_{kj} - \sum_{j'\neq j}\sum_{k}\left(s_{kj'}s_{j'}\right)d\ln r_{kj'}\right]\right\}$$

A Uniform pricing across geography

In this section, we detail a model of uniform pricing. Assume there is an infinite number of product types and a continuum of geographies. Lenders set a uniform price for each product type p. Let $j \in G(i,p)$ denote the set of geographies bank i offers product p within. Let $j(p)$ denote the markets of product type p. Then, the problem of the lenders is

$$\max_{\{r_{ij}\}} \sum_{p} \sum_{j \in G(i,p)} \left(r_{ij} l_{ij} - \left[c_i + r_f \right] l_{ij} \right) \tag{A1}$$

$$\text{s.t.} \quad l_{ij} = \left(\frac{r_{ij}}{r_j} \right)^{-\eta} \left(\frac{r_j}{R} \right)^{-\theta} L$$

$$r_{ij(p)} = r_{ip}.$$

Substituting the constraints into the objective function, and using $L = \left(\frac{A}{R} \right)^{\frac{1}{\gamma}}$, we can rewrite the problem as

$$\max_{\{r_{ip}\}} R^{\theta} \left(\frac{A}{R} \right)^{\frac{1}{\gamma}} \left\{ \sum_{p} \sum_{j \in G(i,p)} r_j^{\eta-\theta} r_{ip}^{-\eta} \left(r_{ip} - r_f - c_i \right) \right\}. \tag{A2}$$

Optimization from the lender yields the following first-order condition for loan rates,

$$r_{ip} = \left(r_f + c_i \right) \mu \left(\bar{s}_i \right) + \frac{\mu \left(\bar{s}_i \right) - 1}{\mu \left(\bar{s}_i \right)} \left(\theta - \frac{1}{\gamma} \right) \tilde{s}_{ip}^{N} \Pi_i(p), \tag{A3}$$

with

$$\bar{s}_i \equiv \sum_{G(i,p)} s_{ij} l_{ij},$$

$$\mu \left(\bar{s}_i \right) \equiv \frac{\eta \left(1 - \bar{s}_i \right) + \theta \bar{s}_i}{\eta \left(1 - \bar{s}_i \right) + \theta \bar{s}_i - 1},$$

$$\tilde{s}_{ip}^{N} \equiv \sum_{G(i,p)} s_j s_{ij},$$

$$\Pi_i(p) \equiv R^{\theta} L \left\{ \sum_{p} \sum_{j \in G(i,p)} r_j^{\eta-\theta} r_{ip}^{-\eta} \left(r_{ip} - r_f - c_i \right) \right\}.$$

Notice the close resemblance between equation (A3) and the baseline equation (15), with modified notions of market shares affecting the optimal pricing equation under uniform pricing. These modified market shares, $\bar{s}_i$ and $\tilde{s}_{ip}^{N}$, are a weighted average of market-level revenue-based market shares across all locations the lender operates.

Table B1: Distribution of Estimated Noninterest Marginal Costs

Specification	Mean	P1	P5	P10	P50	P90	P95	P99
Loans-only	4.2%	1.2%	1.7%	2.0%	3.0%	4.7%	5.7%	11.9%
Loans and salaries	4.8%	1.4%	2.0%	2.3%	3.4%	5.4%	6.5%	13.8%

Notes. This table shows the distribution of bank-level estimates for noninterest marginal costs. Analysis is based on data at the bank holding company level obtained from FR Y-9C dataset.

B Estimation of Marginal Costs

In this section, we follow Berger, Klapper, and Turk-Ariss (2009) and Corbae and D'Erasmo (2019) to have an empirical estimate for the noninterest marginal costs, c_i. Let NIE_{it} be noninterest expenses for bank i at year t, LN_{it} total loans, W_{it} salaries, and TA_{it} total assets. Then, we can estimate the following panel regression at the bank-year level for the period 1990-2008:[31]

$$\begin{aligned} \ln NIE_{it} =& \beta_0 + \beta_1 \ln LN_{it} + \beta_2 \left(\ln LN_{it}\right)^2 + \beta_3 \ln\left(W_{it}/TA_{it}\right) + \quad \text{(B1)} \\ & \beta_4 \left(\ln\left(W_{it}/TA_{it}\right)\right)^2 + \beta_5 \left(\ln LN_{it}\right)\left(\ln\left(W_{it}/TA_{it}\right)\right) + \epsilon_{it}. \quad \text{(B2)} \end{aligned}$$

The estimate for (noninterest) marginal costs would be

$$\widehat{MC}_{it} = \frac{\partial NIE_{it}}{\partial LN_{it}} = \frac{NIE_{it}}{LN_{it}} \left[\hat{\beta}_1 + 2\hat{\beta}_2 \ln LN_{it} + \hat{\beta}_5 \ln\left(W_{it}/TA_{it}\right)\right]$$

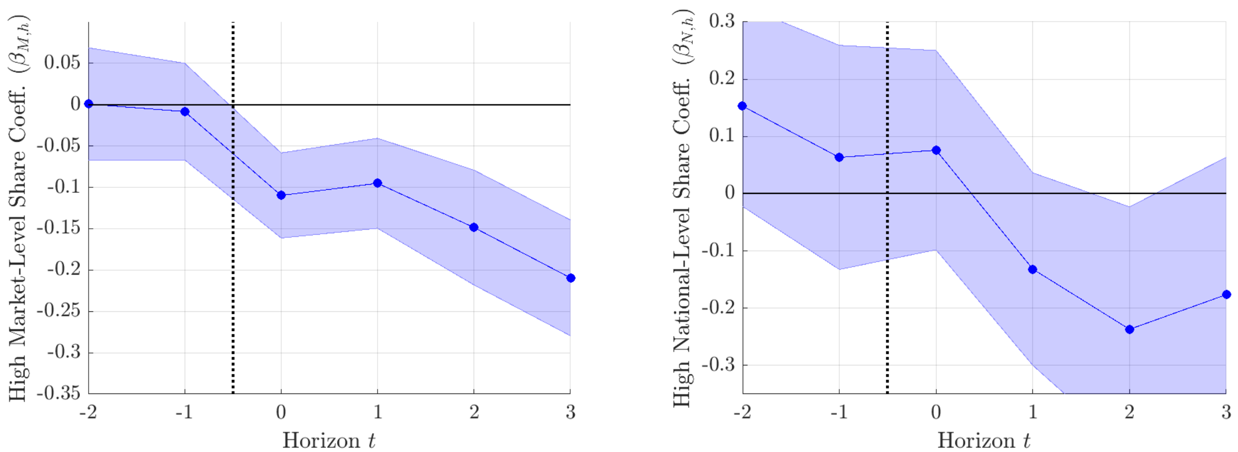
Table B1 shows statistics for the distribution of $\widehat{MC}_{it}$. The table shows results for a version of regression specification B1 that includes only loans, and a version that includes loans and wages (over assets). Results are quite similar across alternatives, and the distributions are broadly aligned with results presented in Section 6.1.

[31] Data is at the bank holding company level, at calendar year, obtained from FR Y-9C "Consolidated Financial Statements for Holding Companies."

C Robustness for Estimation of Differential Pass-through

Figure C1: Differential pass-through estimates for FF1 shock

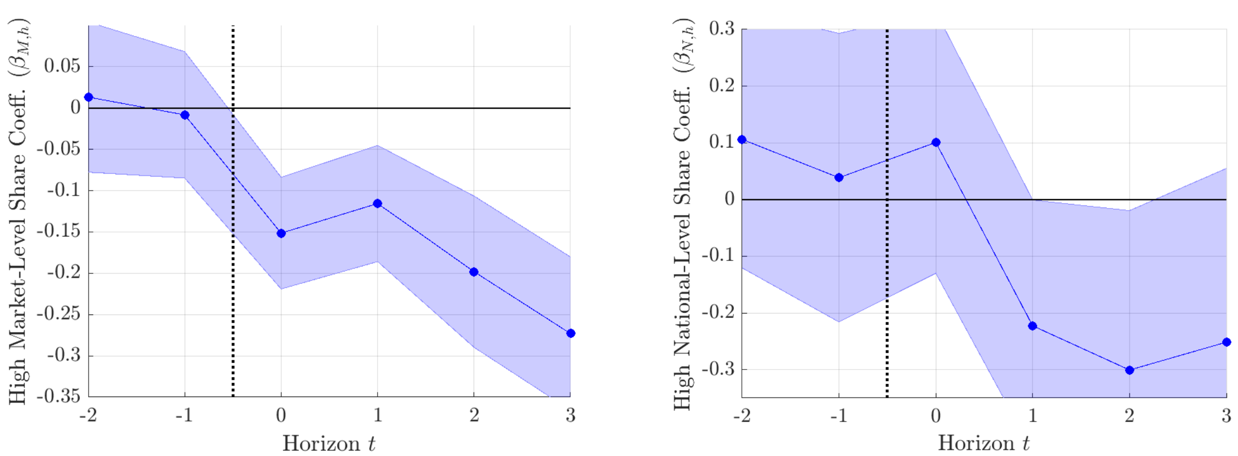
(a) Pass-through by market-level share $\tilde{s}_{ij}$, controlling for $\tilde{s}_{ij}^N$ **(b) Pass-through by national share $\tilde{s}_{ij}^N$, controlling for $\tilde{s}_{ij}$**



Notes. Figure (a) plots the market-level differential pass-through $\beta_{M,h}$ from FF1 to residualized interest rates across stacked events. Figure (b) plots the corresponding national-level coefficient $\beta_{N,h}$ from the same regression.

Figure C2: Differential pass-through estimates for FFMR shock

(a) Pass-through by market-level share $\tilde{s}_{ij}$, controlling for $\tilde{s}_{ij}^N$ **(b) Pass-through by national share $\tilde{s}_{ij}^N$, controlling for $\tilde{s}_{ij}$**



Notes. Figure (a) plots the market-level differential pass-through $\beta_{M,h}$ from FFMR to residualized interest rates across stacked events. Figure (b) plots the corresponding national-level coefficient $\beta_{N,h}$ from the same regression.