Credit Card Market Power*

Kyle Herkenhoff Juan M. Morelli

May 7, 2026

Abstract

How competitive is the U.S. credit card market? What are the potential gains from competitive reforms? We motivate our study by documenting strong correlations between interest rate dispersion and bank market shares in a sample of credit cards matched on a high-dimensional set of traits. We then build a daily panel of millions of credit card *originations* from OCC and Y-14M data, and then measure how pass-through from high-frequency monetary rate changes depends on lenders' market- and national-level shares. We find pass-through rates are 17% lower when banks have large market-level shares and 24% lower for large national-level shares, relative to markets in which their shares are small. We map these reduced-form results into measures of market power by matching our differential pass-through estimates in a novel theory in which national lenders strategically influence market-level and economy-wide interest rates. Despite large differences in national pass-through rates, we find little national-level rate setting power. In contrast, we find strong market-level rate setting power that raises U.S. rates by half a percentage point. Eliminating all sources of market power lowers interest rates by 2.5 percentage points and results in a large expansion of credit. Our empirical results are robust to a naive market definition (24 total markets in the U.S.) or our baseline market definition (960 total markets in the U.S.). Notably, both market definitions yield Herfindahls well above 1800.

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

Keywords: consumer credit, competition, welfare

*Herkenhoff: University of Minnesota, Federal Reserve Bank of Minneapolis, IZA, NBER. Morelli: Federal Reserve Bank of New York. In the early stages of this project, we benefited greatly from insights, codes and conversations with Larry Santucci. Special thanks to Jason Allen and Joaquin Saldain for their excellent discussions. We would also like to thank Adrian Auclert, Juliane Begenau, Matteo Benneton, Dean Corbae, Kyle Dempsey, Lars Hansen, Benjamin Hebert, Hannes Malmberg, Monica Piazessi, Annette Vissing-Jorgensen, Nancy Wallace and participants at various seminars and conferences for helpful comments. Henry Weiland provided excellent research assistance. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily reflect the position of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

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 (2023b)), 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 et al. (2015), Dempsey and Ionescu (2025), and very recently, Drechsler et al. (2025)). 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 costs of imperfect competition in the credit card market (Nelson (2018), Herkenhoff and Raveendranathan (2020), Whited et al. (2021), Galenianos et al. (2021), and Galenianos and Gavazza (2022)).

We contribute to this debate empirically and quantitatively. Our empirical contribution is to cleanly identify differential pass-through rates across markets in which lenders are large versus markets in which lenders are small. Despite the monthly frequency of U.S. bank regulatory data, our insight is to build daily rates based on origination dates and then use high-frequency difference-in-difference estimators to measure how spreads differentially respond to national monetary surprises within-bank, across-markets. Our quantitative contribution is to map these differential pass-through rates into market power by estimating a model of national credit card banks and matching our identified differential pass-through rates. We then use the model to bound the effects of competitive reforms in the credit card market.

Before turning to the model and the causal tests, we motivate our analysis by showing that credit card interest rates (i.e., annual percentage rates or APRs) covary strongly with lender market shares in regulatory data. Our regulatory data splices together credit card issuances from the Office of the Comptroller of the Currency (OCC) Credit Card Metrics (CCM) database from 2008 to 2013 and the Y-14M database from 2014 to 2019 (see the OCC data description in Agarwal et al. (2013) and Y-14M data description in Dempsey and Ionescu (2025)). We use a series of fixed-effects and variance-decomposition exercises to show that over-and-above borrower, bank, market, and product heterogeneity, variation in bank market shares explains a meaningful share of interest rate dispersion.

[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 (2023c).

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

We then move beyond variance decompositions to analyze interest rate dispersion among finely matched cards that are nearly identical in observed risk, income, and product characteristics. Even within these narrow groups, interest rate dispersion remains substantial, and groups with more dispersion in lender market shares also exhibit more dispersion in interest rates. Taken together, these patterns suggest that differences in market structure are an important source of rate variation in credit card lending and provide the key motivation for the theory and empirical tests that follow.

We base our main empirical specifications and tests on the predictions of a novel theory of nationally strategic lenders. To match U.S. market structure and entertain the widest possible set of lender conduct, we allow 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 derive 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.

Our theoretic characterization implies clear empirical tests for bank conduct: any market- or national-share dependence of pass-through rates from unexpected rate cuts into APRs signals deviations from perfect competition. We therefore run within-bank, across-market difference-in-difference estimators, in which we compare responsiveness

[3] In Appendix A.8, contemporaneous work by Burstein et al. (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 et al. (2024) consider oligopsonists who affect national wage levels at single-plant firms. In related work, Morelli et al. (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.

of a given bank's rates to monetary surprises across markets where they have large shares versus small shares. Our within-bank, across-market comparisons are similar to deposit market studies (see Drechsler et al. (2017) and critique by Begenau and Stafford (2023)); however, unlike Drechsler et al. (2017), we rely U.S.-wide markets and 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). To remove the mechanical indexing of incumbent credit cards (Grodzicki (2023b)), we also require data on new originations. At origination banks set lending spreads, and our objective is to measure the sensitivity of those spreads to market conditions at the time of issuance; after origination rates are indexed and thus cannot be used to identify market power. Rather than simply use the monthly structure of the OCC and Y14 data, our insight is to use the origination dates attached to each credit card in the OCC and Y14 data, allowing us to create a daily panel of rates around monetary surprises. To remove noise, we aggregate the rates to the weekly level and then study the responsiveness of interest rates at the bank-week-market level. The thought experiment is to compare rates for borrowers that took out credit cards one week before and one week after a rate cut, in concentrated versus non-concentrated markets.

Our analysis proceeds in three steps. In the first step, we define U.S.-wide credit card markets based on the market segmentation patterns discussed in (i) consulting reports by McKinsey (Fiorio et al. (2014)), (ii) the *Marketing and Acquisition* chapter of the Federal Deposit Insurance Corporation's (FDIC) *Credit Card Activities Manual* (FDIC, 2007), and (iii) the academic marketing literature (Pellandini-Simányi, 2023). We consider two market definitions. Our baseline market definition is based on the aforementioned documents which describe market segmentation on income, demographics, and credit attributes. We intersect four FICO bands (subprime/near prime/prime/super prime), card type (general purpose/non-general purpose cards), product type (co-branded/non-co-branded), loan channel (pre-approved/internet/other) and consumer income ventiles (based on IRS income per capita in their zip code). This yields 960 baseline markets. The naive market definition is the intersection of broad FICO bands (subprime/prime), card type and product type as before, and consumer income terciles. This yields 24 naive markets. We provide detailed descriptions of each market dimension in Section 3.1.

In the second step, we remove bank-time fixed effects to purge the time series movements in interest rates from common bank-level fluctuations in rates. We also include 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. We refer to the residualized first-stage interest rates as *spreads*.

In the third step, we aggregate the spreads into a bank-market-week panel, and then we project the spreads onto interactions of surprise rate cuts on market- and national-level credit card shares. 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 surprise monetary policy shocks, we find that when a bank's market-level share exceeds the 70^{th} percentile, pass through rates are 17% lower than in markets where that bank's market-level share is less than the 70^{th} percentile. The effect is persistent and present in pooled and event-level analyses. We then test the importance of national-level shares for rate setting. We find that when a bank's national-level shares exceed the 98th percentile, pass through rates are 24% lower than in markets where that bank's national-level share is less than the 98th percentile.

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 et al. (2018), Herkenhoff and Raveendranathan (2020), and Grodzicki (2023c)). 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 to other co-moving macroeconomic factors.

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 U.S. credit markets in 2008, and we treat each model period as a 1-year interval in which mobility across FICO bands, product types, loan channels, and income groups is possible. We simulate a 27.5 basis point rate cut, matching the January 2008 surprise rate change, 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 more than 7 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 2.5 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 roughly doubles in size, at the expense of their less productive competitors. With lower interest rates, credit-to-income expands significantly.

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 0.16% 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 0.45%.

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 2 basis points and 45 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.

The rest of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the OCC and Y-14M data, defines our credit card markets, and presents the descriptive evidence that motivates the analysis. Section 4 develops the model and derives the testable implications for share-dependent pass-through. Section 5 implements those tests in the data. Section 6 estimates the model and uses it to quantify the effects of market power and competitive reforms.

2 Literature

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 (2025), Agarwal et al. (2015), and very recently Drechsler et al. (2025)), but they stop short of providing econometric tests for market power. In particular, Drechsler et al. (2025) document spending on advertising, arguing that this type of customer acquisition builds market power. Early work by Ausubel (1991) attributed the lack of pass-through from the cost of funds to market power. However, recent work by Grodzicki (2023c) and Grodzicki (2023b) documents a much higher rate of pass-through in recent years and the growing prevalence of 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. We address the parallel issue raised about uniform geographic pricing in deposit markets (Begenau and Stafford, 2023) by relying on well-established market segmentation patterns and defining U.S.-wide markets.

Several 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 is 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.

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 (2004), Drozd and Nosal (2008), Bauducco and Janiak (2015), Petrosky-Nadeau and Wasmer (2017), Herkenhoff (2019), Braxton et al. (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 (2023a), Nelson (2018), and Galenianos and Gavazza (2022)).[5] There are far fewer papers that consider dynamic, oligopolistic banks (e.g. Herkenhoff and Raveendranathan (2020), Corbae and D'Erasmo (2021), Whited et al. (2021), and Burgués and De Simone (2025b)). 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 et al. (2022)), we deviate from existing work by relaxing assumptions related to the *boundaries of competition*. By relaxing these assumptions, our

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

theory yields novel tests of non-competitive behavior at the market- and national-level.

3 Data

Our analysis is based on a panel of credit card loans obtained by combining the OCC CCM database from 2008 to 2013 with the Y-14M database from 2014 to 2019.

The OCC dataset starts in 2008 and contains account-level information for credit card loans originated by the nine largest banks in the US.[6] Importantly, the OCC data covers the only time period our sample window with objectively large, unexpected interest rate movements. While the identity of the banks in the OCC data 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.[7] 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 self-reported income, among other fields.

The Y-14M database is basically an expansion of the OCC database. The Y-14M coverage is broader, including several smaller banks that are excluded from the OCC, and a broader set of variables, but it still contains nearly identical variables to the OCC database; see Dempsey and Ionescu (2025) for additional discussion of the Y-14M database. Crucially for our study, both the OCC and Y-14M databases include the date of origination of each credit card. This allows us to build a continuous panel of daily originations from 2008 to 2019, which forms the basis for our econometric analysis. We consider an account to be newly originated if the month of origination equals the month the data was reported.

3.1 Market definition

To define credit card markets, we rely on three sources: (i) consulting reports by McKinsey (Fiorio et al. (2014)), (ii) the *Marketing and Acquisition* chapter of the Federal Deposit

[6] 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. "

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

Insurance Corporation's (FDIC) *Credit Card Activities Manual* (FDIC, 2007), and (iii) the academic marketing literature (Pellandini-Simányi, 2023).

The credit card industry targets 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 typesâĂŤrewards, low-rate and subprimeâĂŤto cater to different users.*

This type of market segmentation is common in credit card marketing, and many credit card marketing consultancy firms provide demographic 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."[8]

In the Federal Deposit Insurance Corporation's (FDIC) *Credit Card Activities Manual* (FDIC, 2007), they outline the market segmentation practices used by credit card lenders to target and acquire customers. The FDIC highlights the following segmentation variables, while noting that practitioners rely on even broader sets of variables: product line, geographic location, vintage, acquisition method/marketing channel, and scoring. We elaborate on these segmentation methods below by quoting from the FDIC manual (underlining added),

> *"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... Segmentation by geographic location*

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

captures regional differences in card usage and monitors local economic conditions... Segmentation by the acquisition method separates accounts based on how they were acquired, and segmentation by the marketing channel method separates accounts based on the type of channel utilized... Management can also use other segmentation methods, such as scoring."

We use these three sources of credit market segmentation to justify our credit card market definitions. First, we define a *baseline market* as the interaction of 4 FICO categories (sub-prime, near-prime, prime, and super-prime), card type (general purpose[9] or not, and co-brand or not), income ventile (based on IRS per capita adjusted gross income at the 5-digit zipcode[10]), and loan channel[11] (internet/pre-approved/other). There are 960 possible baseline markets.

Second, we define a *naive market* as the interaction of 2 FICO categories (subprime and prime), card type (general purpose or not, and co-brand or not), and 3 income terciles based on IRS per capita adjusted gross income at the 5-digit zipcode. There are 24 possible naive markets.

In the text, we focus on the *baseline market* definition; however, we show our main results for the naive market definition in the Appendix. We summarize the market definitions below:

I. **Baseline Market:** 4 FICO bins $\times$ card type $\times$ income ventiles $\times$ loan channel

II. **Naive Market:** 2 FICO bins $\times$ card type $\times$ income tercile

Discussion of market boundaries. Our approach to defining markets relies on *practical indicia*, namely documenting distinct, identifiable customer groups. This approach to

[9]General purpose (or universal) credit cards are those that can be used at a variety of merchants, while non-general-purpose cards include private label, business or corporate credit cards. Co-brand credit cards typically relate to products and services, including retail stores, airlines, etc, excluding Oil and Gas cards. Cards that re not co-brand include Oil and Gas co-brand, affinity (e.g., unions or universities), student, and health care. Source: https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-14M

[10]We define markets based on average income at the 5-digit zipcode. Fiorio et al. (2014)'s discussion of the use of Census data suggests that segmentation occurs based on regional income, providing support for our approach. While self-reported borrower income is available in the OCC and Y14 data, it is incompletely populated and thus cannot be used to define markets. We use self-reported income when residualizing interest rates (allowing for a missing self-reported income category to retain all possible cards), but for the purposes of defining markets, we require an income measure for all credit cards in our sample.

[11]We grouped accounts from finer categories in Y-14M data, based on the solicitation position of the issuer: We refer to "internet" as unsolicited accounts based on a customer completing an internet, magazine insert or event marketing application; "pre-approved" as those that were solicited and either pre-approved or classified as invitation to apply (i.e., solicitations that required a customer to undergo a full credit review prior to approval); and "other" as those that do not fall in the previous channels (chiefly, branch applications or third-party purchases).

market definition is widely used in antitrust law and was established in *Brown Shoe Co. v. United States, 370 U.S. 294 (1962)*. To validate our *practical indicia*, we additionally show that our baseline market definition passes the Hypothetical Monopolist Test (HMT) in Section 4. The HMT is an alternative quantitative approach to defining markets, and asks "can a hypothetical monopolist in a given market impose a small (typically 5%), non-transitory price increase?" The HMT is widely adopted by both regulators and courts to define markets.

3.2 Summary Statistics: Borrower and Bank Traits

We begin by summarizing borrower and bank traits in the OCC/Y14 database. We consider two samples in our analysis:

I. **Originations panel:** All credit cards originated (issued) between 3 weeks before and 4 weeks after Federal Open Market Committee (FOMC) events between 2008 and 2019.

II. **Balance sheet panel:** All credit cards on OCC/Y14 bank balance sheets between 3 weeks before and 4 weeks after Federal Open Market Committee (FOMC) events between 2008 and 2019.

We also impose additional restrictions on the micro data. We only retain FOMC events in which the surprise component of the rate change exceeds 5 basis points in absolute value.[12]

Borrower traits. To analyze borrower traits, we rely on the originations panel. Table 1 presents descriptive statistics of a set of continuous account-level variables from our originations dataset over the period 2008-2019. In particular, it shows the mean, median, dispersion, and number of nonmissing observations. The table showcases the large number of observations in our sample, and rich heterogeneity across accounts' characteristics. For instance, the average APR is around 21% with a standard deviation of full 5 percentage points. Also, the utilization rate is around 9% with a standard deviation of 21 percentage points, implying a coefficient of variation of around 2. Credit limits and credit scores also have significant dispersion, while the self-reported income is significantly right-tailed. As for the cycle ending balance, its low mean follows from accounts being newly originated, but we still observe a significant dispersion.

Table 2 presents the corresponding summary statistics for categorical variables. Roughly one-half of our sample consists of general purpose credit cards, and around a fourth are

[12] Appendix C provides a complete list of dates.

Table 1: Descriptive Statistics: Continuous Variables

Variable	Mean	Median	S.D.	Observations
Cycle ending balance	261	0	1,023	13,777,764
APR	20.7%	21.9%	5.1%	14,141,349
Credit score	728	735	72	14,141,349
Credit limit	5,003	3,300	5,471	14,124,019
Self-reported income	39,574	23,421	896,265	11,313,594
Utilization rate	8.9%	0%	20.9%	13,757,813

Table 2: Descriptive Statistics: Categorical Variables

Variable	Fraction	Observations
General purpose	47.56%	14,141,349
Co-brand	24.60%	14,141,349
Internet channel	65.73%	14,141,349
Pre-approved channel	11.64%	14,141,349
Other channel	22.63%	14,141,349
Fixed interest rate	22.79%	14,092,076
Promo balances	9.65%	13,660,455

co-branded. As for the loan channels, roughly two-thirds of our sample were originated through internet, a tenth were pre-approved and invited to apply, while the remaining were originated through other channels. Regarding interest rate types, roughly one-fifth of the accounts in our sample exhibit fixed interest rates, while a tenth of the accounts have positive promotional balances.

Bank traits. To analyze bank traits, we rely on the full balance sheet sample. Let i denote bank and j denote market. Using the market definition in Section 3.1, we compute a bank's *market-level share* s_{ij} using interest rates r_{ij} and balances l_{ij} on *all* existing accounts,

$$s_{ij} = \frac{r_{ij} l_{ij}}{\sum_i r_{ij} l_{ij}}. \tag{1}$$

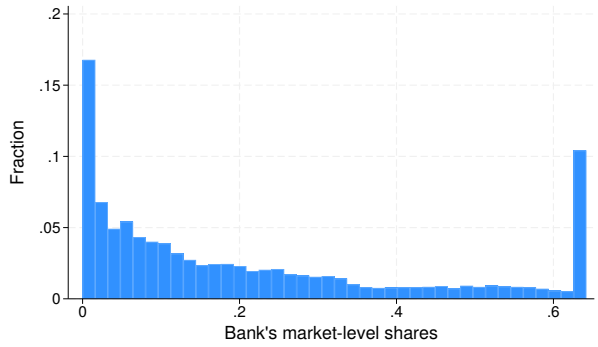
We also define the *national-level share* s_{ij}^N to be the ratio of a bank's balances in a market over aggregate balances across all banks and markets in a given period,

$$s_{ij}^N = \frac{r_{ij} l_{ij}}{\sum_j \sum_i r_{ij} l_{ij}}. \tag{2}$$

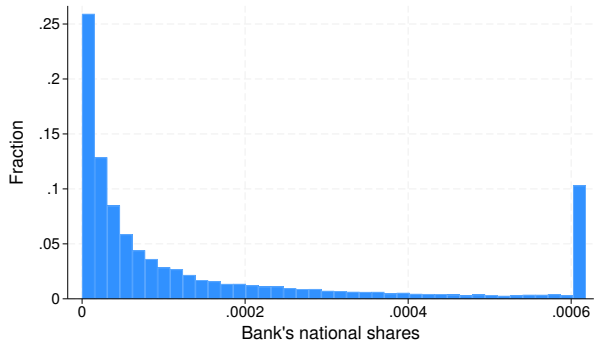
This measure is motivated by our theory in Section 4, and it captures the importance of a bank's credit cards in a given market ($r_{ij} l_{ij}$) relative to the size of the national credit

Figure 1: Distribution of Banks' Market-level Shares and National-level Shares

(a) Bank Market-level Shares



(b) Bank National-level Shares



Notes: Panel (a) is a histogram of market-level shares s_{ij}, computed using equation (1). Panel (b) is a histogram of national-level shares s_{ij}^N, computed using equation (2). The sample is all cards on banks balance sheets (see text for more discussion). The right tail is winsorized at the 10% level. We apply the baseline market definition.

card market ($\sum_j \sum_i r_{ij} l_{ij}$). Despite a common numerator, market-level and national-level shares are imperfectly correlated. Arbitrary configurations of high/low market-level and high/low national-level shares are possible, as we discuss below.

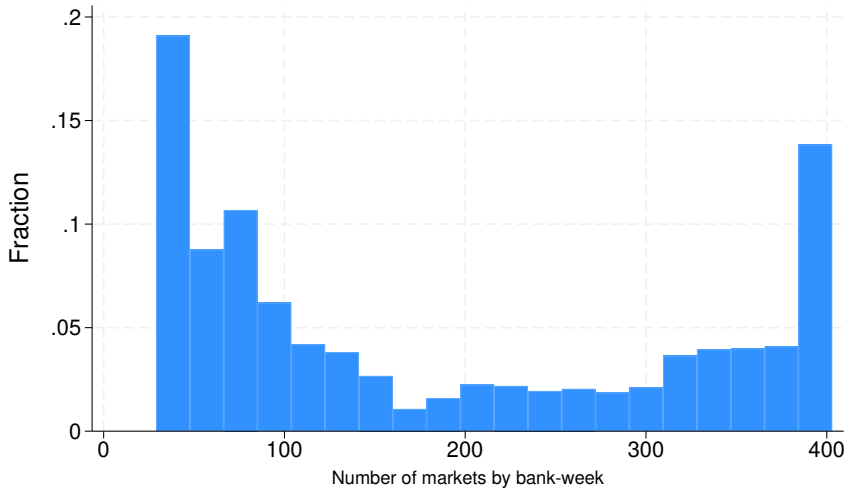
Panel (a) of Figure 1 shows the distribution of banks' market-level shares over our sample period, winsorizing values beyond the 90$^{\text{th}}$ percentile (for confidentiality reasons). The distribution is significantly right-tailed with nontrivial density all up to the upper bound, denoting a significant fraction of markets having lenders with sizeable shares. The Herfindahl-Hirschman Index (HHI) is 0.47 over the entire sample period, indicating significant concentration. Thus, each market has concentration equivalent to two equally sized banks. The Department of Justice (DOJ) and Federal Trade Commission (FTC) define highly concentrated markets as those with an HHI above 0.18, which is well-exceeded in our sample of banks. Even for the naive market definition, the HHI is 0.36.

Panel (b) shows the distribution of national-level shares, winsorizing at the 90$^{\text{th}}$ percentile (for confidentiality reasons). The national share distribution also has a fat right tail. Note that the mean national share moves towards zero since the denominator is now a national aggregate.

In addition to concentrated market positions, banks in the OCC/Y14 data operate in many markets. Figure 2 shows the distribution of the number of markets in which each bank operates in any given week, winsorizing values beyond the 90$^{\text{th}}$ percentile (for confidentiality reasons). The median bank issues credit cards in approximately 130

markets in any given week, but there is a fat tail of banks originating cards in 400 or more markets in any given week. The distribution is dispersed over a wide range, with the inter-decile range being 374 markets.

Figure 2: Distribution of Number of Markets Banks Operate in



Notes: This is a histogram of the number of markets each bank operates in during a given week. We apply the baseline market definition.

3.3 Motivating Market Power: Covariance of Rates and Market Shares

Lastly, before turning to the model and developing causal empirical tests, we provide various sources of evidence that interest rates and bank market shares covary significantly.

Variance Decomposition. Let n index individual credit cards. Each credit card is associated with a bank $i(n)$, market $j(n)$, and origination week t. Consider a panel regression of credit card n's effective APR r_{nt} on an arbitrary set of fixed effects $FE_{n,i(n),j(n)}$. In what follows, we will consider time, market-share, national-share, bank, and borrower fixed effects. We estimate the following OLS regression,

$$r_{nt} = \alpha_0 + FE_{n,i(n),j(n)} + \epsilon_{ijt} \tag{3}$$

We estimate the explanatory power of the fixed effects separately at first, and then jointly below. Table 3 reports the share of variation in credit card interest rates explained by alternative fixed-effects when included separately in equation (3). Bank fixed effects account for the largest fraction of explained variation, followed by market and borrower

fixed effects, highlighting the importance of persistent heterogeneity at the lender, market, and borrower levels.[13] More surprisingly, market-share fixed effects account for more than 22% of interest rate variation, and national-level shares account for around 5.0% of interest rate variation.

Table 3: Explained Variation from Alternative Fixed Effects

Specification	R^2
Time fixed effects	12.7%
Market-share fixed effects	22.6%
National-share fixed effects	4.9%
Bank fixed effects	46.3%
Market fixed effects	44.4%
Borrower fixed effects	34.6%

Notes: This table reports the R-squared from estimating equation (3), including each row's fixed-effects separately. We apply the baseline market definition.

Next, we estimate high-dimensional fixed effects regression and provide a standard variance decomposition. Unlike equation (3), we now allow all fixed effects to interact with time. The combined covariates explain 74% of variation in interest rates. Among the explainable component of rates, Table 4 reports the variance decomposition. Market fixed effects, which summarize an individual's FICO group, income ventile, card type, and loan channel explain roughly 53% of interest rate variation. These individual traits are the dominant factor. Finer-grain borrower traits only explain an additional 6.5% of interest rate variation. On the other hand, market-share-by-week and national-share-by-week respectively explain 28% and 18% of interest rate dispersion, conditional on all other fixed effects.

Matched cards. While the variance decomposition suggests that market shares are a key determinant of interest rates, there are many imperfections with such analysis, including limitations of the flexibility and dimensionality of fixed effects. Instead, we consider the determinants of interest rate dispersion among finely-matched credit-cards. To examine how APR varies while holding account characteristics truly constant, we construct highly granular groups and study how interest rate dispersion within-groups varies with market shares.

[13]Borrower fixed effects are based on the following variables: FICO, credit limit, credit balance, utilization rate, self-reported income, interest rate type flag, multiple bank relationship flag, multiple credit card flag, and promo flag. We split FICO into 4 broad groups, and within each group, we compute deciles of the FICO score. We use ventiles of the other continuous variables for fixed effects.

Table 4: Variance Decomposition, Baseline Market

	Market Share	**National Share**	**Bank FE**	**Market FE**	**Borrower FE**
Market Share	0.279				
National Share	-0.040	0.185			
Bank FE	-0.018	-0.016	0.117		
Market FE	-0.116	-0.136	0.090	0.533	
Borrower FE	-0.009	0.009	-0.0127	0.020	0.065

Notes: Let $\widehat{r}_{nt}$ denote the predicted interest rate when all fixed effects are included together in equation (3), and let $\widehat{r}^{X}_{nt}$ denote the predicted interest rate when only one set of fixed effects for factor X is used. The table reports $cov(\widehat{r}^{X}_{nt}, \widehat{r}^{Z}_{nt})/var(\widehat{r}_{nt})$ for row factor X and column factor Z, where $X, Z \in \{$ Market Share, National Share, Bank, Market, Borrower $\}$. We apply the baseline market definition.

We proceed in three steps. In the first step, accounts are grouped into partitions by card type (general purpose or not, co-brand or not), loan channel, rate type, promotional-balance flag, income bins, and FICO bins. The income bins are defined using self-reported income with \$1,000 increments up to \$10,000,000, with a final bin capturing all values above \$10,000,000. FICO scores are split into 10-point intervals (e.g., 500-510, 510-520, etc.). This defined around 2,000 groups indexed by g. In the second step, we isolate each group of matched individuals and compute the interquartile range of interest rates within each finely-partitioned group g, IQR_g. In the third step, we measure how interest rate dispersion within-group covaries with bank market share dispersion within-group.

Figure 3 plots the distribution of the interquartile range of APRs across each group, $\{IQR_g\}$. The average interquartile range is 5.7 percentage points. This means that there is significant rate dispersion, even among arguably equivalent individuals in terms of credit risk, income, and product type.

Next, we test whether interest rate dispersion within-group is explained by market-share dispersion within-group. Panel (a) of Figure 4 illustrates the binscatter of interest rate IQR within-group (i.e, IQR_g) against market-share dispersion within-group; panel (b) plots the standard deviation of within-group APR. The figure reveals a strong correlation (R2 of $60\% - 70\%$). Groups with significant variation in interest rates are also exposed to significant variation in market concentration. This evidence suggests that even conditional credit risk, income, and product type, market-share variation can account for a significant share of interest rate variation. However, this evidence is not causal.

In what follows, we develop a theory of national rate setting banks. We use the theory, in conjunction with the data, to derive formal econometric tests for market power among credit-card lenders. We then estimate the theory to quantify the costs of bank market power.

Figure 3: Distribution of the interquartile range of APRs across each matched group

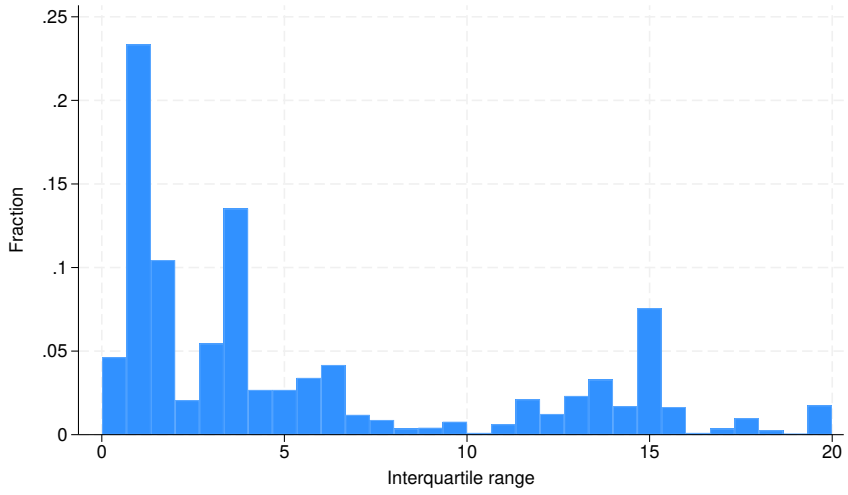
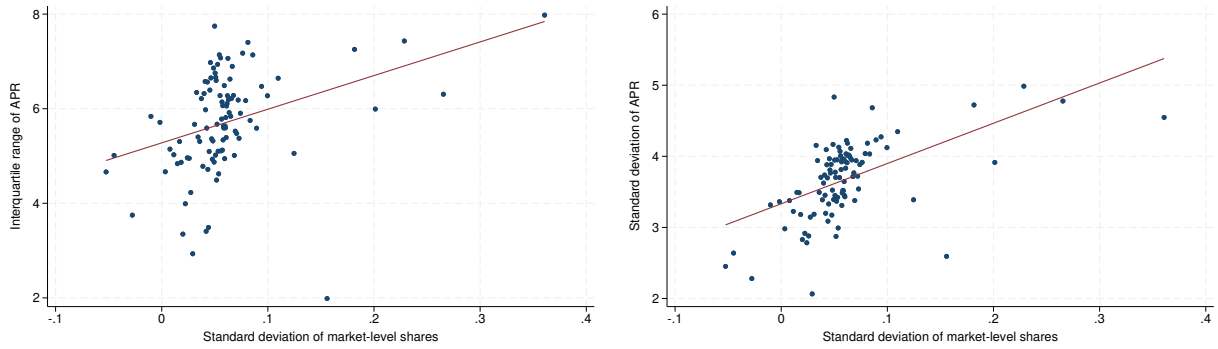


Figure 4: Binscatter of interest rate dispersion against market share dispersion

(a) Interquartile Range of APR

(b) Standard Deviation of APR



Notes: Figure shows the binscatter of interest rate dispersion within-group against market-share dispersion within-group, with percentiles on the x-axis. Panel (a) plots the interquartile range of APRs across each group, while panel (b) plots the standard deviation of APRs across each group.

4 Theory

To guide our subsequent empirical analysis, 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.

Environment. The economy is populated by a stand-in household and a finite number N of credit card issuing banks $i \in \{1, \ldots, N\}$. Those lenders are distributed across a finite number of markets indexed by $j \in \{1, \ldots, J\}$. There are $N_j \in \{1, \ldots, N\}$ 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)). We additionally allow for preference shifters ϕ_j at the market-level (i.e., households simply prefer certain product types over other product types, ceteris paribus).

We provide a concrete interpretation of these substitution parameters based on our market definition in Section 3.1. 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 to higher income zipcodes. 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 house-

hold. The resulting household problem is given by[14]

$$\max_{\{l_{ij}\},C_1,C_2} \quad u\left(C_1, C_2\right) \tag{4}$$

$$C_1 \leq y - \sum_{i,j} r_{ij} l_{ij} + \Pi, \quad C_2 \leq L \tag{5}$$

$$L = \left[\sum_{j=1}^{J} \phi_j l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \quad l_j = \left[\sum_{i=1}^{N_j} l_{ij}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \tag{6}$$

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

$$l_{ij} = \phi_j^{\theta} \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L, \quad l_j = \phi_j^{\theta} \left(\frac{r_j}{R}\right)^{-\theta} L, \quad R = \frac{u_2(C_1, L)}{u_1(C_1, L)}, \tag{7}$$

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

$$R = \left[\sum_{j=1}^{J} \phi_j^{\theta} r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}, \quad r_j = \left[\sum_{i=1}^{N_j} r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \quad RL \equiv \sum_{j=1}^{J} r_j l_j, \quad r_j l_j \equiv \sum_{i=1}^{N_j} r_{ij} l_{ij} \tag{8}$$

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 rate r_f is presumed to be set outside of the credit card market (i.e., banks do not influence r_f regardless of competitive structure). We assume the marginal cost of funds is bank-specific, not market specific.[15] Banks operate in an exogenously given number of markets,

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

[15] 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 dependent on affiliate-level cash flows compared with funding of loans by independent banks. Cremers et al. (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

$J(i)$.

Competitive structure. We assume that banks engage in Bertrand competition over interest rates r_{ij} and understand their "largeness" and impact on both market- and national-level aggregates. We refer to this competitive structure as *national oligopoly*. We contrast this to three other market structures: (1) perfect competition, in which banks are price takers, (2) monopolistic competition, in which banks are no longer price takers but ignore their impact on market- and national-level aggregates, and (3) oligopolistic competition, in which banks understand their impact on market-level aggregates but ignore the national-level influence of their behavior.

Nash Equilibrium. An equilibrium is an economy-wide vector of interest rates $\{r_{ij}\}$ such that (1) for each focal bank, their vector of market-level interest rates is a best-response to the vector of competitor interest rates, and (2) credit services and goods markets clear.

4.1 Characterization

Next, we theoretically characterize interest rate setting behavior in order to derive testable implications. To make progress, we assume households have linear preferences over final goods and separable CRRA preferences over credit services:

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

This yields the following isoelastic aggregate demand curve:

$$L = \left(\frac{A}{R}\right)^{\frac{1}{\gamma}} \tag{9}$$

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:

$$\Pi_i = \max_{\{r_{ij}\}} \sum_{j \in J(i)} \left\{ r_{ij} l_{ij}(r_{ij}, r_j, R) - \left[c_i + r_f\right] l_{ij}(r_{ij}, r_j, R) \right\}. \tag{10}$$

provide supportive evidence by showing that a bank's lending is uncorrelated with local deposit-market concentration.

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

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

There are two central components of optimal pricing: (1) the lenders market-level share s_{ij}, and (2) the lenders national-level share s_{ij}^N:[16]

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

The market-level share captures the lenders' relative size within the market. The national-level share captures whether a lender's position within a market is nationally consequential. The numerator is still market specific. The national-level share can be written as the product of the the market-level share and the relative size of the market in the aggregate economy s_j:

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

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

$$r_{ij} = \mu(s_{ij})(r_f + c_i) + (\mu(s_{ij}) - 1)\left(\theta - \frac{1}{\gamma}\right) s_{ij}^N \frac{\Pi_i}{l_{ij}}, \quad \mu(s_{ij}) = \frac{\eta(1 - s_{ij}) + \theta s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij} - 1}. \quad (11)$$

While equation (11) is quite complex, we make headway on characterizing the national oligopoly rate setting behavior under the assumption of symmetric markets. We build up to those results by characterizing equation (11) under standard forms of competition, including perfect competition, monopolistic competition, and market-level oligopoly. These characterization results will directly inform our empirical tests of the nature of bank competition in the credit card market.

Case 1: Perfect Competition. When banks do not internalize any component of the demand function, the only equilibrium is one in which equation (11) simplifies to marginal

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

cost pricing,

$$r_{ij} = r_f + c_i, \tag{12}$$

and thus $\mu(s_{ij}) = 1$. The equilibrium features zero profits, given the constant returns to scale technology.

Case 2: Monopolistic Competition. When banks internalize the downward sloping nature of demand, but ignore their effects on market-level aggregates and national-level aggregates (i.e., banks act as if $s_{ij} = 0$ and $s_{ij}^N = 0$), markups become constant and cease to depend on size, $\mu(s_{ij}) = \frac{\eta}{\eta-1}$. Equation (11) simplifies to $r_{ij} = \frac{\eta}{\eta-1}(r_f + c_i)$.

Case 3: Market-level Oligopoly Competition. When 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 (i.e., banks act as if only $s_{ij}^N = 0$), rate setting parallels the formulas in Atkeson and Burstein (2008). Equation (11) simplifies to a share-dependent markup $\mu(s_{ij})$ over the bank's marginal cost of funds:

$$r_{ij} = \left[c_i + r_f\right] \mu(s_{ij}), \quad \mu(s_{ij}) = \frac{\eta\left(1 - s_{ij}\right) + \theta s_{ij}}{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - 1}. \tag{13}$$

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.

It is also useful to study the properties of the market-level Nash equilibrium in this case. Most variants of Atkeson and Burstein (2008) with multiplicative aggregate shocks are **block-recursive** (see for example, Berger et al. (2022)), meaning that the resulting market shares and markups are independent of the aggregate shock (for example, aggregate TFP in Berger et al. (2022) does not alter market-level shares and markdowns). 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 to L, R, and other multiplicative aggregates. Proposition 4.1 formalizes this argument.

Proposition 4.1 (Market-Level Oligopoly Nash Equilibrium)**.** *Taking competitor actions as given, the market-j equilibrium is defined by a fixed point in bank market-level shares:*

$$s_{ij} = \left(\frac{\left(c_i + r_f\right) \mu(s_{ij})}{\left[\sum_{k \in j} \left(\left(c_k + r_f\right) \mu(s_{kj})\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}} \right)^{1-\eta}, \qquad \forall i \in j. \tag{14}$$

Market-level shares depend on r_f, but are independent of R, L, and other aggregates, including endowments.

Case 4: National-level Oligopoly with Symmetric Markets. Suppose now that banks internalize their national size. Additionally assume that 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-level oligopoly economy:

$$r_{ij} = \mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right], \quad \mu\left(s_{ij}, s_{ij}^N, J_i\right) \equiv \frac{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - J_i\left(\theta - \frac{1}{\gamma}\right) s_{ij}^N}{\eta\left(1 - s_{ij}\right) + \theta s_{ij} - J_i\left(\theta - \frac{1}{\gamma}\right) s_{ij}^N - 1} \tag{15}$$

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 (13).

As before, the system is *not* block recursive with respect to r_f in either market-level or national shares. Proposition 4.2 formally establishes this.

Proposition 4.2 (Symmetric National-Level Oligopoly Nash Equilibrium)**.** *The symmetric-*

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

$$s_{ij} = \left(\frac{\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]}{\left[\sum_i \left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}} \right)^{1-\eta}, \quad s_j = \phi_j^\theta \left(\frac{\left[\sum \left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1}{1-\eta}}}{\left[\sum_j \phi_j^\theta \left[\sum_i \left(\mu\left(s_{ij}, s_{ij}^N, J_i\right)\left[r_f + c_i\right]\right)^{1-\eta}\right]^{\frac{1-\theta}{1-\eta}}\right]^{\frac{1}{1-\theta}}} \right)^{1-\theta}, \quad s_{ij}^N = s_j s_{ij} \ \forall ij, \tag{16}$$

Market-level and national-level shares depend on r_f*, but are independent of* R*,* L*, and other aggregates, including endowments.*

Next, we turn to the properties of interest rates setting in response to risk-free rate changes. To do so, we extend the pass-through rate characterization of Amiti et al. (2016) and Berger et al. (2022) to national oligopoly. Our primary object of interest is the semi-elasticity of interest rates with respect to the risk-free rate, $\frac{d \ln r_{ij}}{dr_f}$, henceforth the *pass-through rate*. Proposition 4.3 shows that the pass-through rate depends non-monotonically on market-level and national-level shares.

Proposition 4.3 (Symmetric National-Level Oligopoly Pass-Through)**.** *The semi-elasticity of interest rates with respect to the risk-free rate is proportional to the pass-through factor* m_{ij}^N*:*

$$\frac{d \ln r_{ij}}{dr_f} \propto \frac{1}{\left(1 - m_{ij}^N\right)} \tag{17}$$

where

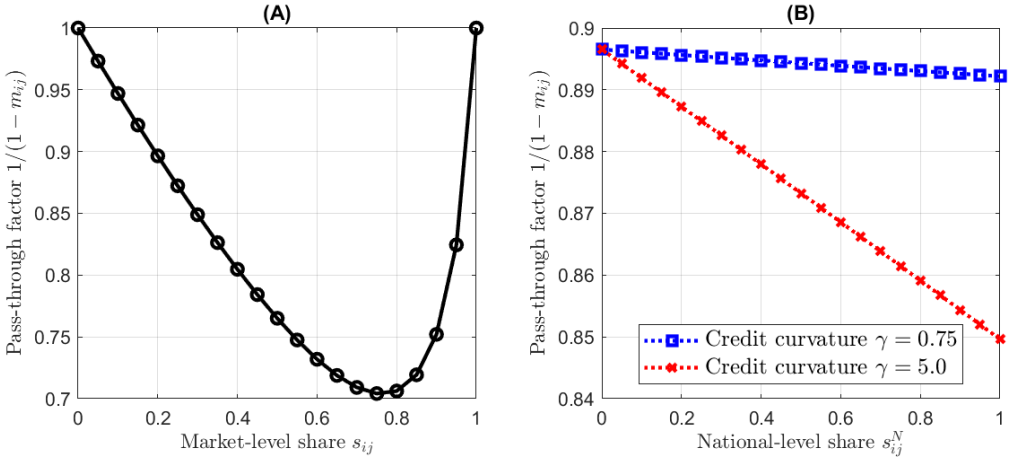
$$m_{ij}^N = \frac{\left(\epsilon_{ij} - \eta\right)\left(\eta - 1\right)\left(1 - s_{ij}\right) + \left(\epsilon_{ij} - \epsilon_{ij}^M\right)\left(\theta - 1\right) s_{ij}^N s_{ij}\left(1 - s_j\right)}{\epsilon_{ij}\left(\epsilon_{ij} - 1\right)}$$

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

The *pass-through factor*, $\frac{1}{1 - m_{ij}^N}$, is illustrated in Figure 5. Holding national-level shares fixed, panel (A) shows that up to a market share of roughly 80%, as a bank's market-level footprint expands, pass-through rates fall. However, beyond a market-level share of 80% pass-through rates increase. This U-shape pattern of pass-through rates is pervasive in this class of models (Amiti et al. (2016), Berger et al. (2022) among others).[17] Holding market-level shares fixed, panel (B) repeats this exercise and shows that pass-through rates monotonically fall in national-level shares. Crucial to the national-level pass-through rates is γ, which governs how responsive the representative household is to

[17] Unlike earlier work, however, it is worth noting that the pass-through factor is not unity for pure monopolist $s_{ij} = 1$ banks.

Figure 5: Pass-through comparison, market v. national oligopoly



Notes. Parameters are from Table 8. Panel (A) varies market-level shares, holding national-level shares at their mean. Panel (B) varies national-level shares holding market-level shares at their mean. Panel (B) plots the pass-through factor for two values of γ (credit service utility curvature). Panel (A) is invariant to γ.

aggregate interest rates. When households are very responsive ($\gamma = 0.75$), pass-through rates do not vary much with national shares. Figure 5 makes clear that over a broad range of the data, pass-through rates are expected to fall when banks expand their footprint; however, for extreme values of concentration, pass-through rates may rise again.

4.2 Testable Implications

We exploit the model's structure and non-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 and national-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.

Testing for Market-level Oligopoly. Consider **Case 3**, in which banks compete strategically in markets but ignore their influence on national aggregates. We first express equation (13) in logs which yields additive separability of bank funding costs and markups:

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

Consider two markets $j = H$ and $j = L$ in which bank i has a high market-level share and low market-level share, respectively. 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 the risk free rate changes, $r_{f,t+1} \neq r_{f,t}$. We define the double difference of log interest rates across markets and time as

$$\Delta_{H,t} \ln r_{i,j,t} \equiv \Delta_{HL} \ln r_{i,j,t+1} - \Delta_{HL} \ln r_{i,j,t}. \tag{18}$$

With this notation in hand, Proposition 4.4 characterizes market-share dependence of the double difference estimator.

Proposition 4.4 (Market-level Pass-through)**.** *Under perfect competition or monopolistic competition $\Delta_{H,t} \ln r_{i,j,t} = 0$ and is therefore 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.*

Proposition 4.4 provides us with our first testable implication. Under perfect or monopolistic competition, there is no market-level share dependence of pass-through rates. We implement this test in the next section by building a high-frequency event study around surprise monetary rate cuts. We then test for differential effects of surprise rate cuts on interest rates in high and low concentration markets.

Testing for National-level Oligopoly. Next, consider national competition and take logs of equation (11). Consider two markets $j = H$ and $j = L$ that are otherwise identical (i.e., $j = H$ and $j = L$ have the same vector of market-level shares), except the national footprint of market $j = H$ is larger than the national footprint of market $j = L$ ($s_H > s_L$). This variation potentially exists when markets have different taste shifters $\phi_H > \phi_L$, but identical configurations of competitors within each market. Consider bank i that operates in both markets. Bank i's national-level shares differ across markets (i.e. $s^N_{i,H,t} > s^N_{i,L,t}$), but its market-level shares do not, $s_{i,H,t} = s_{i,L,t}$. Define the difference in log interest rate between high and low national share as

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

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,

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

With this notation in hand, Proposition 4.5 characterizes national-share dependence of the double difference estimator.

Proposition 4.5 (National-level Pass-through)**.** *Assuming identical market-level shares, under perfect competition, monopolistic competition, or market-level oligopoly* $\Delta^N_{H,t} \ln r_{i,j,t} = 0$ *and is therefore independent of national-level shares. Under national-level oligopoly,* $\Delta^N_{H,t} \ln r_{i,j,t}$ *depends on national-level shares and is not necessarily equal to zero.*

Proposition 4.5 provides us with our second testable implication. Under perfect, monopolistic, or (market-level) oligopolistic competition, there is no national-level share dependence of pass-through rates, conditional on market-level shares.

The dependence of $\Delta^N_{H,t} r_{i,j,t}$ on national shares is implicit in system (16) and formally demonstrated in Proposition 4.3. To numerically illustrate the national-share dependence of markups, we simulate a rate cut and plot changes in markups as a function of market and national shares.[18] We simulate a 27.5 basis point reduction in r_f. Figure 6 illustrates how lenders adjust their markups in response to a rate cut based on the estimated parameters in Section 6. The x-axis is the lenders national-level share s^N_{ij} and the y-axis is the percent change in markups. Each color is one of the nine distinct lenders in the U.S. economy.

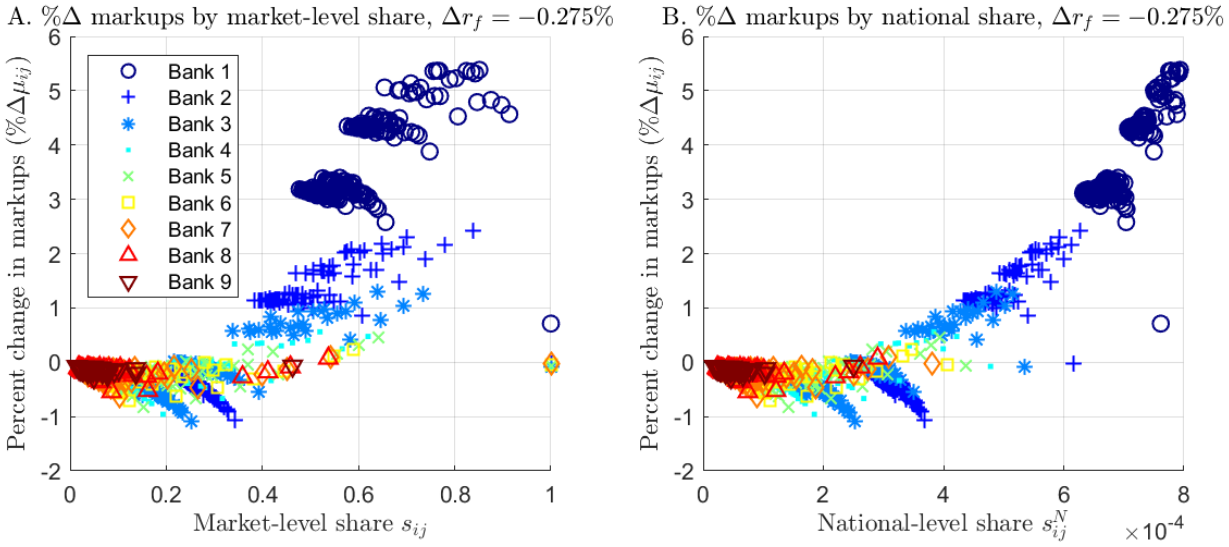
Figure 6 clearly illustrates national-share-dependent pass-through rates. Fixing a bank (e.g. the purple dots), we see that within that bank, spreads are only cut at very low national shares, and spreads are actually increased at very high national shares. This differential pass-through is the basis of our testable implications in Section 5.

5 Identified Elasticities

In this section, we test proposition 4.4 and 4.5 by exploiting a high-frequency account-level panel dataset of interest rates at origination over 2008-2019. We combine this dataset with identified monetary policy shocks to estimate the differential pass-through within-bank, across-market following unexpected movements in the policy rate over this period. Our empirical strategy proceeds in two steps:

[18] We use parameters from Table 8.

Figure 6: Pass-through from risk free rate to markups under national oligopoly



Notes. A 100 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 8.

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 fixed effects, including a full bank by time set of 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 for 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, proposition 4.4 and 4.5 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 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.

We consider two cases for residualization: *baseline* and *naive*. The naive case residualizes the data using a parsimonious set of fixed effects (FE), including day-of-week FEs, bank by time FEs, market- and national-level shares by time FEs, and borrower chracteristics by time FEs. The set of borrower characteristics includes bins on FICO and self-reported real income, and flags on multiple banking relations, multiple credit cards, secured, and securitized status. The baseline residualization case expands to include market FEs. It also enhances the set of borrower characteristics to include bins on credit limit, cycle ending balance, and utilization rate, as well as flags on interest rate type and promotional balances.

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, w_t week fixed effects (FE), dow_t day-of-week FEs, α_j market FEs, α_i bank FEs, and $\widetilde{sh}^M_{ijt}$ and $\widetilde{sh}^N_{ijt}$ fixed effects for quantiles of banks' market- (s_{ijt}) and national-level shares (s^N_{ijt}), respectively. We use 100 quantiles for market-level shares ($\widetilde{sh}^M_{ijt}$) and 100 quantiles for national-level shares ($\widetilde{sh}^N_{ijt}$). Let FS_n denote 40 bins of an individual's FICO score, constructed as deciles within each broad FICO category defining a market. Let X_n be a vector of additional borrower-level controls, including ventiles on the aforementioned continuous variables.

Event window by event window, we residualize the data using the following specification,

$$\begin{aligned} \log APR_{nt} = \beta_0 + w_t + dow_t + \alpha_j + \widetilde{sh}^M_{ijt} + \widetilde{sh}^N_{ijt} + \alpha_i + FS_n + \Gamma X_n + ... \\ + w_t \cdot \left(\widetilde{sh}^M_{ijt} + \widetilde{sh}^N_{ijt}\right) + w_t \cdot (\alpha_i + FS_n + \Omega_t X_n) + \epsilon_{nt} \end{aligned} \tag{20}$$

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

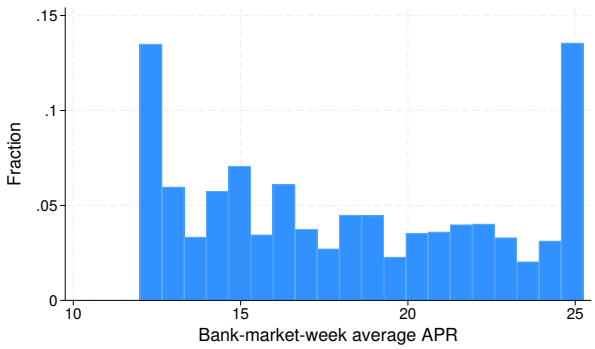
$$Y_{nt} = \hat{\epsilon}_{nt} + \widehat{w_t \cdot \widetilde{sh}^{M}_{ijt}} + \widehat{w_t \cdot \widetilde{sh}^{N}_{ijt}} \tag{21}$$

where *hatted* variables denote projected values. Since our goal of residualizing the data is to isolate a time varying markup, our residualized spreads Y_{nt} include (1) the true residual, (2) market-level share-time variation, and (3) national-level share-time variation.

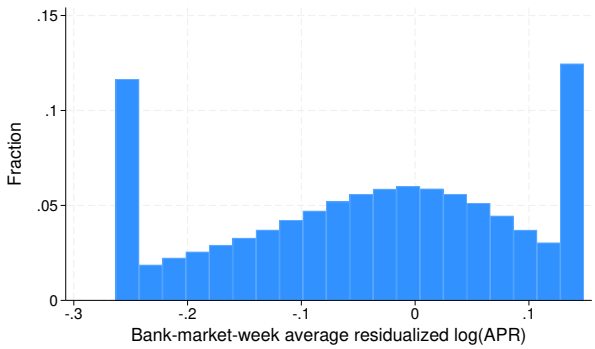
Panel (a) of Figure 7 shows the distribution of interest rates from our sample, and panel (b) shows the distribution of spreads (i.e., residuals Y_{nt}), both truncated at the bottom/top 10^{th} percentiles. Despite the residualization procedure purging various dimensions of variation, the resulting spreads still exhibit nontrivial dispersion to be exploited in the regressions aimed at measuring the differential pass-through within-bank across markets.

Figure 7: Distribution of Interest Rates and Spreads

(a) Distribution of APR (Levels)



(b) Distribution of Residualized log(APR)



5.2 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. Our baseline analysis focuses on the Jan 22, 2008 FOMC event since it involved the largest unexpected rate cut in our sample. But we also present results for other stacked FOMC events: big rate cuts in 2008 ("big cuts 2008"), all FOMC events in 2008 ("All 2008"), and all FOMC events in 2008-2019 ("All events"); see Section 3 for our definition of events.

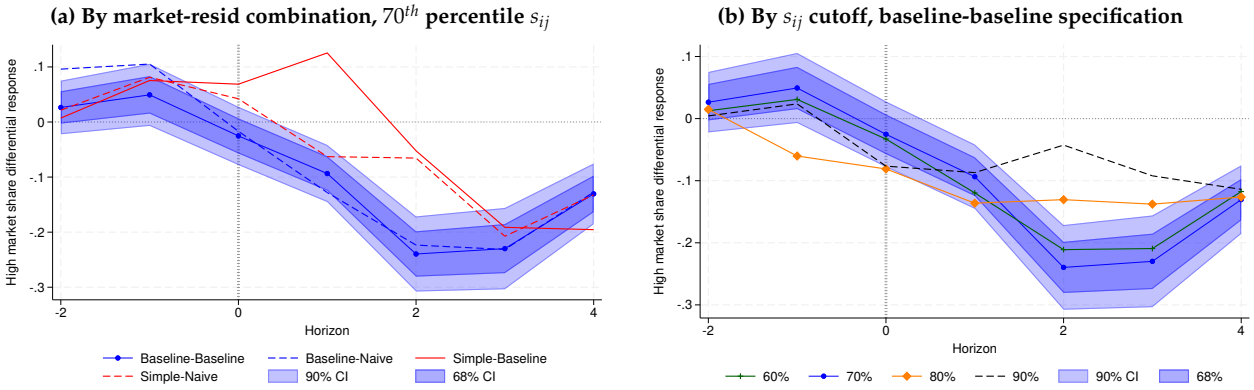
Let τ denote an FOMC event, FF_τ the monetary policy shock, $\mathbb{I}^{M,high}_{ij,\tau}$ a dummy for

a high market-level share, $\mathbb{I}_{ij,\tau}^{N,high}$ a dummy for high national-level share. Both market- and national-level share cutoffs are computed one-month prior to the FOMC event.[19] Define $\Delta_h Y_{ij\tau} = Y_{ij,\tau+h} - Y_{ij,\tau-3}$.[20] For each horizon $h \in \{-2, ..., 4\}$, the local projections specification is given by

$$\Delta_h Y_{ij,\tau} = \beta_{0h} + \beta_{Mh} FF_\tau \cdot \mathbb{I}_{ij,\tau}^{M,high} + \beta_{Nh} FF_\tau \cdot \mathbb{I}_{ij,\tau}^{N,high} + \rho_{1h} Y_{ij,\tau-3} + \alpha_{j\tau h} + \epsilon_{ij,\tau+h}, \quad (22)$$

where $\alpha_{j\tau h}$ is a market by event window FE. If $\beta_{Mh} < 0$, then lenders with large market-level shares have lower pass-through. Similarly, $\beta_{Nh} < 0$ implies that if the bank-market pair is large at the national level then there is lower pass-through. In all the regressions that follow, standard errors are clustered at the market-event level and we compute 68% and 90% confidence intervals.

Figure 8: Differential pass-through of high market-level shares



Notes. Figure plots the differential pass-through $\beta_{M,h}$ from FF4 to residualized interest rates for the January 2008 event, where $\beta_{M,h}$ is defined by equation (22). In Panel (a), $\mathbb{I}_{ijt}^{M,high}$ is an indicator for whether the bank's market-level share exceeds the 70^{th} percentile. Each line represents a different combination of market definition and residualization procedure, while the shaded areas correspond to 68% and 90% confidence intervals for the baseline combination. Panel (b) focuses on the baseline combination, with different lines showing estimates for $\beta_{M,h}$ as we vary the cutoffs; confidence intervals are for the 70^{th} percentile cutoff. In both panels, standard errors are clustered at the market level.

Market-level shares. We begin by analyzing differential pass-through across market-level shares in response to the January 2008 MP shock. In Figure 8, we plot the coefficients from equation (22). In Panel (a), $\mathbb{I}_{ijt}^{M,high}$ is an indicator for whether the bank's market-level share exceeds the 70^{th} percentile, with lines representing different combinations of

[19] For the Jan-08 event we use contemporaneous shares since data only starts on Jan-08.
[20] We winsorize this variable at the 1% level to remove outliers.

market definitions and residualization procedures. The figure shows that two weeks after the monetary shock, the coefficients on high market-level shares (β_{Mh}) are significant and negative. Point estimates lie between $\beta_{Mh} = 0.05$ and $\beta_{Mh} = -0.25$ over the horizon $h \in \{-2, ..., 4\}$.

Panel (b) focuses on our baseline combination, with different lines showing estimates for $\beta_{M,h}$ as we vary the cutoffs from the 60^{th} to the 90^{th} percentile. For the weeks following the FOMC January 2008 event, the differential pass-through is negative yet milder as we increase the cutoff.

To interpret the coefficients, we must convert the recovered semi-elasticity point estimates into pass-through rates. In the empirical section, we define the pass-through rate to be the change in APR with respect to the change in the risk free rate ($\frac{dAPR}{dFF}$). Differentiating equation (22) with respect to FF_τ (line 1) and the comparing across high and low market shares (line 2), we have

$$\begin{aligned} \frac{dln\,(APR)}{dFF} &= \frac{1}{APR}\frac{dAPR}{dFF} = \beta_{Mh}\mathbb{I}_{ijt}^{M,high} \\ \Rightarrow \quad \frac{dAPR}{dFF}^{high} &- \frac{dAPR}{dFF}^{low} = \beta_{Mh} \times APR. \end{aligned} \tag{23}$$

Thus, if the average estimated β_{Mh} is -0.17, and the average residual interest rate (exponentiated) is almost exactly 1pp, a high market-level share implies a 17% lower pass-through rate compared to markets operated by the same bank in which the market-level share is low.

We succinctly summarize how the differential pass-through rates vary across combinations of market definitions, residualization procedures, and sample periods by computing the average pass-through over the first four weeks after the MP shock. In particular, define the average change in residualized interest rates over the first four weeks as

$$\overline{\Delta Y}_{ij,\tau,4} \equiv \frac{1}{4}\sum_{h=1}^{4}\Delta_h Y_{ij,\tau} = \left(\frac{1}{4}\sum_{h=1}^{4} Y_{ij,\tau+h}\right) - Y_{ij,\tau-3}. \tag{24}$$

Then, we can estimate the following OLS regression:

$$\overline{\Delta Y}_{ij,\tau} = \bar{\beta}_0 + \bar{\beta}_M\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{M,high} + \bar{\beta}_N\, FF_\tau \cdot \mathbb{I}_{ij,\tau}^{N,high} + \bar{\rho}_1 Y_{ij,\tau-3} + \bar{\alpha}_{j\tau} + \bar{\varepsilon}_{ij,\tau}. \tag{25}$$

Table 5 presents the results, with market-time-clustered standard errors shown in parenthesis. Each column represents a different sample, and each row represents a different combination of market definition and residualization procedure.[21] The table shows that

[21] Big policy rate cuts in 2008 include January, April, October, and December FOMC events; see Appendix

the average estimate for β_M is negative and significant across most combinations, showcasing the robustness of our main result.

Table 5: Differential market-level pass-through by sample and combination, 70^{th} percentile s_{ij}

	January 2008	Big cuts 2008	All 2008	All events
	(1)	(2)	(3)	(4)
Baseline market				
Baseline residualization	-0.17	-0.29	-0.12	-0.08
	(0.03)	(0.03)	(0.03)	(0.02)
Naive residualization	-0.19	-0.40	-0.18	-0.15
	(0.03)	(0.03)	(0.03)	(0.02)
Simple market				
Baseline residualization	-0.08	-0.20	-0.06	-0.03
	(0.10)	(0.10)	(0.08)	(0.07)
Naive residualization	-0.12	-0.25	-0.12	-0.08
	(0.06)	(0.10)	(0.07)	(0.06)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

Notes. Table shows the average estimate for $\beta_{M,h}$, as defined by equation (25), over horizons $h \in \{1, .., 4\}$. When we estimate equation (25) we only include market-level shares, and drop national-level shares. Columns represent single or stacked events; rows represent combinations of market definitions and residualization procedures. Standard errors, shown in parenthesis, are clustered at the market-time level.

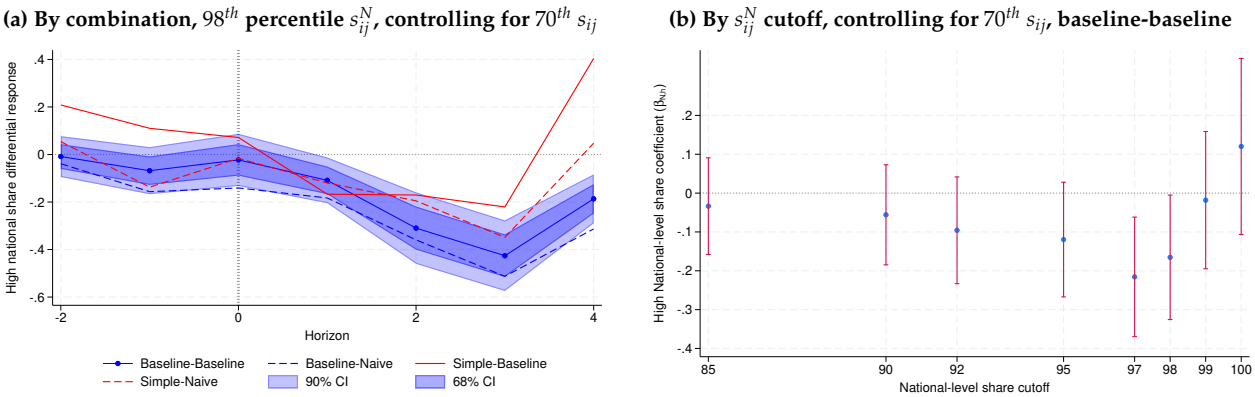
National-level shares. In Figure 9, we plot the high national-level share coefficients ($\beta_{N,h}$) in equation (22) for the January 2008 event. In panel (a), the high national-level share cutoff is fixed at the 98^{th} percentile, controlling for the 70^{th} percentile of market-level shares. Different lines represent different combinations of market definition and residualization. Panel (b) plots the average differential national-level pass-through coefficient $\beta_{N,h}$ over the first four weeks after the MP shock, as we vary the cutoff defining high national-level shares. Vertical lines capture 90% confidence intervals.

Both panels show that the coefficients on high national-level shares ($\beta_{N,h}$) are significant and negative in the first four weeks after the shock. Again, since the average residual interest rate (exponentiated) is almost exactly 1pp, a high national-level share implies a 24% lower pass-through rate compared with markets operated by the same bank in which the national share is low.

In Table 6, we summarize how the differential pass-through varies with the sample periods and combination of market definition and residualization procedure. For both the January 2008 and large rate cuts of 2008, we find that the average estimate for β_N is

C for a list of events.

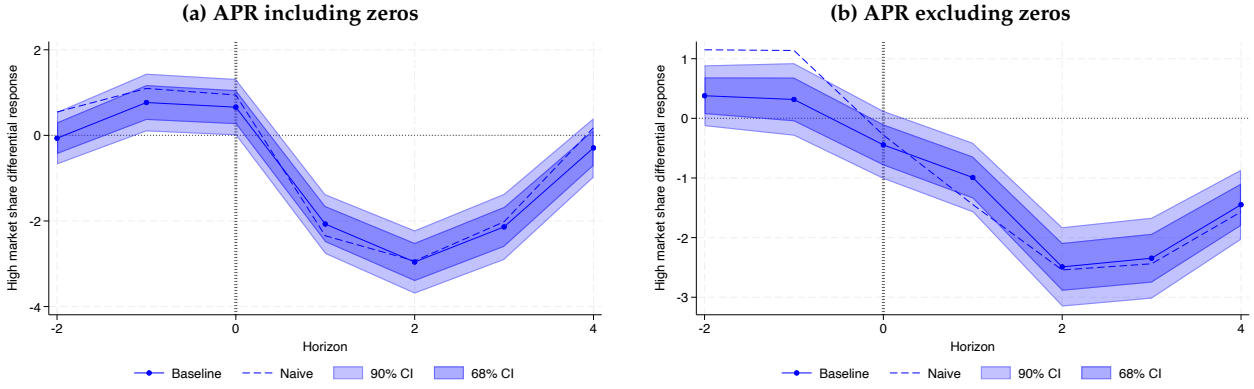
Figure 9: Differential pass-through of high national-level shares



Notes. Panel (a) plots the differential national-level pass-through coefficient $\beta_{N,h}$ from FF4 to residualized interest rate in the January 2008 event, where $\beta_{N,h}$ is defined by equation (22). Each line represents a different combination of market definition and residualization procedure, while the shaded areas correspond to 68% and 90% confidence intervals for the baseline combination. Panel (b) plots the average differential national-level pass-through coefficient $\beta_{N,h}$ over the first four weeks after the MP shock, as we vary the cutoff defining high national-level shares. Vertical lines capture 90% confidence intervals. Standard errors are clustered at the market-time level.

negative and significant across most combinations. However, point estimates stop being significant as we stack more events, pinpointing the relevance of large shocks to the policy rate for identification of national differential pass-through.

Figure 10: Differential pass-through for APR, market-level 70^{th} percentile s_{ij}



Notes. Figure shows the market-level differential pass-through for the residualized APR (in levels), for our baseline specification (solid lines) and naive residualization (dashed). Shaded areas correspond to 68% and 90% confidence intervals. Standard errors are clustered at the market-time level.

Table 6: Differential national-level pass-through by sample and combination, 98^{th} percentile s_{ij}^N, controlling for 70^{th} percentile s_{ij}

	January 2008	Big cuts 2008	All 2008	All events
	(1)	(2)	(3)	(4)
Baseline market				
Baseline residualization	-0.24	-0.16	0.05	-0.001
	(0.05)	(0.07)	(0.06)	(0.05)
Naive residualization	-0.33	-0.34	-0.01	-0.05
	(0.06)	(0.07)	(0.07)	(0.05)
Simple market				
Baseline residualization	-0.04	-0.12	0.08	0.09
	(0.15)	(0.16)	(0.15)	(0.12)
Naive residualization	-0.15	-0.16	0.05	0.05
	(0.09)	(0.13)	(0.14)	(0.12)
Lagged dependent	Yes	Yes	Yes	Yes
Market-event FE	Yes	Yes	Yes	Yes

Notes. Table shows the average estimate for $\beta_{N,h}$, as defined by equation (25), over horizons $h \in \{1, .., 4\}$. Columns represent single or stacked events; rows represent combinations of market definitions and residualization procedures. Standard errors, shown in parenthesis, are clustered at the market-time level.

Pass-through in levels. While our main analysis focuses on share-dependent pass-through in log APR spreads, the model predicts similar qualitative effects for the level of residualized APR. Figure 10 plots the differential pass-through in levels for the baseline market definition, for both the baseline and naive residualizations. Panel (a) includes zero APR and panel (b) excludes them. In both cases, the differential pass-through is negative and statistically significant during the first four weeks following the shock, consistent with the results for log spreads.

Non-rate attributes. Thus far, we have focused on the pass-through of monetary policy shocks to borrowing rates. Lenders, however, may also adjust other margins of loan supply, such as outstanding balances, fees, and credit limits. Table 7 reports market-level differential pass-through estimates for these alternative outcomes, based on equation (25), for the baseline market definition. While estimates for the residualized APR are negative and significant, estimates for the alternative dependent variables are small or statistically insignificant, indicating no meaningful differential adjustment along these margins.

Table 7: Differential market-level pass-through for alternative dependent variables, 70^{th} percentile s_{ij} cutoff, January 2008 event

	APR (level)	APR (positive)	Balances	Fees	Limits
	(1)	(2)	(3)	(4)	(5)
Baseline residualization	-1.86	-1.89	26.30	0.79	400.17
	(0.35)	(0.28)	(65.72)	(1.20)	(300.88)
Naive residualization	-1.73	-2.05	37.52	4.71	190.24
	(0.48)	(0.31)	(89.59)	(1.66)	(276.40)
Lagged dependent	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes

Notes. Table shows the average estimate for $\beta_{M,h}$, as defined by equation (25), over horizons $h \in \{1, .., 4\}$ for the January 2008 event and our baseline market definition. Columns represent alternative dependent variables; rows depict residualization procedures. Standard errors, shown in parenthesis, are clustered at the market-time level.

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 $J = 960$ based on the OCC CCM and Y-14M databases as well as our baseline market definition.[22] Our model economy requires the specification of eight 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, the preference shifter for credit services, and the distribution of market tastes: $\{r_f, \{c_i\}, \eta, \theta, \{J(i)\}, \gamma, A, \{\phi_j\}\}$.

We set $r_f = 1.3\%$, which is the average 10-year real interest rate reported by the Cleveland Fed in 2008.[23] We assume that bank lending costs are evenly distributed over the interval $[\underline{c}, \bar{c}]$. We estimate the bounds of bank costs to match average interest rates and

[22] Due to the small number of markets and banks, we simulate the model 10 times and report averages.

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

their standard deviation. We invert A so that the ratio of aggregate revolving credit to aggregate after-tax wage income is 16.76%, which we compute in the 2007 SCF.[24]

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 4.4. We then estimate $\{J(i)\}$ so that the probability bank i operates in market j is inversely proportional to its costs $P_{ij} \propto -bc_i$.[25] We estimate b to target the variance of ownership shares observed in our data. We impose that the taste shifters are log-linear in market size, $\phi_j = \frac{exp(\beta_\phi N_j)}{\sum_j exp(\beta_\phi N_j)}$. When $\beta_\phi > 0$, consumers prefer markets populated by more banks. This covariance is commonly observed in deposit markets as well Morelli et al. (2024). We estimate β_ϕ to match the tail (p90 and above) of the national-share distribution.

Lastly, we infer the parameters that govern market- and national-level oligopolistic behavior, $\{\eta, \theta, \gamma\}$, from the pass-through regressions in equation (22) and the aggregate Herfindahl. We map the regressions to the model using the following steps:

Step 1: First, we simulate a 27.5 basis point reduction in the risk free rate r_f. This corresponds to the surprise component of the federal funds rate in January 2008. 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 $\Delta \log r_{ijt} = \ln r_{ijt+1} - \ln r_{ijt}$ in an identical manner to equations (20) and (21). Since we estimate our regression in differences, we regress the change in interest rates on a constant, the bank fixed effect ($\widetilde{\alpha}_i$), dummies for date t market-level share centiles ($\widetilde{sh}_{ijt}$), and dummies for date t national-level share centiles ($\widetilde{sh}^N_{ijt}$).[26] We remove the constant and common bank-time variation as in equation (21):

$$\Delta \log r_{ijt} = \widetilde{\beta}_0 + \widetilde{\alpha}_i + \widetilde{sh}_{ijt} + \widetilde{sh}^N_{ijt} + \epsilon_{ijt} \tag{26}$$

$$\widehat{\Delta \log r_{ijt}} = \Delta \log r_{ijt} - \widetilde{\beta}_0 - \widetilde{\alpha}_i. \tag{27}$$

Step 3: We then estimate equation (22) on the residualized data, treating our simulated data as a single event with horizon h. We regress differenced residuals – assuming one

[24] We isolate those with positive credit card balances to compute this ratio. We apply a 25% average tax rate to aggregate wage income, a commonly adopted rule-of-thumb.

[25] The probability a bank owns one of the N_j slots is proportional to $P_{ij} = max\{a - bc_i, 0\}$, where $a = \frac{1}{2}$. 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.

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

h and one event – on a constant, market fixed effect, an interaction between the change in the risk free rate and whether that particular bank's date t market-level share is above a cutoff ($\Delta r_{ft} \times \mathbb{I}_{ijt}^{M,high}$), and an interaction between the change in the risk free rate and whether that particular bank's national-level share is above a cutoff ($\Delta r_{ft} \times \mathbb{I}_{ijt}^{N,high}$):

$$\widehat{\Delta \log r_{ijt}} = \widetilde{\beta}_0 + \widetilde{\alpha}_j + \widetilde{\beta}_M \left(\Delta r_{ft} \times \mathbb{I}_{ijt}^{M,high} \right) + \widetilde{\beta}_N \left(\Delta r_{ft} \times \mathbb{I}_{ijt}^{N,high} \right) + u_{ijt}. \tag{28}$$

$\widetilde{\beta}_M$ 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 (22).

In terms of identification of bank market power, we show the Jacobian for η, θ, and γ in the appendix. η governs willingness to substitute across banks within a market, and most directly controls the average market-level Herfindahl.[27] Conditional on η, the non-linearities in (11) allow us to separately identify γ from θ. When national shares are near-zero, differential pass-through rates across high and low market-level shares identifies θ. Conditional on θ, differential pass-through across high- and low- national shares identifies γ.

Estimation results. Table 8 reports our estimated model parameters and the corresponding model/data moments that yield identification. We estimate an intra-market elasticity of substitution of $\eta = 3.17$ and an inter-market elasticity of substitution of $\theta = 1.45$. As we discuss below, these elasticities imply spreads of 1 percentage point in the most competitive markets and up to 7 percentage points in the least competitive markets. These estimates imply that our model markets pass the hypothetical monopolist test. A hypothetical monopolist that controls an entire market can raise interest rates by significantly more than 5%.[28]

Our estimate for curvature over credit services of $\gamma = 0.75$ implies that $\theta > \frac{1}{\gamma}$, so that markups expand when a bank's national shares grow. This implies significant sensitivity of aggregate credit to lending rates, limiting national market power (see Figure 5, Panel (B)).

In terms of bank funding costs, we estimate that the lowest bank cost is a single basis point spread over the risk free rate, and the highest bank cost is an 800 basis point spread over the risk-free rate. In Appendix D, we discuss how our estimated bank costs compare to various measures of bank-level noninterest marginal costs (Berger et al. (2009) and

[27] We compute Herfindahls in every market in our data, and then take their unweighted mean. Similar results obtain with weighting.

[28] Comparing the markups from a competitive market to a monopolist market, we see $\eta/(\eta-1) - \theta/(\theta-1) \approx 3$.

Table 8: Model moments versus data

Var.	Description	Value	Moment	Model	Data
A	Credit Service Utility Shifter	0.11	Credit to income	0.168	0.168
$\underline{c}$	Lower bound bank cost of funds	0.001	Average of r_{ij}	0.070	0.061
$\overline{c}$	Upper bound bank cost of funds	0.08	Standard deviation r_{ij}	0.032	0.045
η	Intramarket elasticity	3.17	Average HHI	0.493	0.470
θ	Intermarket elasticity	1.46	Slope s_{ij} p70	-0.171	-0.173
γ	Curvature over credit services L	0.75	Slope s_{ij}^N p98, controlling s_{ij} p70	-0.120	-0.114
b	Cov. ownership prob. & bank cost	4.31	SD of number of markets each bank operates in	137.25	149.00
β	Cov. taste & market size	9.9e-03	s_{ij}^N 90^{th} percentile	0.0006	0.0006

Corbae and D'Erasmo (2019)). Our baseline cost estimates imply that the mean interest rate across banks, adjusted for chargeoffs and inflation, is 7.0% in the model and 6.1% in the data.[29]

Non-targeted moments. Next, we examine the model's ability to replicate the data profile of market shares. First, we compare market shares in the model and data in Figure 11. Panel A of Figure 11 plots the probability distribution function of quantity shares s_{ij} in the model and data. Despite only targeting the Herfindahl, the model does remarkably well at generating the overall shape of the distribution, although it moderately overstates the number of low-share competitors and high-share competitors. Panel B of Figure 11 shows that the model accurately replicates the shape of the distribution of national shares, despite only targeting p90 of the distribution.

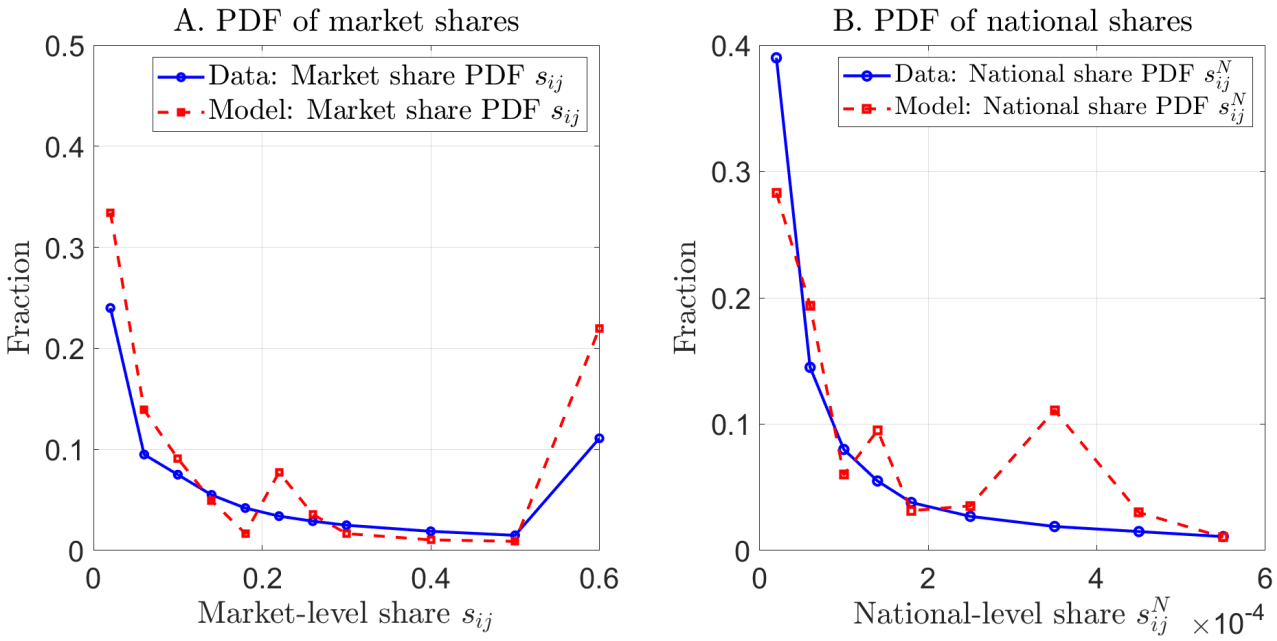
Finally, Figure 12 plots the model's interest rate spread ($r_{ij} - c_i - r_f$) in percentage points. Given the low base rate $r_f = 1.3\%$, the large percent markups implied by θ translate into very reasonable percentage point markups. The markup distribution rarely exceeds 5 percentage points, and the median spread is around 3 percentage points. Our model's distribution of spreads broadly agrees with 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.

6.2 Macroeconomic consequences of bank market power

We measure the consequences of market- and national-level oligopolistic competition by comparing four economies: (1) the baseline market- and national-level oligopoly model (r_{ij} is defined by equation (11)), (2) the market-level-only oligopoly model (r_{ij} is defined

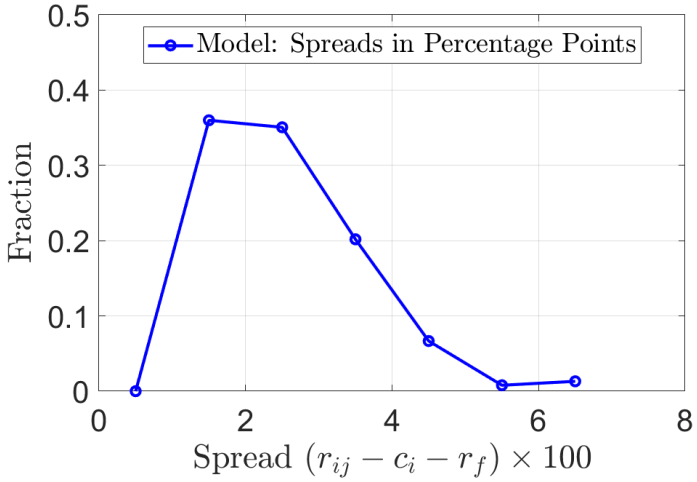
[29] We subtract the average chargeoff rate in 2008 from each bank's interest rate (https://fred.stlouisfed.org/series/CORCCACBS), and we subtract average annual inflation in 2008 (https://fred.stlouisfed.org/series/FPCPITOTLZGUSA) from each bank's interest rate prior to computing moments.

Figure 11: National and market-level shares in model versus data



Notes. Panel A plots the distribution of $s_{i,j}$ in the model and data. Panel B plots the distribution of $s^N_{i,j}$ in the model and data. Data is taken from Figure 1.

Figure 12: Model implied credit card interest rate spreads



Notes. This is a plot of the model's spread in percentage points $r_{ij} - c_i - r_f$.

by equation (13)), (3) monopolistic competition, and (4) the competitive economy (r_{ij} is defined by equation (12)).[30]

Given national allocations $\{C_1^N, C_2^N\}$ and counterfactual allocations $\{C_1^{CF}, C_2^{CF}\}$, we compute the consumption equivalent welfare gains λ as follows:

$$u(C_1^N(1+\lambda), C_2^N) = u(C_1^{CF}, C_2^{CF})$$

National- to market-level oligopoly. Table 9 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 0.006%. 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 2 basis points. Figure 13 graphically illustrates the small difference in national versus market-level interest rates. On the y-axis is the percent changes in the national rate minus the market-level oligopoly rate (this is a 'percent of a percent' and thus 6% indicates a very small interest rate movement of less than 3 basis points), so a positive number indicates higher rates in the national equilibrium. The graph shows that lower-cost (who begin with a low r_{ij} on the x-axis), high national-share lenders have higher initial national rates, and thus lower rates the most when we move to market-level oligopoly. However, the overall magnitude of interest rate reductions is small.

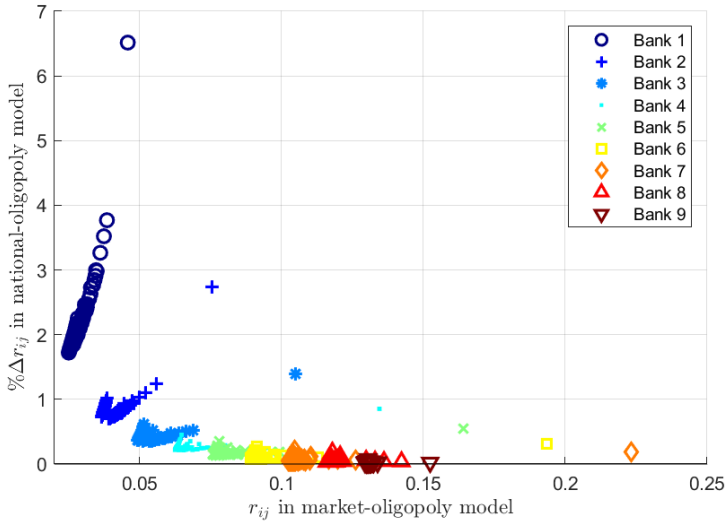
The 2 basis point reduction in interest rates yields a 0.4 percentage point expansion of the credit market. Despite the relatively large expansion of the credit market, the rate cuts translate to small consumption gains. This is due – in part – to the decline in aggregate lender profits which partially 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 increase by 50% 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 $1.36 \times \left(= \frac{\eta}{\eta-1}\right)$.

We report the results in Column (3) of Table 9. Moving from national oligopoly to monopolistic pricing yields a consumption equivalent gain of 0.1% when allowing profits to adjust, and 0.17% when holding lender profits fixed. Interest rates fall by 45 basis points, generating a large 8 percentage point expansion in the credit-to-income ratio.

[30] In economies (2) through (4), 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 13: 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 8.

Table 9: 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. (%)	–	0.006	0.099	0.161
Welfare gain leaving national eq., Π fixed (%)	–	0.009	0.165	0.448
Average interest rate (Percent)	7.03	7.01	6.57	4.50
National HHI	0.46	0.46	0.55	0.55
Profit to income (Percent)	0.29	0.28	0.22	0.00
Credit to income (Percent)	16.76	17.17	24.84	41.08

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 income is Π/y. Credit to income is $\sum_{i,j} l_{ij}/y$.

Thus, our estimation suggests that there are significant potential gains from reforms that target strategic market-level price setting in the credit card market.

National oligopoly to perfect competition. Lastly, we consider the transition from national oligopoly to competitive pricing ($\mu_{ij} = 1, \forall ij$) in Column (4) of Table 9. Competitive pricing yields a consumption equivalent welfare gain of 0.16% when allowing profits to adjust, and 0.45% when holding lender profits fixed. The competitive allocation lowers interest rates by 2.5 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 due to the 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, households borrow more and credit-to-income increases to 41%.[31].

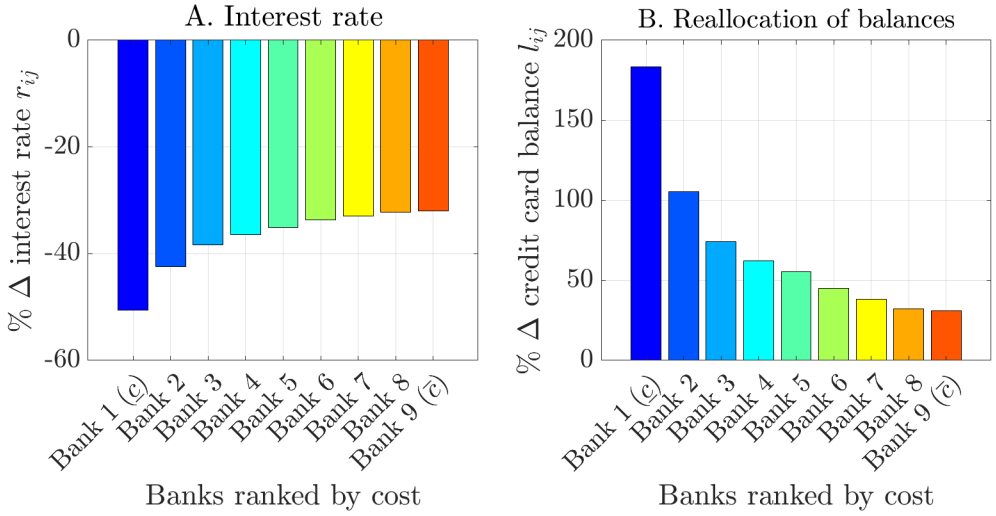
Reallocation. What drives the welfare gains and credit expansion? Reallocation of loans from high-cost lenders to low-cost lenders. High-cost lenders begin with the greatest markups and thus cut their interest rates more in the competitive equilibrium. Thus balances flow towards low cost lenders, generating welfare gains.

Figure 14 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 double in size at the expense of high-cost lenders. The competitive allocation is clearly more concentrated than the original economy with national oligopolists.

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.

[31]The magnitude of these results aligns with other studies, such as Burgués and De Simone (2025a)

Figure 14: 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 8.

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 OCC and Y-14M 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 our 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 17% lower compared to all other markets in which the bank operates. When a bank's national-level share exceeds the top 98$^{\text{th}}$ percentile, pass-through rates are 24% lower compared to all other markets in which the bank operates.

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 2.5 percentage points. The gains are driven by low-cost lenders cutting markups

more and expanding disproportionately. With lower interest rates, the consumer credit market more than doubles. 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 0.16% and 0.45% 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.

References

AGARWAL, S., S. CHOMSISENGPHET, N. MAHONEY, AND J. STROEBEL (2013): "Regulating consumer financial products: Evidence from credit cards," Tech. rep., National Bureau of Economic Research.

——— (2015): "Regulating consumer financial products: Evidence from credit cards," *The Quarterly Journal of Economics*, 130, 111–164.

——— (2018): "Do banks pass through credit expansions to consumers who want to borrow?" *The Quarterly Journal of Economics*, 133, 129–190.

AMITI, M., O. ITSKHOKI, AND J. KONINGS (2016): "International shocks and domestic prices: how large are strategic complementarities?" NBER Working Paper 22119, National Bureau of Economic Research.

ATKESON, A. AND A. BURSTEIN (2008): "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 98, 1998–2031.

AUSUBEL, L. M. (1991): "The failure of competition in the credit card market," *The American Economic Review*, 50–81.

BAUDUCCO, S. AND A. JANIAK (2015): *On the welfare cost of bank concentration*, CEA, Centro de Economía Aplicada, Ingeniería Industrial, Universidad de Chile.

BAUER, M. D. AND E. T. SWANSON (2023): "A Reassessment of Monetary Policy Surprises and High-Frequency Identification," *NBER Macroeconomics Annual*, 37, 87–155.

BEGENAU, J. AND E. STAFFORD (2023): "Uniform rate setting and the deposit channel," *Available at SSRN 4136858*.

BERGER, A. N., L. F. KLAPPER, AND R. TURK-ARISS (2009): "Bank Competition and Financial Stability," *Journal of Financial Services Research*, 35, 99–118.

BERGER, D., K. HERKENHOFF, AND S. MONGEY (2022): "Labor market power," *American Economic Review*, 112, 1147–93.

BRAXTON, J. C., G. PHILLIPS, AND K. HERKENHOFF (2019): "Can the unemployed borrow? implications for public insurance," in *2019 Meeting Papers*, Society for Economic Dynamics, 323.

BURGUÉS, F. AND R. DE SIMONE (2025a): "Bank market power and credit allocation," *Working paper*.

——— (2025b): "Taxation when markets are not competitive: Evidence from a loan tax," *Working paper*.

BURSTEIN, A., V. M. CARVALHO, AND B. GRASSI (2023): "Bottom-up markup fluctuations," Tech. rep., Mimeo.

CAMPELLO, M. (2002): "Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy," *The Journal of Finance*, 57, 2773–2805.

CHAN, M., K. KROFT, E. MATTANA, AND I. MOURIFIÉ (2024): "An empirical framework for matching with imperfect competition," Tech. rep., National Bureau of Economic Research.

CLAYTON, C. AND A. SCHAAB (2022): "Multinational banks and financial stability," *The Quarterly Journal of Economics*, 137, 1681–1736.

CORBAE, D. AND P. D'ERASMO (2019): "Capital requirements in a quantitative model of banking industry dynamics," Tech. rep., National Bureau of Economic Research.

——— (2021): "Capital buffers in a quantitative model of banking industry dynamics," *Econometrica*, 89, 2975–3023.

CREMERS, K. J. M., R. HUANG, AND Z. SAUTNER (2011): "Internal Capital Markets and Corporate Politics in a Banking Group," *The Review of Financial Studies*, 24, 358–401.

DEMPSEY, K. AND F. IONESCU (2025): "Default Risk and Pricing in the U.S. Credit Card Market," *Working Paper*.

DICK, A. A. AND A. LEHNERT (2010): "Personal bankruptcy and credit market competition," *The Journal of finance*, 65, 655–686.

DRECHSLER, I., H. JUNG, W. PENG, D. SUPERA, AND G. ZHOU (2025): "Credit card banking," Tech. rep., Staff Reports.

DRECHSLER, I., A. SAVOV, AND P. SCHNABL (2017): "The deposits channel of monetary policy," *The Quarterly Journal of Economics*, 132, 1819–1876.

DROZD, L. A. AND J. B. NOSAL (2008): "Competing for Customers: A Search Model of the Market for Unsecured Credit," *Unpublished Manuscript, University of Wisconsin*.

EVANS, D. S. AND R. SCHMALENSEE (2005): *Paying with plastic: the digital revolution in buying and borrowing*, MIT Press.

FDIC, F. D. I. C. (2007): "Credit Card Activities Manual: Chapter V. - Marketing and Acquisition," Tech. rep., FDIC.

FIORIO, L., R. MAU, J. STEITZ, AND T. WELANDER (2014): "New frontiers in credit card segmentation: Tapping unmet consumer needs," *McKinsey, May*.

GALENIANOS, M. AND A. GAVAZZA (2022): "Regulatory interventions in consumer financial markets: The case of credit cards," *Journal of the European Economic Association*, 20, 1897–1932.

GALENIANOS, M., T. H. LAW, AND J. NOSAL (2021): "Market Power in Credit Markets," *Available at SSRN*.

GÖDL-HANISCH, I. (2022): "Bank Concentration and Monetary Policy Pass-Through," *FDIC Center for Financial Research Paper No. 2022-06*.

GRODZICKI, D. (2023a): "Competition and Customer Acquisition in the US Credit Card Market," *SSRN working paper*.

——— (2023b): "Credit cards and the floating rate channel of monetary policy," *Applied Economics Letters*, 30, 249–254.

——— (2023c): "The evolution of competition in the credit card market," *Available at SSRN 4493211*.

HECKMANN-DRAISBACH, L. AND J. MOERTEL (2020): "Hampered interest rate pass-through: A supply side story?" *Deutsche Bundesbank Discussion Paper*.

HERKENHOFF, K. F. (2019): "The impact of consumer credit access on unemployment," *The Review of Economic Studies*, 86, 2605–2642.

HERKENHOFF, K. F. AND G. RAVEENDRANATHAN (2020): "Who bears the welfare costs of monopoly? The case of the credit card industry," Tech. rep., National Bureau of Economic Research.

JAROCIÅĎSKI, M. AND P. KARADI (2020): "Deconstructing Monetary Policy SurprisesâĂŤThe Role of Information Shocks," *American Economic Journal: Macroeconomics*, 12, 1âĂŞ43.

JORDÀ, Ò. (2005): "Estimation and inference of impulse responses by local projections," *American economic review*, 95, 161–182.

KNITTEL, C. R. AND V. STANGO (2003): "Price ceilings as focal points for tacit collusion: Evidence from credit cards," *American Economic Review*, 93, 1703–1729.

MORELLI, J. M., M. MORETTI, AND V. VENKATESWARAN (2024): "Geographical Diversification in Banking: A Structural Evaluation," *Working Paper*.

MORELLI, J. M., P. OTTONELLO, AND D. J. PEREZ (2022): "Global banks and systemic debt crises," *Econometrica*, 90, 749–798.

NAKAMURA, E. AND J. STEINSSON (2018): "Identification in macroeconomics," *Journal of Economic Perspectives*, 32, 59–86.

NELSON, S. (2018): "Private information and price regulation in the us credit card market," *Unpublished working paper*.

PELLANDINI-SIMÁNYI, L. (2023): "Algorithmic classifications in credit marketing: How marketing shapes inequalities," *Marketing Theory*, 14705931231160828.

PETROSKY-NADEAU, N. AND E. WASMER (2017): *Labor, credit, and goods markets: The macroeconomics of search and unemployment*, MIT press.

RAVEENDRANATHAN, G. (2020): "Revolving credit lines and targeted search," *Journal of Economic Dynamics and Control*, 118, 103964.

STEARNS, D. L. (2007): "âĂIJThink of it as MoneyâĂİ: A History of the VISA Payment System, 1970–1984," .

VERBOVEN, F. (1996): "The nested logit model and representative consumer theory," *Economics Letters*, 50, 57–63.

WASMER, E. AND P. WEIL (2004): "The macroeconomics of labor and credit market imperfections," *American Economic Review*.

WHITED, T. M., Y. WU, AND K. XIAO (2021): "Low interest rates and risk incentives for banks with market power," *Journal of Monetary Economics*, 121, 155–174.

WILDFANG, K. C. AND R. W. MARTH (2005): "The persistence of antitrust controversy and litigation in credit card networks," *Antitrust LJ*, 73, 675.

ONLINE APPENDIX

A Derivations

- We repeat the household problem:

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

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

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

- We make the following normalization assumption, $\sum_j \phi_j = \overline{\phi} = 1$. This assumption implies that with identical banks and markets, aggregate allocations are unchanged , $L = \left[\sum_j \phi_j l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} = \bar{l}\left[\sum_j \phi_j\right]^{\frac{\theta}{\theta-1}} = \bar{l}$.
- **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:

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

  - 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

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

– *Substituing, this yields the bank-market inverse demand curve:*

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

- **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:
  $$\mathcal{L} = u(C_1, C_2) + \lambda \left[y - \sum_j r_j l_j - C_1 + \Pi\right] + \mu \left[\left[\sum_j \phi_j l_j^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} - C_2\right]$$
  - *This yields the market level demand curve:*
  $$l_j = \phi_j^\theta \left(\frac{r_j}{R}\right)^{-\theta} L$$

- **Bank-market level demand:** putting the aggregate, market, and bank-market demand curves together yields:
$$l_{ij} = \phi_j^\theta \left(\frac{r_{ij}}{r_j}\right)^{-\eta} \left(\frac{r_j}{R}\right)^{-\theta} L$$

- **Ideal price indeces:**
  - Recover aggregate price indexes using the market level demand curve:
  $$RL \equiv \sum_j r_j l_j$$
  $$RL = \sum_j r_j \phi_j^\theta \left(\frac{r_j}{R}\right)^{-\theta} L$$
  $$R = \left[\sum_j \phi_j^\theta r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}$$

– 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

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

- Substituting into the firm's problem and factoring out aggregates and shifters (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:

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

$$\implies r_{ij} = \left[c_i + r_f\right]\frac{\left[\eta\left(1-s_{ij}\right) + \theta s_{ij}\right]}{\left[\eta\left(1-s_{ij}\right) + \theta s_{ij} - 1\right]} \tag{A1}$$

- To prevent negative markups, we must restrict parameters such that $\eta, \theta > 1$.

- **Proposition 4.1:**
  - **Proof:** 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} (equation A1) to obtain the fixed point formula in the text:

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

□

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:

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

  - Overall market shares are given by

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

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

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

  - 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:

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

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

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

where we have dropped the positive scalar $A^{\frac{1}{\gamma}}$ from the objective.

- FOC for r_{ij} :

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

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

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

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

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

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

- Suppose the markets are identical $r_i = r_{ij}$,$l_{ij} = l_i$, $\phi_j = 1$, 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:

$$r_{ij} = \frac{\eta \left(1 - s_{ij} \right) + \theta s_{ij} - J_i \left(\theta - \frac{1}{\gamma} \right) s_{ij}^N}{\eta \left(1 - s_{ij} \right) + \theta s_{ij} - J_i \left(\theta - \frac{1}{\gamma} \right) s_{ij}^N - 1} \left[r_f + c_i \right] \tag{A2}$$

- **Proposition 4.2**
  - **Proof:** The Nash equlibrium is a fixed point in national-level and market-level shares. Use $s_{ij} = \left(\frac{r_{ij}}{r_j} \right)^{1-\eta}$ and $s_j = \phi_j^{\theta} \left(\frac{r_j}{R} \right)^{1-\theta}$ which implies $s_{ij} = \left(\frac{r_{ij}}{\left[\sum_i r_{ij}^{1-\eta} \right]^{\frac{1}{1-\eta}}} \right)^{1-\eta}$. Let $\mu(s_{ij}, s_{ij}^N, J_i) = \frac{\eta\left(1-s_{ij}\right)+\theta s_{ij}-J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N}{\eta\left(1-s_{ij}\right)+\theta s_{ij}-J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^N-1}$. Substituting r_{ij} (equation A2) into the expression for s_{ij}, we have

$$s_{ij} = \left(\frac{\mu(s_{ij}, s_{ij}^N, J_i) \left[r_f + c_i \right]}{\left[\sum_i \mu(s_{ij}, s_{ij}^N, J_i)^{1-\eta} \left[r_f + c_i \right]^{1-\eta} \right]^{\frac{1}{1-\eta}}} \right)^{1-\eta}.$$

- Note that $r_j = \left[\sum_i \mu(s_{ij}, s_{ij}^N, J_i)^{1-\eta} \left[r_f + c_i\right]^{1-\eta}\right]^{\frac{1}{1-\eta}}$. Use the expression $R = \left[\sum_j \phi_j^\theta r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}$ to see $s_j = \phi_j^\theta \left(\frac{r_j}{\left[\sum_j \phi_j^\theta r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}}\right)^{1-\theta}$. Again, substitute for r_j to reach the expression in the text.

□

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 $\{r_{ij}\}$.
  - This yields market and aggregate prices: $R = \left[\sum_j \phi_j^\theta r_j^{1-\theta}\right]^{\frac{1}{1-\theta}}$, $\quad r_j = \left[\sum_i r_{ij}^{1-\eta}\right]^{\frac{1}{1-\eta}}$
  - Solve for bank, market, and national shares $s_{ij} = \left(\frac{r_{ij}}{r_j}\right)^{1-\eta}$, $s_j = \phi_j^\theta \left(\frac{r_j}{R}\right)^{1-\theta}$, $s_{ij}^N = s_j s_{ij}$.
  - Use the FOC of the lenders to update the interest rate:

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

  - Iterate until convergence.

A.4 Symmetric national oligopoly pass-through characterization

Proposition 4.3

- **Proof:** Assume identical markets and we remove the taste shifters ($\phi_j = 1, \forall j$). 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 $s_{ij}^N = s_{ij}^N\left(r_{ij}, \{r_{-ij}\}\right)$.
- Thus $\mu\left(s_{ij}, s_{ij}^N, J_i\right) = \mu\left(r_{ij}, \{r_{-ij}\}\right)$ and $\ln r_{ij} = \ln\left[c_i + r_f\right] + \ln \mu\left(r_{ij}, \{r_{-ij}\}\right)$.
- 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:

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

- Put it together

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

$$\Longrightarrow\ m_{iij}=\frac{-\left(\left(\eta-\theta\right)s_{ij}+J_i\left(\theta-\frac{1}{\gamma}\right)s_{ij}^{N}\right)\left(\eta-1\right)\left(1-s_{ij}\right)-J_i\left(\theta-\frac{1}{\gamma}\right)\left(\theta-1\right)s_{ij}^{N}s_{ij}\left(1-s_{j}\right)}{\epsilon_{ij}\left(\epsilon_{ij}-1\right)}$$

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

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

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

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

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

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

$$\frac{\partial \ln s_j}{\partial \ln r_{kj'}}=-\left(1-\theta\right)s_{kj'}s_{j'}$$

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

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

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

$$LI+NI=\frac{1}{\left(1-m_{iij}\right)}\left(-\frac{\mu_{ij}}{\epsilon_{ij}}\right)\left\{-\left(1-\eta\right)\frac{\partial\log\epsilon_{ij}}{\partial\log s_{ij}}\sum_{k\neq i}s_{kj}d\ln r_{kj}+\left(1-\theta\right)\frac{\partial\log\epsilon_{ij}}{\partial\log s_j}\left[\left(1-s_j\right)\sum_{k\neq i}s_{kj}d\ln r_{kj}-\sum_{j'\neq j}\sum_{k}\left(s_{kj'}s_{j'}\right)d\ln r_{kj'}\right]\right\}$$

- Clearly

$$\frac{d\ln r_{ij}}{dr_f}\propto\frac{1}{\left(1-m_{iij}\right)}$$

- For simplicity of notation, we relabel m_{iij}as m_{ij}^{N} in the main text.

□

A.5 Testable implications

Proposition 4.4

Proof: In perfect competition and monopolistic competition $\mu(s_{ij})=1$ and $\mu(s_{ij})=\frac{\eta}{\eta-1}$ are both constant, respectively. This implies $\Delta_{H,t}\ln r_{i,j,t}=0$.

With market-level oligopoly, equation (14) 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.

□

Proposition 4.5

Proof: As in proposition 4.5, perfect competition and monopolistic competition trivially yield national-share independence, since markups are constant and independent of size.

Under market-level oligopoly, equation (13) governs rate setting. Since the vectors $\{s_{i,H,t}\}$ and $\{s_{i,L,t}\}$ are identical, the resulting market-level oligopoly equilibrium in both markets is identical at time t and $t+1$. Thus, market-level oligopoly yields national-share independence.

Lastly, with national-level oligopoly, equation (11) depends on $s^N_{i,H,t}$ and $s^N_{i,L,t}$, independently of the vector of market-level shares $\{s_{i,H,t}\}$ and $\{s_{i,L,t}\}$.

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. For ease of exposition, we remove the taste shifters ($\phi_j = 1, \forall j$). Then, the problem of the lenders is

$$\begin{aligned} \max_{\{r_{ij}\}} & \sum_p \sum_{j \in G(i,p)} \left(r_{ij} l_{ij} - \left[c_i + r_f \right] l_{ij} \right) \\ \text{s.t.} \quad & l_{ij} = \left(\frac{r_{ij}}{r_j} \right)^{-\eta} \left(\frac{r_j}{R} \right)^{-\theta} L \\ & r_{ij(p)} = r_{ip}. \end{aligned} \tag{A3}$$

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

$$\max_{\{r_{ip}\}} R^\theta \left(\frac{A}{R} \right)^{\frac{1}{\gamma}} \left\{ \sum_p \sum_{j \in G(i,p)} r_j^{\eta-\theta} r_{ip}^{-\eta} \left(r_{ip} - r_f - c_i \right) \right\}. \tag{A4}$$

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

$$r_{ip} = \left(r_f + c_i \right) \mu\left(\bar{s}_i \right) + \frac{\mu\left(\bar{s}_i \right) - 1}{\mu\left(\bar{s}_i \right)} \left(\theta - \frac{1}{\gamma} \right) \tilde{s}^N_{ip} \Pi_i(p), \tag{A5}$$

with

$$\begin{aligned}
\bar{s}_i &\equiv \sum_{G(i,p)} s_{ij} l_{ij}, \\
\mu\left(\bar{s}_i\right) &\equiv \frac{\eta\left(1-\bar{s}_i\right)+\theta \bar{s}_i}{\eta\left(1-\bar{s}_i\right)+\theta \bar{s}_i-1}, \\
\widetilde{s}_{ip}^{N} &\equiv \sum_{G(i,p)} s_j s_{ij}, \\
\Pi_i(p) &\equiv R^{\theta} L\left\{\sum_{p} \sum_{j \in G(i,p)} r_j^{\eta-\theta} r_{ip}^{-\eta}\left(r_{ip}-r_f-c_i\right)\right\}.
\end{aligned}$$

Notice the close resemblance between equation (A5) and the baseline equation (11), with modified notions of market shares affecting the optimal pricing equation under uniform pricing. These modified market shares, $\bar{s}_i$ and $\widetilde{s}_{ip}^{N}$, are a weighted average of market-level revenue-based market shares across all locations the lender operates.

A Testable implications

In this section, we provide proofs of the testable implications.

Proposition 4.4:

Proof: In perfect competition and monopolistic competition $\mu(s_{ij}) = 1$ and $\mu(s_{ij}) = \frac{\eta}{\eta-1}$ are both constant, respectively. This implies $\Delta_{H,t} \ln r_{i,j,t} = 0$. With oligopolistic competition, equation (14) 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.

□

Proposition 4.5:

Proof: Perfect competition and monopolistic competition trivially yield national-share independence, since markups are constant and independent of size. Under market-level oligopoly, equation (13) governs rate setting. Since the vectors $\{s_{i,H,t}\}$ and $\{s_{i,L,t}\}$ are identical, the resulting equilibrium in both markets, and results shares, are identical at time t and $t+1$. Thus, national shares do not predict markups. On the other hand, when banks are large nationally, equation (11) depends on $s_{i,H,t}^{N}$ and $\{s_{i,L,t}^{N}\}$, independently of the vector of market-level shares $\{s_{i,H,t}\}$ and $\{s_{i,L,t}\}$.

□

B Geographical Market Definition

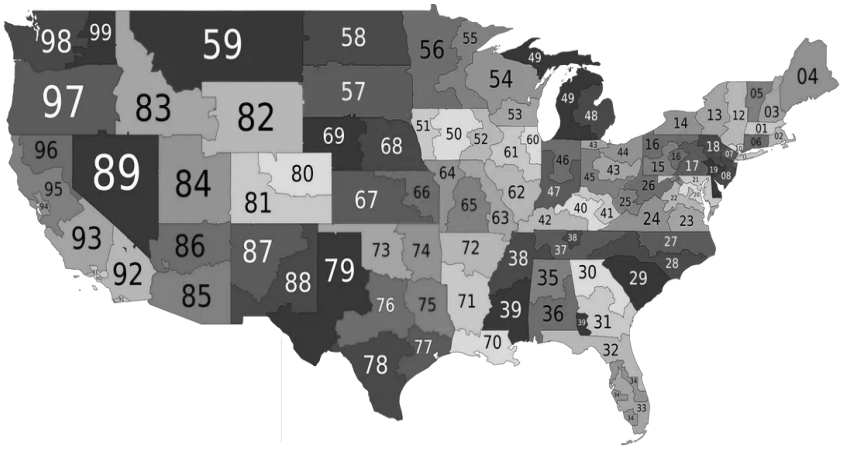


Figure B1: US Map of Two-digit Zip Codes

In this section, we perform robustness analysis by considering an alternative definition of a market that incorporates a geographical dimension. This is motivated by past references arguing that geography is a relevant dimension for market definition. As mentioned in Section 3.1, the FDIC's *Credit Card Activities Manual* states that segmentation by geographic location captures regional differences in card usage and economic conditions. The McKinsey report also mentions geography as being traditionally relevant for credit card issuers to target consumers, which is further corroborated by the MNI Targeted Media article.

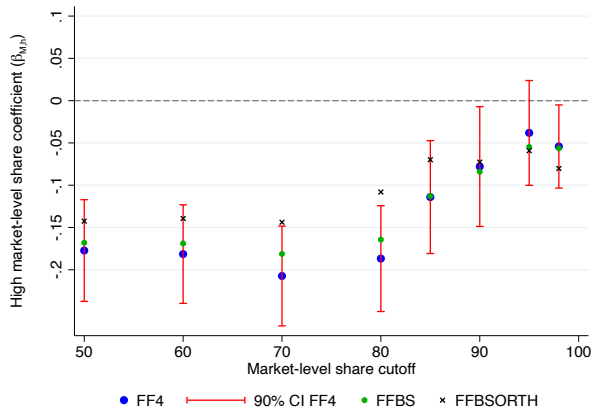
Given these references, we define the geographical area of relevance for a market to be the first 2 digits of a zip code, which generally covers an area greater than an MSA, as shown in Figure B1. In addition to the previously cited literature, we support our geographical consideration by evaluating the relevance of geography on pricing. Table B1 shows the R^2 of a regression of the residualized log interest rate onto market-by-time fixed effects, sequentially adding dimensions for the market definition. The analysis is performed with and without the geographical dimension in the market definition. As the table shows, the R^2 roughly doubles when including the geographical dimension, suggesting that geography is an important source of variation for credit card pricing. These results are very much aligned with arguments provided by the cited articles.

Table B1: Relevance of Geography on Pricing

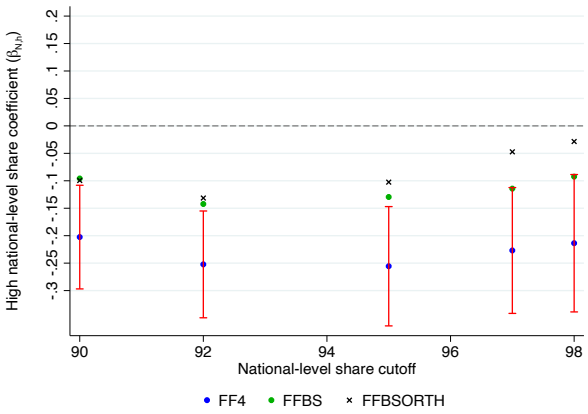
Dependent: Bank-market-week Residual log(APR)		
	No Geography	Geography
(1): Week-GP	13.4%	31.1%
(2): Week-GP-CB	15.0%	36.4%
(3): Week-GP-CB-FICO	18.9%	48.3%

Figure B2: Differential pass-through by market- and national-level shares cutoffs

(a) Market-level



(b) National-level



Given the relevance of geography for credit card pricing, we considered the alternative definition of a market to be the combination of credit card type, product type, FICO group, loan channel, and 2-digit zip code. We then carried out the residualization procedure described in Section 5.1 to obtain the residualized log interest rates, and estimated the pass-through regression in equation (22) using the residualized data. Figure B2 shows the market- and national-level differential pass-through results as we vary the cutoff for the definition of high shares. Similar to our baseline results, banks with a high market-level share have lower pass-through rates, and the same is true for banks with a high national-level share. The results are very much aligned with the main analysis, suggesting that adding the geographical dimension does not alter the main conclusions of the paper.

C Monetary Policy Shocks and FOMC Events

In this section we provide details on the measures for MP shocks and the selection of FOMC events. The shocks used as benchmarks for the selection of events are labeled FF4, FFJK, and FFBS, and are constructed, respectively, as: the change in the 3-month ahead

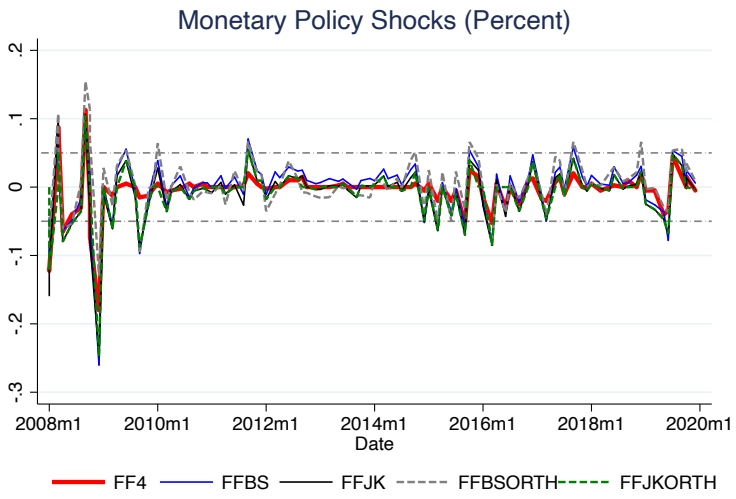
Fed Funds rate futures over a 30-minute window around the FOMC announcement; the first principal component over surprises in the current month and 3-month ahead Fed Funds futures and in the first four quarterly Eurodollar futures contracts, ED1âĂŞED4; and the first principal component of surprises in ED1âĂŞED4. These measures were constructed by JarociÅĎski and Karadi (2020) and Bauer and Swanson (2023), and are publicly available online. An FOMC event is included in our analysis if either of these shocks is greater or equal than 5 bps in absolute value. Table C1 shows the set of FOMC events that satisfy this filter, with the sign of the shock shown in parenthesis, and Figure C1 shows the time-series for the various measures of MP shocks. Further, we aggregate consecutive FOMC events into one (i.e., those in January 2008 and in March 2008).

Table C1: FOMC Events

22jan2008 (-)	25jun2008 (-)	23sep2009 (-)	28oct2015 (+)
30jan2008 (-)	16sep2008 (+)	21sep2011 (+)	16mar2016 (-)
11mar2008 (+)	16dec2008 (-)	17dec2014 (-)	20sep2017 (+)
18mar2008 (+)	18mar2009 (-)	18mar2015 (-)	19jun2019 (-)
30apr2008 (-)	24jun2009 (+)	17sep2015 (-)	31jul2019 (+)

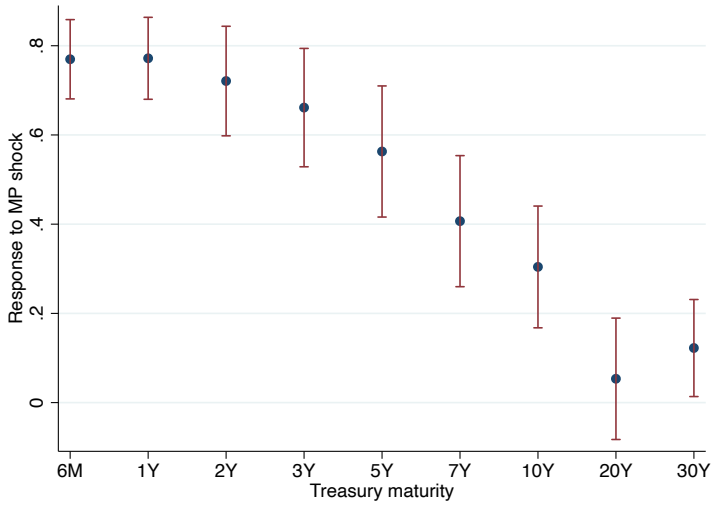
Notes: Table shows the set of FOMC events used in our empirical analysis; in parenthesis is the sign of the shock.

Figure C1: Monetary Policy Shocks



Notes: Figure shows the time-series for various measures of MP shocks. 'FF4' is the change in the 3-month ahead Fed Funds rate futures over a 30-minute window around the FOMC announcement. 'FFBS' and 'FFJK' are the first principle component over of the surprises in interest rate derivatives with maturities from 1 month to 1 year as constructed by Bauer and Swanson (2023) and JarociÅĎski and Karadi (2020), respectively. 'FFBSORTH' and 'FFJKORTH' are shocks to the policy rate that are stripped from any *news* component.

Figure C2: Monetary Policy Shocks



Notes: Figure shows the response of various constant maturity treasuries (x-scale) to the FF4 MP shock. Vertical lines represent 90% confidence intervals. Sample period is 1990-2019.

D Estimation of Marginal Costs

In this section, we follow Berger et al. (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:[32]

$$\ln NIE_{it} = \beta_0 + \beta_1 \ln LN_{it} + \beta_2 \left(\ln LN_{it}\right)^2 + \beta_3 \ln\left(W_{it}/TA_{it}\right) + \tag{D1}$$

$$\beta_4 \left(\ln\left(W_{it}/TA_{it}\right)\right)^2 + \beta_5 \left(\ln LN_{it}\right)\left(\ln\left(W_{it}/TA_{it}\right)\right) + \epsilon_{it}. \tag{D2}$$

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 D1: 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.

Table D1 shows statistics for the distribution of $\widehat{MC}_{it}$. The table shows results for a version of regression specification D1 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.

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