Wide or Narrow?
Competition and Scope in Financial Intermediation*

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Abstract

We study the role of scope in financial intermediation. Using new credit registry data on US firms, we show that in the market for small business lending, multi-product banks benefit from economies of scope across products but exploit their market power to steer firms into more profitable, less regulated products. To quantify these forces and the welfare implications of scope, we develop and estimate an equilibrium model of firm credit provision where banks compete with more specialized non-bank financial intermediaries. In counterfactual simulations, we show that market power and bank steering increase prices and reduce welfare for small firms. These losses, however, are less than the gains from cost synergies. We also simulate equilibrium effects of alternative banking regulations. Our results highlight the need for regulation to recognize the multi-product nature of financial intermediaries.

Keywords: Economies of scope, cost synergies, banking, fintech, competition, market power, steering, small business lending.

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1 Introduction

Over the last three decades, many companies have widened the scope of their product offerings.[1] This trend is nuanced in the context of financial intermediation. Depository institutions—banks—have grown dramatically in scope, while competing non-depository institutions—non-bank intermediaries such as fintech or peer-to-peer lenders—have largely remained narrow, specializing in specific assets or consumer segments.[2] From a welfare perspective, wide scope has benefits and costs. Wide product scope can reduce intermediation costs through synergies (e.g., Egan et al., 2022)[3] and benefit consumers who value a broader set of offerings. These benefits, however, may increase bank market power and their ability to distort consumer choices. Thus, the welfare effects of scope in financial intermediation are ambiguous.

While intermediary scope is a central and salient feature in financial intermediation, there is limited empirical research analyzing its equilibrium effects and welfare implications. Moreover, little is understood regarding how scope impacts wide banks' and narrow non-banks' endogenous responses to financial regulation and, importantly, how these responses impact their customers' real outcomes. Failing to account for the multi-product nature of financial intermediaries can lead to unintended consequences and welfare losses from current and future financial regulations. This paper fills this important gap in the literature in the context of small business lending in the United States.

The market for small business lending is an optimal setting to study the effects of scope in financial intermediation for several reasons. First, non-banks have increased their presence in this market and are actively competing with banks (Gopal and Schnabl, 2020). Non-banks are narrower in scope than banks and often specialize in a single product. These differences in scope across lenders allow us to study these institutions' strategic interactions and cost structures. Second, the ability of small businesses to invest, grow and create jobs is often challenged by financial constraints and the lack of credit availability (Evans and Jovanovic, 1989; Whited and Wu, 2006; Rauh, 2006; Kerr and Nanda, 2010; Barrot, 2016; Adelino et al., 2017).[4] Firms' challenges to access funding and the differentiation of credit products grant market power to banks and allows them to charge substantial mark-ups. Finally, small business lending is a market where cost synergies with other products in the banks' balance sheets can be quantitatively important. From the point of view of banks, offering a credit card or a loan to a small business might be complementary (e.g., similar screening and monitoring technology) to offering a credit card or a loan to a household.

We study these issues using novel panel data from a major US commercial credit reporting bureau. The dataset contains detailed information on credit products and performance for over 12 million

[1] See Hoberg and Phillips, 2021.

[2] These changes are often viewed as a result of changes in regulation, competition, and consumer demand (Cetorelli et al., 2017; Avraham et al., 2012)

[3] These synergies may arise through, for example, wide banks being able to reallocate resources within the firm at lower costs (Almeida et al., 2015; Matvos et al., 2018; Folta et al., 2016).

[4] In fact, over the last decade large banks have retreated from particular segments of small business lending, further limiting financing options for small firms (Bord et al., 2018; Chen et al., 2017).

firms from 2009 to 2019. A key comparative advantage of our data with respect to other datasets in the literature is the availability of data for both banks and non-banks.[5] Observing both banks and non-banks allows us to compare financial intermediaries that significantly differ in both their asset and liability structures. Moreover, our data has exceptional coverage for very small businesses. The median firm in our sample has less than five employees and is eight years old. During our sample period, 45% of firms borrowed at least once from the four largest banks (i.e., Wells Fargo, JP Morgan Chase, Citibank and Bank of America), 47% from other banks and 42% from non-banks. Moreover, 90% of firms use credit cards, while 18% borrow via term loans. The most popular product in our sample period is a corporate credit card offered by the four largest banks. Overall, these data allow us to get a full picture of small business lending in the US and the strategic interactions of all players in the market.

In the first part of the paper, we document key trends in the market for small business lending. We show, consistent with previous findings in the literature, that since 2013, banks have retreated from the market for business term loans (Gopal and Schnabl, 2020; Bord et al., 2018). Our data reveal, however, that banks have increased their share of business credit cards over the same period. In particular, we find that banks have expanded credit card lending more in areas were they already had a large share of other products such as mortgages and deposits. Non-banks, in contrast, have increased their share in term loans but have kept a constant share in credit cards. We provide reduced-form evidence showing that these trends are driven by regulatory cost increases in issuing small-sized term loans relative to credit cards and larger term loans, rather than by changes in firm credit demand.

Next, we show how banks' incentives to reduce small-sized term loans distort firms' product and quantity choices. While credit cards and term loans both provide credit to firms, they are imperfect substitutes. Credit cards are optimal to satisfy payment and liquidity needs, while term loans are better for investment purposes (DeMarzo and Sannikov, 2006; DeMarzo and Fishman, 2007). In the data, we observe two patterns that are consistent with scope-driven supply-side distortions to firm choices. First, we observe that term loans originated by banks bunch at a loan amount of $50K (i.e., the regulation threshold). We do not find similar bunching for term loans originated by non-banks. Second, we find that after the regulation, a larger fraction of firms max-out their credit cards when borrowing from banks relative to non-banks. These distortions have real effects: distorted firms have higher defaults, lower credit score growth, lower sales growth and lower survival rates. Together, these facts suggest that banks are steering firms that prefer smaller terms loans into larger term loans and credit cards.

Motivated by the reduced-form evidence, we develop a structural model of demand and supply of firm credit. Our model incorporates key channels through which scope can influence the behavior of banks, their competitors and their customers. In particular, we allow for market power, cost synergies, multi-product steering, and competition between multi-product and specialized lenders. The data and

[5]Comparable datasets in coverage come from bank regulators and therefore, definitionally, do not cover non-banks.

our reduced-form results suggest that these channels are quantitatively important in this market. We estimate our model using our novel micro-data on small business credit. We find that firms have a strong preference for multi-product banks. Banks' market power allows them to steer firms to high-markup products. Moreover, our results show that banks enjoy cost synergies across different products. These cost advantages lower their marginal costs and are partially pass-through to firms via lower interest rates. In our setting, cost synergies are quantitatively larger *across* assets, rather than between assets and liabilities. These findings highlight that, even though the literature has emphasized cost complementarities between assets and liabilities (Diamond and Dybvig, 1983; Diamond and Rajan, 2001, 2000; Egan et al., 2017), it is also important to account for cost synergies across different asset classes. Analysis quantifying only assets-to-liabilities synergies provides an incomplete picture, particularly given the multi-product nature of banks.

In the last part of the paper, we use the estimated parameters to run counterfactuals and quantify their equilibrium effects and welfare implications. First, we simulate scenarios where we remove cost synergies, bank steering or both. When lenders cannot benefit from cost synergies, firm welfare decreases due to higher interest rates for credit cards (despite lower steering by banks). When lenders are not able to steer firms, both firm welfare and bank profits increase. The increase in bank profits suggests that steering acts as a prisoner's dilemma for banks: all banks would like to commit not to steer, but find it optimal to unilaterally steer if the rest do not. Finally, when we remove both steering and cost synergies, the overall effect on welfare is negative. This suggests that the benefits from cost synergies dominate the losses from steering, and wider scope has positive welfare implications.

Our model also allows us to evaluate the role of non-banks in this market. We first consider the effects of eliminating non-bank competition. As expected, we find that banks increase their steering and interest rates for credit cards go up by almost 30%. The big winners are Top 4 banks with 32% higher profits. In this market, non-bank competitors prevent banks from increasing interest rates and steering. Not accounting for these competitors could result in an underestimation of banks' market power. Second, we simulate a scenario equivalent to eliminating regulations that generate cost differentials between banks and non-banks. Equilibrium effects lead to higher firm welfare and higher lender profits relative to the baseline. However, banks are able to capture most of the gains from less regulation thanks to their ability to steer firms into higher mark-up products. Overall, the results in this paper highlight the importance of accounting for the multi-product nature of financial intermediaries when designing financial regulation. This conclusion applies both to macro and micro regulations, and opens the door for future work evaluating the implications of scope in financial intermediation.

2 Related Literature

In this paper we focus on the role of cost synergies and market power when studying scope in financial intermediation. Previous work studying horizontal mergers has shown that, absent costs synergies, mergers often reduce consumer surplus through increases in prices due to greater market power (see, e.g., Farrell and Shapiro, 1990; Werden, 1996; Nocke and Schutz, 2018; and, in the context of bank consolidation, Tarantino et al., 2021). In fact, policy guidelines to approve horizontal mergers in the US and Europe rely on quantifying this trade-off between cost synergies and market power.[6] Most of the literature, however, has focused on quantifying economies of scale. We show that similar trade-offs exist when analyzing welfare effects of economies of scope. Similarly to Crouzet and Mehrotra (2020), we find that having a wider scope gives banks a competitive advantage, both in terms of costs and market power, relative to their more-specialized competitors. Moreover, we show spillover effects across markets via the balance sheet of multi-product banks. These results resemble findings in previous work on vertical integration of multi-product firms (see, e.g., Luco and Marshall, 2020).

Scope is also at the core of the traditional banking literature. By taking deposits and using them to fund loans, traditional banks are, by definition, firms with a wide scope. By transforming these short-term liabilities into long-term assets banks can benefit from cost complementarities in their balance sheets (Diamond and Dybvig, 1983; Egan et al., 2017). An extensive body of research has proposed theories to explain why banks engage in both deposit-taking and lending activities (see, e.g., Calomiris and Kahn, 1991; Diamond and Rajan, 2000, 2001; Kashyap et al., 2002; Gatev and Strahan, 2006). Many of these theories assume cost complementarities arising from synergies across products in the bank's balance sheet. Combining rich micro-data with structural techniques, recent empirical papers have tried to quantify these cost synergies. Egan et al. (2022) estimates a consumer demand system for deposits and a production function for assets to estimate banks' productivity. The authors find that a bank's asset productivity is correlated with its deposit productivity. Aguirregabiria et al. (2017) estimates a structural model of oligopolistic competition in the banking industry, and finds evidence of significant economies of scope between deposits and loans at the branch level. Diamond et al. (2021) estimates a flexible bank's cost function allowing for cost synergies between the various borrowing and lending businesses of a bank. In their setting, cost synergies between banks' liquid and illiquid assets are positive. Our paper contributes to this debate by showing that cost complementarities *across* assets can also be quantitatively important. This is relevant because it establishes a link between household and corporate assets in the bank's balance sheet (see, e.g., Berger et al., 2022, Fonseca and Wang, 2022). Given our results, regulating consumer products can have spillover effects on corporate products due to the multi-product nature of banks.

This paper is also related to recent work documenting increased competition between banks and non-banks (see, e.g., Hanson et al., 2015; Buchak et al., 2018b; Jiang, 2020; Fuster et al., 2019; Begenau and Landvoigt, 2022; Xiao, 2020). This literature evaluates the effects of regulating entities (i.e., banks vs. non-banks) that are performing the same function (i.e., credit provision). In the context of the U.S. market for syndicated corporate loans, Irani et al. (2021) shows how under-capitalized

[6] See, e.g., U.S. Department of Justice and Federal Trade Commission (2010), *Horizontal Merger Guidelines*, available at https://www.justice.gov/atr/horizontal-merger-guidelines-08192010; and U.S. Federal Trade Commision (2013), "Horizontal Merger Investigation Data: Fiscal Years 1996-2011," available at https://www.ftc.gov/os/2013/01/130104horizontalmergerreport.pdf. [17] Werden, G.J. (1996), "A Robust Test for Consumer Enhancing Mergers Amo

banks removed many of these loans from their balance sheets after the increase in capital requirements implemented by Basel III. Moreover, their results provide evidence that bank capital constraints are an important predictor of non-bank entry in the market. We show similar results for the behavior of banks and non-banks in the corporate term-loan market after Basel III. However, we also find that, when capital requirements for term loans increased relative to credit cards, banks increased their exposure to the latter. In our setting, banks' multi-product incentives led to steering of firm and had (negative) real effects on firm outcomes. Similar distortions have been documented by Lian and Ma (2020) and Greenwald et al. (2020) in the context of credit for larger firms. This paper contributes to this work by highlighting the unintended consequences and spillovers of regulating some products in banks' balance sheet, but not others.

Finally, our paper contributes to the extensive empirical literature studying the bank-lending channel and its impact on real outcomes, using detailed micro-data (Khwaja and Mian, 2008; Paravisini, 2008; Schnabl, 2012; Kashyap and Stein, 2000; Jiménez et al., 2012, 2014; Khwaja and Mian, 2008; Paravisini et al., 2015; Ivashina et al., 2020). Our paper also belongs to the large literature studying the industrial organization and regulation of financial markets. Recent papers have studied markets for retail deposits (Egan et al., 2022; Albertazzi et al., 2022), insurance (Koijen and Yogo, 2016; Barbu, 2022), mortgages (Buchak et al., 2018a; Benetton, 2021; Robles-Garcia, 2022), personal loans (Cuesta and Sepúlveda, 2021), corporate lending (Crawford et al., 2018), pensions (Hastings et al., 2013) and credit cards (Nelson, 2018; Galenianos and Gavazza, 2020).

3 Data and Key Facts

3.1 Data

We exploit a new dataset from a major US commercial credit reporting bureau. The bureau collects information from participating lenders on their lending relationships with firms.[7] The dataset covers four lender types: the four largest banks (i.e., Citi, Wells Fargo, Bank of America, and Chase), other banks, non-bank lenders, and credit unions. The data has a panel structure, with information on firms' credit products over time. Our sample period starts in March 2009 and ends in September 2019, with snapshots every six-months. We observe a total of 12.4 million borrowing firms in our sample. The average firm in our sample borrows for 4.6 years. Each year, the average coverage is around 6 million borrower firms and 16 million non-borrower firms. For each firm, we observe industry classification, age, number of employees, sales, credit score (analogous to a consumer FICO score) and establishment location at the zipcode level.

[7] According to the data provider, the set of reporting lenders covers most of the relevant market.

Table 1: SUMMARY STATISTICS FOR CREDIT BUREAU FIRM-LEVEL DATA

	N	Mean	SD	p5	p50	p95
FIRM CHARACTERISTICS						
Age (years)	11,917,634	8	8	0	4	25
<5 employees	4,931,666	0.61	0.49	0	1	1
Risk score	11,205,065	61	50	9	63	95
NUMBER OF PRODUCTS						
All	112,703,249	1	1	1	1	3
Credit cards	99,028,805	1	1	1	1	3
Term loans	13,674,444	2	3	1	1	4
Top 4 banks	39,520,772	1	1	1	1	2
Other lenders	73,182,477	1	2	1	1	3
LIMITS ($K)						
All	112,703,249	32	47	1	10	68
Credit cards	99,028,805	18	59	1	9	40
Term loans	13,674,444	138	237	10	41	470
Top 4 banks	39,520,772	28	65	1	10	83
Other lenders	73,182,477	35	68	1	13	55
BALANCES ($K)						
All	112,703,249	16	200	0	2	38
Credit cards	99,028,805	4	40	0	1	16
Term loans	13,674,444	101	162	2	25	356
Top 4 banks	39,520,772	6	33	0	2	23
Other lenders	73,182,477	21	43	0	1	51
FRACTION OF DELINQUENCIES						
All	112,703,249	0.046	0.210	0	0	0
Credit cards	99,028,805	0.049	0.221	0	0	0
Term loans	13,674,444	0.021	0.140	0	0	0
Top 4 banks	39,520,772	0.043	0.066	0	0	0
Other lenders	73,182,477	0.068	0.251	0	0	1

Notes: This table shows summary statistics for borrower firms in our sample from a major US commercial credit bureau. Statistics for the number of products, credit limits, total balances and fraction of delinquencies is evaluate at the level of firm, credit product, lender type, and six-month period. Delinquencies describe being more than 60 days in delinquency in the three years after originating the credit product. Firm characteristics (age, number of employees and risk score at the time when the firm originated its first credit product in our sample) are defined at the firm level. Top 4 banks include Citi, Wells Fargo, Bank of America, and Chase.

Each snapshot contains firm-level information on 113 million credit products for reporting lenders. For each of these products we observe the type of product, total balances, credit limits, and whether any of them is currently delinquent. Product types include term loans, credit cards, credit lines, and leases.[8] Almost 90% of firms in our sample have at least one credit card, and 18% of firms hold at least one term loan. Firms borrow across different lender types throughout our sample period: 45% from the four largest banks, 47% from other banks and 42% from non-banks.

Table 1 shows summary statistics for our key variables. The average firm in our sample is eight years old, with the 95th percentile being 25 years old and the median 4 years old. Roughly 60% of firms in the dataset have five or fewer employees.[9] The average credit score for a borrower firm is 61 (which is higher than survey reported credit scores for non-borrowing firms). The median firm has, on average, one product each snapshot. Credit limits for firms are on average \$32K (\$18K for credit cards and \$138K for term loans). On average, firm balances for credit cards are below limits.[10] Almost 30% of firms have credit card utilization rates equal to 100% (i.e., their balance is equal to their limit). Moreover, about 5% of products are delinquent in our sample, with credit cards having larger delinquency rates than term loans.

Like most credit registries, our data does not report information on interest rates. To overcome this limitation, we complement our data with data on interest rates from RateWatch. Every month, RateWatch reports average interest rates for business credit cards and term loans offered by a lender in a given branch. Table 2 shows summary statistics for these data. Average interest rates for credit cards and term loans are 11.78% and 7.36%, respectively. Banks charge slightly higher rates than non-banks for both types of products.

Table 2: SUMMARY STATISTICS FOR INTEREST RATES (RATEWATCH DATA)

			Interest Rates				
Lender	Product	N	Mean	SD	p5	p50	p95
All	All	477,357	10.15	3.58	4.35	9.99	15.60
Banks	Credit Cards	156,458	11.83	3.09	7.65	11.65	16.90
Banks	Term Loans	72,804	5.23	3.10	0.00	6.00	9.00
Non-Banks	Credit Cards	238,912	10.75	2.33	7.50	9.99	14.90
Non-Banks	Term Loans	9,183	5.02	3.05	0.00	6.00	9.00

Note: This table shows summary statistics for interest rates from RateWatch data. Credit cards include all personal and business credit cards. Term loans include small business loans for \$50K.

Finally, we collect aggregate data for other products at the lender level for each zipcode. In partic-

[8] In the remaining of the paper, we focus exclusively on credit cards and term loans, dropping leases and credit lines. In our data, 92% of credit lines are originated by firms with more than 50 employees. Credit cards are effectively the credit lines for small businesses. We also drop products originated by credit unions. Our restricted sample after dropping credit unions, leases and credit lines has 12.4 million borrower firms. That is, we drop 8% of our sample.

[9] Our data provider claims that the strength of their data is for *very* small businesses. Their coverage is representative and close to total number in the Census Bureau data.

[10] Sometimes we observe balances for term loans that are below limits due to pre-payments.

ular, we use (1) lender market share data for residential mortgage originations reported by the Home Mortgage Disclosure Act (HMDA), (2) lender market share data for deposits from the Summary of Deposits, and (3) number of branches from each lender also from the Summary of Deposits. All these data are aggregated at the three-digit zipcode level for every six-month period.

3.2 Key Fact: Shift in Product Sales Across Lenders

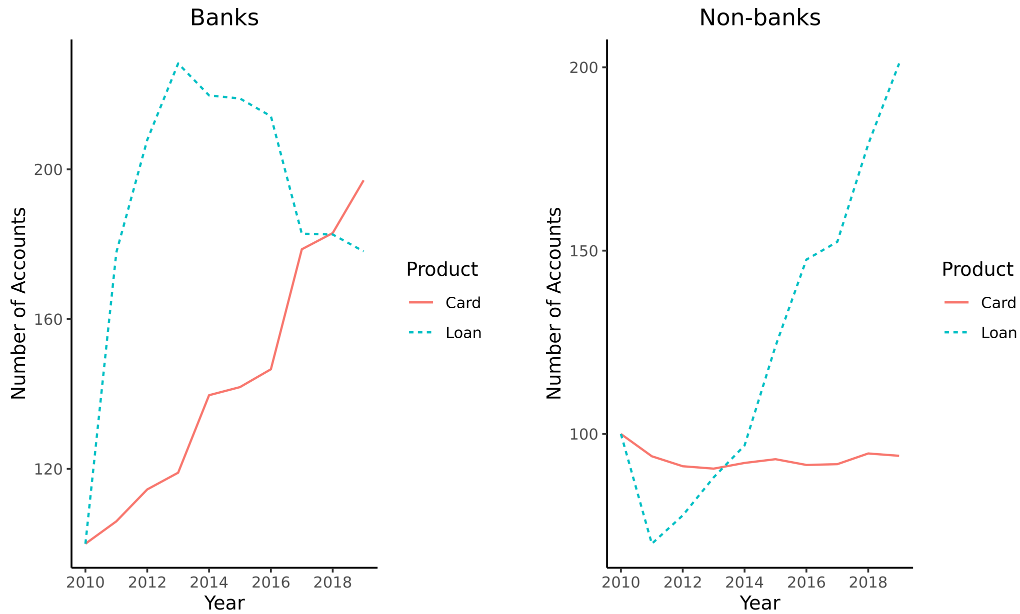
Over the last decade, we have seen a shift in product specialization across different types of lenders. Panel A in Figure 1 shows how banks have been increasing their sales of corporate credit cards. Moreover, since 2013 they have steadily been reducing their share in corporate term loans. Panel B in Figure 1 illustrates how non-banks have not changed their sales of corporate credit cards, but have significantly increased their sales of corporate term loans. The latter has a steeper trend after 2013. Figure A.1 shows that these changes in the corporate credit card market are driven by sales of banks to small firms (defined as less than 50 employees). We complement the literature by documenting this important heterogeneity jointly across lenders (banks and non-banks) and product types (term loans and credit cards). We find that the "exit" by large banks from the small business loan market has been selective. Banks have reduced their exposure to small business term loans, but have increased their exposure to small business credit cards. This result has important implications for regulation and transmission mechanism of credit supply shocks. For example, if banks had completely retreated from small business lending, then crises like COVID-19 affecting small business performance would have limited impact on banks. However, this would not be the case if banks had increased their share in business credit cards (like we document).

These quantity changes for banks and non-banks across credit cards and term loans are not driven by changes in prices. Figure 2 plots average rates across products for each type of lender. Credit card rates are about 100% higher than those for term loans throughout our entire time period. Moreover, banks have increased their credit card rates after 2013, while non-banks credit card rates has remained fairly constant. There are no large changes in term loan rates for both banks and non-banks.

4 Reduced-Form Evidence

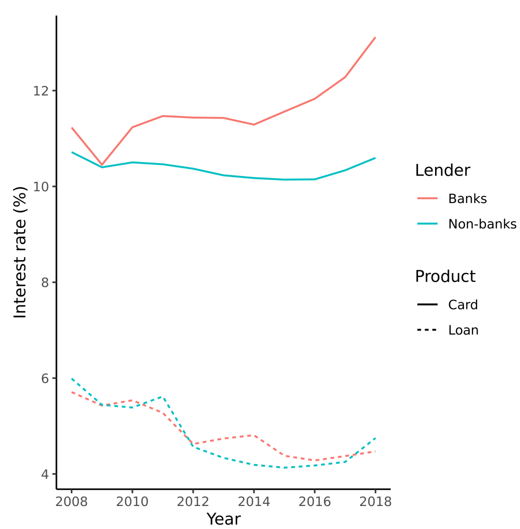
The goal of this section is to provide empirical evidence of the key drivers of the facts described in Section 3.2. We argue that the shift in bank specialization across products is driven by two supply-side mechanisms. First, after a change in regulation increasing the marginal cost for small-size term loans, multi-product banks have incentives to steer firms into less costly (more profitable) products, namely credit cards and large-size term loans. These supply-side distortions led firms to choose sub-optimal products and loan amounts. Second, banks had incentives to shift their product offerings towards markets where they could benefit from cost synergies across products (e.g., deposits and mortgages). Lower marginal costs can benefit firms if passed-through in the form of lower interest rates.

Figure 1: LENDER SPECIALIZATION ACROSS PRODUCTS



Notes: Both panels show percentage changes in the number of credit cards (solid line) and terms loans (dashed line) relative to 2010 (normalized to 100). The left panel described banks and the right panel non-banks. The sample period is March 2010 to September 2019.

Figure 2: PRICE DATA FROM RATEWATCH



Notes: The figure plots six-month interest rates (RateWatch data) from March 2008 to September 2019. Solid line represent credit cards and dashed lines refer to term loans. Banks are plotted in red lines and non-banks are represented by blue lines. Credit cards include all personal and business credit cards. Term loans include small business loans for $50K.

Table 3: RISK WEIGHTS OVER TIME AND ACROSS PRODUCTS

	RETAIL TERM LOANS	RETAIL CREDIT CARDS	CORPORATE TERM LOANS
Basel II - SA	75%	75%	100%
Basel III -SA	75%	45%	85%

Note: Table reports risk weights for business products for banks using standard approach. Retail refers to products aimed for small businesses, while corporate labels products for larger firms. Source: Report by FSB, "Evaluation of the effects of financial regulatory reforms on small and medium-sized enterprise (SME) financing" (2019).

4.1 Ruling Out Demand Explanation

The patterns described in Section 3.2 could be explained by contemporaneous changes on the demand side or sorting of firms into different lenders and product types. To rule out these alternative explanations, we need to disentangle credit supply from credit demand. Only then we can credibly claim that the observed changes in quantities and prices are driven by lenders' multi-product incentives.

To do so, we implement a triple-difference identification strategy. We exploit variation across credit cards and term loans; across banks and non-banks; and over time. In particular, we use variation from a change in risk weight regulation in 2013, and compare lender and firm behavior before and after the policy change. Table 3 shows regulatory risk weights associated with small business lending (by banks). Basel II regulation set a risk weight of 75% for both term loans and credit cards. In 2013, when Basell III was implemented, the risk weight on credit cards to small businesses decreased to 45%.[11] Under the new regulation, the incentives of capital constrained banks changed, and credit cards became preferable to term loans, all else equal. The intuition is that Basel III was a shock that increased the cost of providing term loans relative to credit cards for banks, which re-acted by substituting sales across both products.

We consider the following regression:

$$y_{ijlt} = \beta CC_j \times Banks_l \times PostBaselIII_t + \gamma_{jl} + \gamma_{jt} + \gamma_{lt} + \gamma_i + \epsilon_{ijlt}, \tag{1}$$

where y_{ijlt} is the outcome of interest (e.g., number of accounts; credit limits) for firm i related to product j issued by lender type l at time t; CC_j is a dummy equal to one if the product is a credit card; $Bank_l$ is a dummy equal to one for products originated by banks; $PostBaselIII_t$ is a dummy equal to one for the period after the implementation of Basel III (after 2013); γ_{jl} are product-lender type fixed effects; γ_{jt} are product-time fixed effects; and γ_{lt} are lender type-time fixed effects; γ_i are firm fixed effects. We saturate the regression by including firm, lender-time, lender-product and

[11] The rule became effective for advanced-approaches banks on January 1, 2014, while for the non-advanced-approaches banks it became effective on January 1, 2015. So there could be some delay in behavior for banks.

Table 4: TRIPLE DIFFERENCE RESULTS

	ACCOUNTS (1)	CREDIT LIMITS (LOG) (2)
Bank X Credit Card X Post	0.20***	0.33***
	(0.02)	(0.01)
R^2	0.40	0.78
R^2 ADJUSTED	0.35	0.75
Y MEAN	0.96	9.01
Y SD	0.93	1.36
OBSERVATIONS	1990135	1244136

Notes: The definition of *Banks* is restricted to the Top 4. Standard errors are clustered at the firm level.

product-time fixed effects in an attempt to control for the sources of endogeneity driven by unobserved heterogeneity. The coefficient of interest is β, which captures the triple interaction: the differential effect for banks (relative to non-banks) in credit cards (relative to term loans) after the implementation of Basel III (relative to before).

Table 4 shows results from estimating Equation (1). Coefficients on the triple interaction are statistically significant and large in magnitude. We find that banks increase the number of credit cards by about 0.20, which implies about a 20% increase (average number of products is almost one). Limits also increase by approximately \$2.6K for credit cards from banks after Basel III. This change is equivalent to a 13% increase in the average limit.

One limitation of Equation (1) is that it does not control for time-varying firm level variation in demand that could be differential across products and lender types. For example, after 2013 firms that are more likely to have a relation with a bank experience an increase in uncertainty, leading them to demand more credit cards to smooth cash flow risk. To address this concern, we focus on a subset of firms with multiple banking relationships and estimate an empirical model à la Khwaja and Mian (2008). An identifying assumption in Khwaja and Mian (2008) is that a firm is indifferent between borrowing from two banks. This condition may not hold in presence of banks' specialization (Paravisini et al., 2015; Ivashina et al., 2020). Our rich panel data on different products allows us to refine the assumption by exploiting variation within firm across lender types *separately* for different products. By considering each product market separately and adding firm-time and firm-lender fixed effects our approach tries to control for selection and specialization concerns. However, we would still have identification concerns if firms perceive credit cards offered by banks differently depending on firm unobservable characteristics that are correlated to the supply shock. Despite these limitations, we believe our strategy is an improvement relative to the existing literature which confounds different products. The downside of running this specification is that the data requirement is stricter, as we only consider firms with two credit cards (or term loans) with two different lender types.

Our empirical model à la Khwaja and Mian (2008) is the following:

$$y_{ibt}^{CC} = \alpha^{CC} Banks_b + \beta^{CC} Banks_b \times PostBaselIII_t + \gamma_{it}^{CC} + \gamma_{ib}^{CC} + \epsilon_{ibt}^{CC}, \tag{2}$$

$$y_{ibt}^{TL} = \alpha^{TL} Banks_b + \beta^{TL} Top4_b \times PostBaselIII_t + \gamma_{ib}^{TL} + \gamma_{it}^{TL} + \epsilon_{ibt}^{TL}, \tag{3}$$

where γ_{it}^{CC} are interacted firm-time fixed effects absorbing the firm level demand for credit cards; γ_{it}^{TL} are interacted firm-time fixed effects absorbing the firm level demand for term loans. This specification tries to control for unobserved demand factors that could be driving observed changes in outcomes.

Table 5 show estimates for Equations (2) and (3), respectively. Panel A reports estimates using only credit card observations, while Panel B uses only term loans. Results show that after 2013 banks increased their number of credit cards with the same firm relative to non-banks. Most notably, a firm with at least one credit card from both a bank and a non-bank experience a 0.09 increase in the number of credit card trades with the bank after 2013 relative to increase in the same period of a non-bank.

We find similar results for credit limits. We added the effect on balances, since they can be interpreted as a more demand-driven outcome than limits (determined by supply). Balances also respond, but less than limits and as a result utilization rates fall. The significantly lower response of balances relative to limits supports our supply-side mechanism. Interestingly we do not find differential changes in arrears for credit cards originated by banks after 2013 relative to other banks and non-banks. Results for term loans are also consistent with a supply-side story in which banks have incentives to shift small businesses from term loans to credit cards, relative to non-banks. Our conclusion from these empirical exercises is that the patterns in Section 4.2 are unlikely to be explained solely by demand factors.

4.2 Supply Mechanism #1: Banks Distorting Firms' Choices

After ruling out demand-side explanations in Section 4.1, we now present empirical evidence that banks distorted product and quantity choices of firms. After a change in regulation increasing the cost of issuing small-size term loans, banks shifted firms demanding these products to either credit cards or large-size term loans. Industry reports have discussed this type of steering of small firms by banks. For example, Mills and McCarthy (2014) provides suggestive evidence of an "increasing propensity of some of the largest banks to push businesses with less than \$2 million in revenue to their automated, higher-yielding credit card products, even if the business owner in question is seeking project-based financing." We further explore this mechanism with our detailed administrative data.

4.2.1 Distortion Towards Credit Cards

Figure 3 plots the distribution of credit card utilization rates (i.e., the ratio of credit card balances over limits) for banks and non-banks. Banks have a significantly larger share of firms with 100% utilization

Table 5: Khwaja-Mian Regression Results

Panel A: Credit Cards

	Accounts	Limit (log)	Balance ($)	Utilization (%)	Delinquent (%)
	(1)	(2)	(3)	(4)	(5)
Bank X Post	0.09***	0.19***	549.07***	-6.03***	-0.00
	(0.00)	(0.01)	(127.06)	(0.22)	(0.00)
R^2	0.88	0.93	0.91	0.85	0.76
R^2 adjusted	0.74	0.84	0.80	0.68	0.48
Y mean	1.21	9.00	3702.84	23.81	0.01
Firm-time F.E.	Yes	Yes	Yes	Yes	Yes
Firm-lender F.E.	Yes	Yes	Yes	Yes	Yes
Observations	435804	262274	262166	262166	435804

Panel B: Term loans

	Accounts	Limit (log)	Balance ($)	Utilization (%)	Delinquent (%)
	(1)	(2)	(3)	(4)	(5)
Bank X Post	-0.87***	-0.50***	-12032.99**	6.64**	-0.00
	(0.13)	(0.04)	(5735.93)	(3.36)	(0.00)
R^2	0.86	0.90	0.87	0.83	0.73
R^2 adjusted	0.69	0.75	0.67	0.59	0.38
Y mean	1.59	10.89	68071.28	60.32	0.00
Firm-time F.E.	Yes	Yes	Yes	Yes	Yes
Firm-lender F.E.	Yes	Yes	Yes	Yes	Yes
Observations	40067	14758	14708	14708	40067

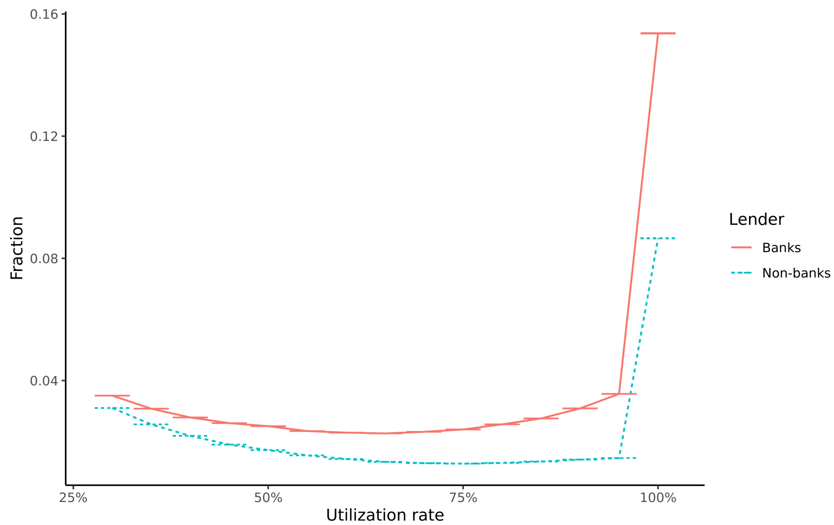
Notes: Panels A and B restrict the sample to credit cards and term loans, respectively. The definition of *Banks* is restricted to the Top 4. Standard errors are clustered at the firm level.

rates (i.e., maxing out their credit cards every period). Our claim is that lenders are steering firms, who wanted a small-size term loan, into credit cards. These firms are using the entire limit because, as previous work has shown, firms demanding term loans usually want them for investment purposes (as opposed to credit lines that are used for liquidity reasons). In fact, Figure 4 shows how these firms have worse real outcomes. For example, they have higher probability of default, lower sales growth, higher probability of lowering their credit score and lower probability of survival.

4.2.2 Distortion Towards Borrowing Larger Amounts

Figure 5 plots the distribution of loan amounts for term loans for banks and non-banks. There is bunching at the $50K limit for term loans offered by banks. Moreover, banks issue less term loans below $50K than non-banks. Non-banks, on the other hand, have a smooth distribution around the

Figure 3: Credit Card Utilization for banks and non-banks



Notes: This figure plots the distribution of the credit card utilization rate, defined as the ratio of balance over credit card limit. It shows the distribution for banks (solid line) and non-banks (dashed line). The horizontal lines represent standard errors. Firms are grouped in the x-axis depending on their average utilization rate.

$50K limit. This bunching mass remains significant after controlling for observable firm characteristics. We interpret these patterns as lenders steering some firms to borrow *at least* $50K. Figure 6 shows that there is also a discontinuity in default rates around the $50K limit for firm borrowing from banks.[12] These firms also have lower probability of survival and higher probability of worsening their credit scores.

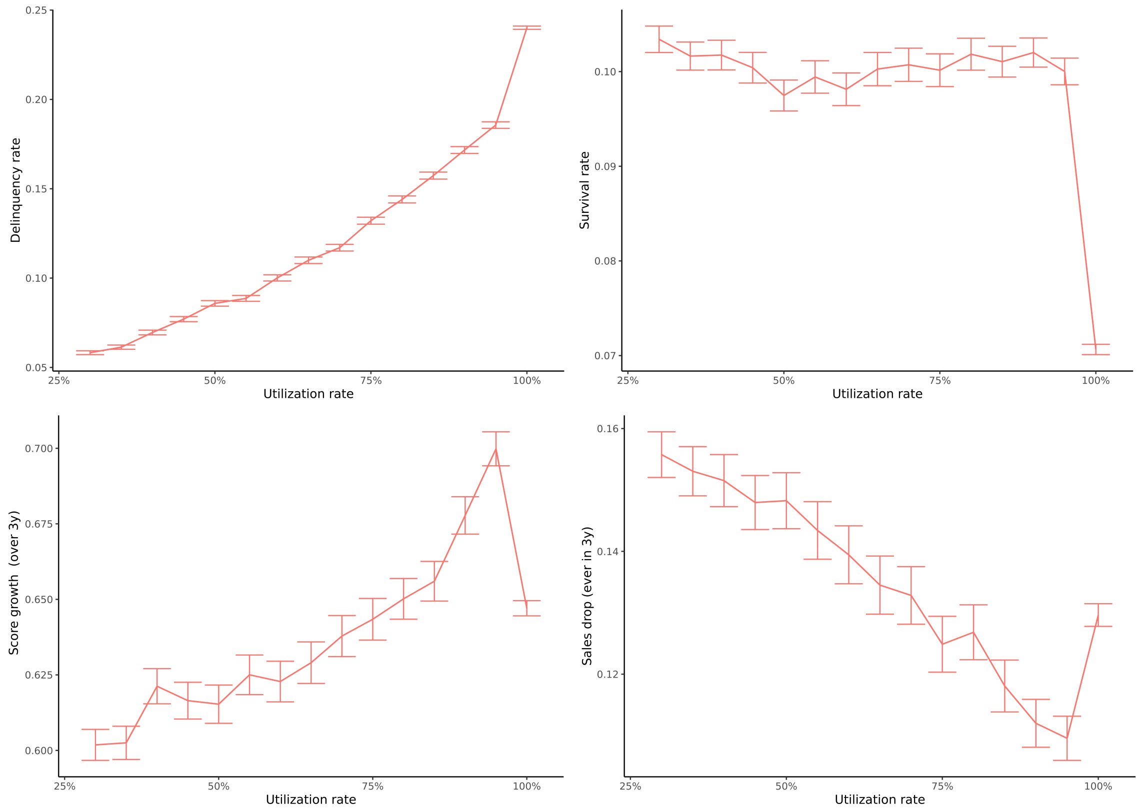
4.3 Supply Mechanism #2: Banks Facing Cost Synergies

This section explores whether the patterns in previous sections can (partly) be driven by cost synergies. In particular, we consider whether lenders are more likely to promote their small-business credit cards in markets where they already have a high market share for other product and customer segments. We extend our within firm-time-product analysis (Khwaja-Mian regressions) in Section 4.1 by adding interactions with preexisting market shares for deposits and mortgages. We estimate the following regressions:

$$\begin{aligned} y_{ilt}^{CC} = & \alpha^{CC} Banks_l + \beta^{CC} Banks_l \times PostBaselIII_t \\ & + \lambda^{CC} Banks_l \times PostBaselIII_t \times Share_{l,2010}^{K} \\ & + \gamma_{it}^{CC} + \gamma_{il}^{CC} + \epsilon_{ilt}^{CC}, \end{aligned} \tag{4}$$

[12] We measure default as being more than 60 days delinquent in the three years after origination. The results are qualitatively and quantitatively similar when we consider other variables for loan performance.

Figure 4: REAL OUTCOMES FOR CREDIT CARDS

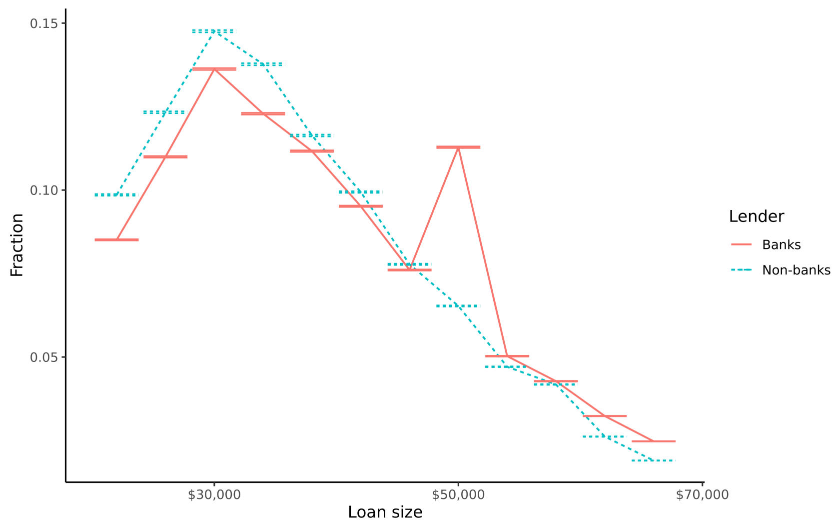


Notes: This figure plots firm outcomes by credit card utilization rate, defined as the ratio of balance over credit card limit. The upper left graph shows the fraction of firms that become 60-days within three years. The upper right shows the probability that the firm survives for three years. The lower left shows the probability that the firm's credit score improves within three years. The lower right shows the probability that the firm's sales decrease within three years. Firms are grouped in the x-axis depending on their average utilization rate. The vertical lines in all figures represent standard errors.

where, mirroring equation (2), y_{ilt} is the number of accounts for firm i issued by lender type l at time t (ran separately for credit cards and term loans); $Bank_l$ is a dummy equal to one for products originated by a bank; $PostBaselIII_t$ is a dummy equal to one for the period after the implementation of Basel III (after 2013); γ_{it} are interacted firm-time fixed effects absorbing the firm level demand for credit cards; γ_{it}^{CC} are interacted firm-time fixed effects absorbing the firm level demand for term loans. Moreover, $Share_{l,2010}^{K}$ is an indicator equal to one if the market share for product K of the largest, multi-product banks' in a given zip code is above the median in 2010 (i.e., at the beginning of our sample). This interaction term tests how the shift of multi-product banks towards credit cards after Basel III varies with the banks' market share in other products.

Table 6 shows estimates for equation (4). First, banks are more likely to increase the number of credit card accounts in zipcodes where they already had a credit card market share above the

Figure 5: TERM LOAN SIZES FOR BANKS AND NON-BANKS

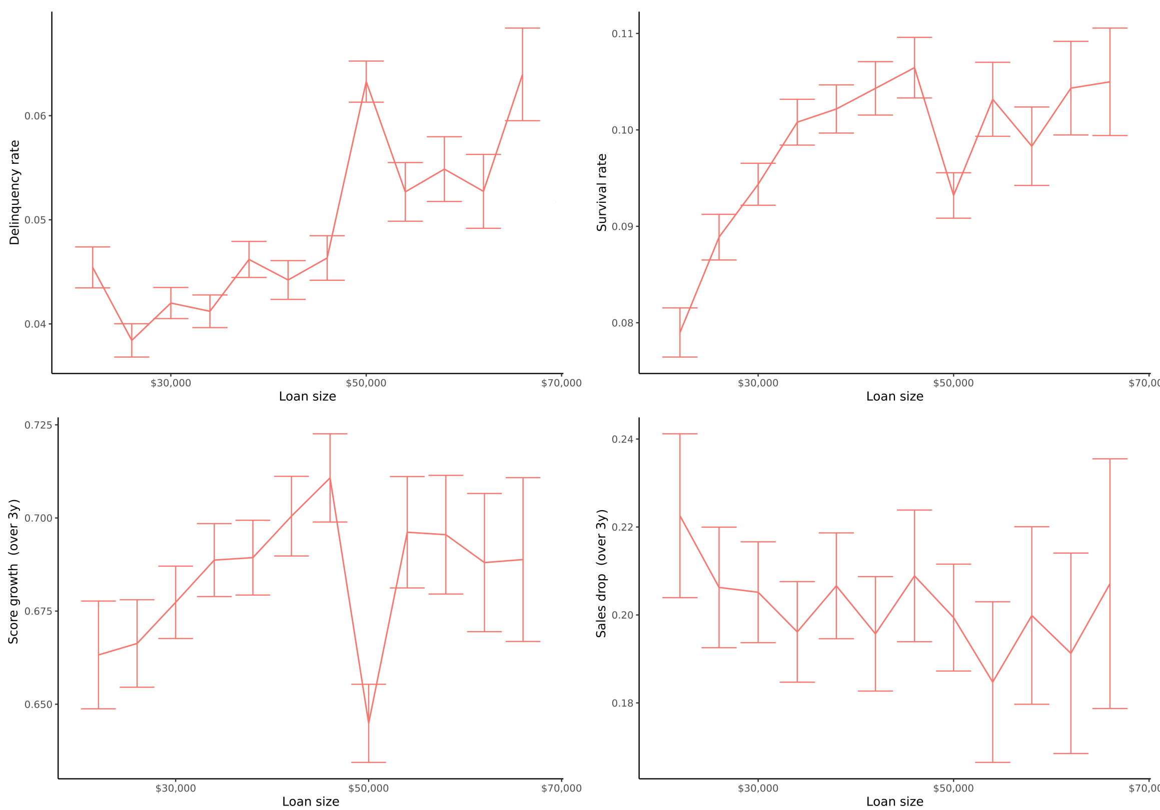


Notes: This figure plots the distribution of term loan amounts in dollars for banks (solid line) and non-banks (dashed line). Firms are grouped in the x-axis depending on their term loan amount. The horizontal lines in both figures represent standard errors.

median. This result suggests that *within-product* market power and size can be a factor driving some of the results. Moreover, banks also increased the number of credit card accounts in zipcodes where they already had a market share above the median for deposits, residential and commercial mortgages. That is, banks' increase credit cards in areas where they already had a better position in *other* products. These results suggest that, after controlling for demand and firm selection, synergies across products can be quantitatively important.[13]

[13] Synergies across small business and household finance products is particularly policy-relevant, because business credit cards face very little regulation, specially when compared to the amount of regulation for other consumer financial products. Banks' shifting of small businesses towards their automated, higher-profit (unregulated) corporate credit cards resembles banks' strategies in the (now regulated) consumer credit card market before regulation (see, e.g., Nelson, 2018; Galenianos and Gavazza, 2020; Agarwal et al., 2015).

Figure 6: REAL OUTCOMES FOR TERM LOAN SIZES



Notes: This figure plots outcomes by loan size. The upper left plot shows the fraction of firms that become 60-days delinquent within three years. The upper right plot shows the probability that the firm survives for three years. The lower left plot shows the probability that the firm's credit score increases within three years. The lower right plot shows the probability that sales decline within three years. Firms are grouped in the x-axis depending on their term loan amount. The vertical lines in all figures represent standard errors.

Table 6: KHWAJA-MIAN REGRESSION RESULTS FOR CREDIT CARDS

PANEL A: CORPORATE PRODUCTS

Dependent Variable: Number of Accounts	(1) Credit Cards	(2) Term Loans	(3) Commercial Mortgages
Bank X Post	0.05***	0.11***	0.08***
	(0.01)	(0.01)	(0.01)
Bank X Post X High Share Credit Card	0.07***		
	(0.01)		
Bank X Post X High Share Term Loans		-0.04**	
		(0.01)	
Bank X Post X High Share Commercial Mortgages			0.04***
			(0.01)
R^2	0.88	0.88	0.78
R^2 ADJUSTED	0.74	0.74	0.56
Y MEAN	1.21	1.21	1.21
FIRM-TIME F.E.	Yes	Yes	Yes
FIRM-LENDER TYPE F.E.	Yes	Yes	Yes
OBSERVATIONS	436415	436415	436415

PANEL B: HOUSEHOLD PRODUCTS

Dependent Variable: Number of Accounts	(1) Deposits	(2) Residential Mortgages
Bank X Post	0.04***	0.05***
	(0.01)	(0.01)
Bank X Post X High Share Deposits	0.08***	
	(0.01)	
Bank X Post X High Share Residential Mortgages		0.07***
		(0.01)
R^2	0.88	0.88
R^2 ADJUSTED	0.74	0.74
Y MEAN	1.21	1.21
FIRM-TIME F.E.	Yes	Yes
FIRM-LENDER TYPE F.E.	Yes	Yes
OBSERVATIONS	436415	422914

Notes: The sample is for credit cards only. The dependent variable is the number of accounts. Panel A (B) focuses on corporate (household) products. In this specification, the definition of "Banks" is restricted to the Top 4. Standard errors are clustered at the firm level.

5 Model

In this section we develop a model of demand and supply of firm credit, motivated by the empirical facts and the reduced-form results. The model incorporates market power, cost synergies, loan size and product distortions, and competition between multi-product and specialized lenders.

5.1 Firm Credit Demand

There is a continuum of firms of mass I_m indexed by i. Firm i demands credit from a lender indexed by l within the set of lenders L_m operating locally in a market. A market m is defined at the county-biyearly level. Santa Clara County in the first six months of the year 2012 is an example of a market. Each firm wants to borrow an optimal amount $\hat{q}_i$. This quantity can be interpreted as an investment opportunity with positive net present value or as capturing optimal capital structure in a reduced-form way. We assume optimal borrowing amounts follow a log-normal distribution with mean $\mu^{\hat{q}}$ and standard deviation $\sigma^{\hat{q}}$, such that $\hat{q}_i \sim ln\,\mathcal{N}(\mu^{\hat{q}}, \sigma^{\hat{q}})$.

We model firm credit demand using a discrete-choice framework featuring rich firm heterogeneity (Berry et al. 1995; Nevo 2000). Firms with heterogeneous preferences over price and other product attributes choose among a menu of products. Lenders can offer up to three types of credit products indexed by j: credit cards (CC), small term loans (TL) and large term loans ($\overline{TL}$). We model large-size terms loans as loans with minimum quantity restrictions $\overline{q}_{jlm}$. The indirect utility that firm i gets from choosing product j from lender type l in market m is:

$$\begin{aligned} U_{ijlm} = &- \alpha\, r_{jlm} + \; X'_{jlm}\, \beta - \psi\, log(\hat{q}_i) \times \mathbb{1}[j = CC] \\ &- \mathbb{1}\left[\hat{q}_i < \overline{q}_{jlm}\right] \Bigg[\gamma_{jlm} \times \mathbb{1}[j = TL] + \lambda \left(\overline{q}_{jlm} - \hat{q}_i\right) \times \mathbb{1}[j = \overline{TL}] \Bigg] \\ &+ \xi_{jlm} + (1 - \sigma)\, \epsilon_{ijlm}, \end{aligned} \tag{5}$$

where r_{jlm} are interest rates; X_{jlm} are observable product characteristic; ξ_{jlm} are unobserved product characteristics and common shocks; ϵ_{ijlm} are taste shocks and are iid extreme value. The parameter σ, with $0 \leq \sigma < 1$, represents the nest parameter and characterizes the correlation of utilities that a firm experiences among all the products across the same lender type. If $\sigma = 0$, the model collapses to a standard logit.

Our specification in equation (5) departs from the standard indirect utility function used in demand estimation in two ways. First, firms borrowing large quantities with credit cards may face additional disutility, captured by ψ. We add this term to match the empirical fact that firms with very large borrowing amounts seldom use credit cards. Second, firms with optimal borrowing amounts $\hat{q}_i$ below the minimum loan amount ($\overline{q}_{jlm}$) have three choices. They can borrow their optimal loan size by choosing either a credit card ($j = CC$) or a small-size term loan ($j = TL$). Alternatively, they can increase the size of their loan to meet the minimum size requirement and qualify for a large term loan ($j = \overline{TL}$). If the latter, there is a difference between the minimum loan size and the optimal credit amount needed for the firm investment project can create a quantity distortion, captured by λ. If the firm chooses the small-size term loan, the firm incurs an additional cost γ_{jlm}. This additional cost is chosen by the lender. For example, lenders can ask firms for additional paperwork or requirements before granting a small-size term loan. We discuss this cost again when modeling supply.

5.2 Lender Credit Supply

The supply side of the model is determined by competing banks and non-banks, which offer differentiated credit products to firms. We model banks as multi-product firms offering both credit cards and term loans, and non-banks as specialized lenders (i.e., they either offer credit cards or term loans, but not both). We also allow banks to (1) include minimum loan size requirements for some of their products ($\overline{q}_{jlm}$), and (2) force firms to face additional costs when taking up small term loans (γ_{jlm}). For example, they may require additional paperwork or incentivize branch officers not to offer small term loans. This is a non-price mechanism that banks can use to affect firm demand across their different products. Hereinafter, we will refer to this non-price mechanism as "steering". Because non-banks are single-product, specialized lenders, they do not have incentives to introduce minimum quantity requirements or additional costs (see Section 4 for reduced-form evidence of this differential behavior of non-banks).

Lender l selling product j in market m earns the following mark-up:

$$\pi_{ijlm} = (r_{jlm} - mc_{jlm})\, q_{ijlm}, \tag{6}$$

where r_{jlm} is interest rates, q_{ijlm} is loan amount, and mc_{jlm} is the lender's heterogeneous marginal cost. Marginal costs can depend on cost synergies across other products offered by the lender. We define marginal costs as:

$$mc_{jlm} = \eta_1\, Deposits_{lm} + \eta_2\, Mortgages_{lm} + \nu_l^S + \nu_j^S + \nu_m^S + \omega_{jlm}, \tag{7}$$

where $Deposits_{lm}$ and $Mortgages_{lm}$ are market shares of lender l in market m for deposits and mortgages, respectively; ν_l^S,ν_j^S and ν_m^S are lender, product and market fixed effects; ω_{jlm} is a shock, unobserved by the econometrician, but known to the lender. This parametrization captures in a reduced-form way potential complementarities across products. For example, a multi-product lender with a large share of residential mortgages in a market may be in a better position than competitors to originate credit cards to small businesses operating in the same market. These cost complementarities can be driven, for example, by information and technological synergies. We also allow, however, for the opposite effect. Multi-product lenders might face higher costs if offering too many product varieties in a market (in line with literature on conglomerates).

Expected profits for a lender type l when facing firm i in market m are:

$$\Pi_{ilm} = \sum_{i \in I_m} \sum_{j \in J_m^l} p_{ijlm} \, \pi_{ijlm} \tag{8}$$

where p_{ijlm} is the probability firm i chooses product j from lender type l in market m; J_m^l is the set of all products offered by the lender type in market m; and π_{jlm} is the product-specific mark-up as define in equation (6).

Both banks and non-banks choose interest rates to maximize expected profits. In addition, banks can choose the level of additional costs γ_{jlm} on their small term loans. A bank's decision depends on how many products it offers, firms' preferences and demand for each of these products and the degree of competition with other lenders in a given market.

5.3 Equilibrium

The equilibrium in this model is characterized by:

1. Each lender simultaneously choosing interest rates (and banks also choosing additional costs γ_{jlm}) so as to maximize ex-ante expected profits as defined in equation (8);
2. Each firm making its optimal choice of product j and lender l (and associated loan amounts) so as to maximize indirect utility as defined in equation (5).

5.4 Key Tradeoffs: Intuition

In this subsection, we briefly discuss the key trade-offs both firms and lenders face in our model. These would be central once we bring the model to the data and simulate counterfactual scenarios.

5.4.1 For Firms

Let us classify firms into two categories depending on their optimal borrowing amounts ($\hat{q}_i$). Firms with optimal borrowing amounts larger than minimum quantity requirements (i.e., $\hat{q}_i > \overline{q}_{jlm}$) can choose between a large term loan or a credit card. Although some firms might prefer a credit card (e.g., revolving credit might be a better way to finance fluctuations in liquidity needs), most firms requiring large loan amounts would prefer a term loan (e.g., better and cheaper way to finance investment). In our model, this would be captured by the parameter ψ.

Firms with optimal borrowing amounts smaller than minimum quantity requirements (i.e., $\hat{q}_i < \overline{q}_{jlm}$) can choose between a small term loan, a large term loan or a credit card. If they choose a large term loan, they need to satisfy the minimum quantity requirement. This would imply firms borrowing a larger amount than it is optimal and incurring larger interest payments. Our model captures this quantity distortion with parameter λ. Alternatively, if they choose a small term loan and borrow their optimal amount, they might face additional costs imposed by the lender (e.g., longer and stricter application process). These additional costs for small term loans are captured by γ_{jlm} in our model. Finally, firms may decide to choose a credit card and borrow their optimal amount. However, credit cards have on average higher interest rates and generate higher disutility (captured by price sensitivity α). Also, credit cards might not be the best financing tool to borrow large amounts intended for investment. We capture this possible disutility from product distortion with parameter ψ.

5.4.2 For Lenders

Lenders face the usual trade-off when setting interest rates. Larger prices increase per loan profits, but decrease market shares if firms can easily substitute to competitors. Banks face an addition trade-off when deciding whether to steer firms away from small term loans (i.e., when choosing γ_{jlm}). Higher γ_{jlm} steers firms into more profitable products for the bank. However, firms can substitute away and choose alternatives from competitors. Steering by banks is only feasible because in our model banks have market power and can extract additional surplus from firms using steering. In an environment with perfect competition, banks would not be able to steer firms.

6 Estimation and Identification

In our model we differentiated between two types of lenders: banks (multi-product) and non-banks (single product). Moreover, banks had the ability to set up minimum size requirements for their term loans. In our estimation, we implement the idea of a minimum size requirement by allowing banks to offer two types of term loans: a small size loan (no minimum quantity requirement) or a larger sized loan (with a minimum quantity requirement of $50K). Therefore, in our estimation, banks offer up to three products (credit cards, small term loans below $50K and large term loans above $50K). Specialized non-banks do not have this option, and only offer one type of term loan independent of loan amount. Moreover, they can provide firms with a credit card or a term loan, but nor both.

In our data, banks are all multi-product. However, they are very heterogeneous in terms of size. Since we want to capture economies of scope separately from economies of scale, we differentiate between the largest four banks (i.e., Citi, Wells Fargo, Bank of America, and Chase) and other banks. We refer to the set of largest banks as the Top 4 banks. We hope that by making this distinction we are able to partly control for firms having a preference for larger lenders.

6.1 Estimating Demand Parameters

In this section we go over the estimation and identification of demand parameters in our model.

6.1.1 Estimation Steps

In this section we describe our estimation strategy to recover all unknown demand parameters.

Step 1: Choose initial values for parameters involving variables that are firm-specific. In our model, these are (1) the mean and standard deviation of the distribution of firms' optimal loan amounts, denoted by $\hat{\theta}_1 = (\mu^{\hat{q}}, \sigma^{\hat{q}})$; and (2) demand parameters depending on optimal loan amounts, denoted by $\hat{\theta}_2 = (\lambda, \gamma, \psi)$.

Step 2: Simulate draws for optimal loan amounts. Assume it follows a log-normal distribution such that $\hat{q}_i \sim ln\, \mathcal{N}(\hat{\mu_0}^{\hat{q}}, \hat{\sigma_0}^{\hat{q}})$.

Step 3: Using simulated optimal loan amounts for each firm ($\hat{q}_i$) and initial values $\hat{\lambda_0}$, $\hat{\gamma_0}_{jlm}$ and $\hat{\psi_0}$, calculate non-linear terms in utility function:

$$\hat{f}(\hat{q}_i, \hat{\lambda_0}, \hat{\gamma_0}, \hat{\psi_0}) = -\,\hat{\psi_0}\, log(\hat{q}_i) \times \mathbb{1}[j = CC] \\ -\, \mathbb{1}\left[\hat{q}_i < \overline{q}_{jlm}\right] \left[\, \hat{\gamma_0}_{jlm} \times \mathbb{1}[j = TL] + \hat{\lambda_0}\left(\overline{q}_{jlm} - \hat{q}_i\right) \times \mathbb{1}[j = \overline{TL}] \,\right]$$

Step 4: Rewrite the utility function in Equation (5) as linear and non-linear terms:

$$U_{ijlm} = \underbrace{-\alpha\, r_{jlm} + X'_{jlm}\,\beta + \xi_{jlm}}_{\delta_{jlm}} + \hat{f}(\hat{q}_i, \hat{\lambda_0}, \hat{\gamma_0}_{jlm}, \hat{\psi_0}) + (1 - \sigma)\, \epsilon_{ijlm}$$

Step 5: Estimate δ_{jlm} using approach in Berry, Levinsohn and Pakes (1995). We include a nest at the lender level, characterized by the nest parameter σ.

Step 6: Regress estimates $\hat{\delta}_{jlm}$ on observable product characteristics to recover $\hat{\alpha}$ and $\hat{\beta}$. Use instrumental variables to solve concerns about price endogeneity and nest parameter (see Identification section below for more details).

Step 7: Use Generalized Method of Moments objective function to estimate parameters $\theta_1 = (\mu^{\hat{q}}, \sigma^{\hat{q}})$ and $\theta_2 = (\lambda, \gamma, \psi)$. For this step we exploit additional bunching moments and variation across lenders and product types (see Identification section below for more details).

6.1.2 Identification

For identification purposes, we can differentiate between linear and non-linear demand parameters. Linear parameters (α, β and σ) are estimated using usual discrete demand methods, as described in Steps 5 and 6 of our estimation strategy. There are two endogeneity concerns. First, interest rates can be correlated with unobservable product characteristics (e.g., quality, advertisement). To address this concern we use a cost-shifter as an instrumental variable for interest rates. In particular, we exploit the regulatory change in banks' capital requirements implemented in Basel III (see Section 4 for more details on the variation we exploit). Second, a lender's own product share is also potentially endogenous. Again, we rely on an instrumental variable approach and use the number of competitors in a market as an instrument.

Non-linear parameters ($\mu^{\hat{q}}$, $\sigma^{\hat{q}}$, λ, γ_{jlm} and ψ) are estimated using Generalized Method of Moments in Step 7 of our estimation strategy. These are the moments we use to identify these parameters:

- For $\mu^{\hat{q}}$ and $\sigma^{\hat{q}}$ we minimize the distance between the observed size distribution of borrowing amounts and the distribution predicted by our model (after accounting for bank steering).

- The quantity distortion λ is identified by the additional mass around \$50K in the distribution of term loan sizes for banks. The intuition is that banks have an incentives to steer firms into larger term loans and firms will bunch at the minimum quantity requirements. See Section 4.2 for additional details on this bunching.

- The additional costs that lenders impose on small term loans (γ_{jlm}) is quantified by comparing term loan amounts offered by banks and non-banks. In particular, we compute the missing mass of banks' distribution for term loans below \$50K.

- The parameter ψ, capturing the disutility of using credit cards for large borrowing amounts, is identified by the difference between credit cards and term loan sizes for non-banks. The intuition is that non-banks are single-product and, therefore, have no incentives to distort firm choices.

6.2 Estimating Supply Parameters

The unknown supply parameters in the model are lender marginal costs for each market-product and cost synergies coefficients (η_1 and η_2). We also do not observe lender steering γ_{jlm}.

6.2.1 Estimation Steps

Our estimation strategy to recover supply parameters follows these steps:

Step 1: We take first-order conditions (hereinafter, FOCs) of lenders' profit functions with respect to lender's choice variables: interest rates and, for banks, also steering (γ_{jlm}). Non-banks have two FOCs per market, one with respect to interest rates for credit cards and another with respect to interest rates for term loans. Two equations to identify two unknown vectors: marginal costs for credit cards and term loans. Banks, on the other hand, have three FOCs per market: two FOCs with respect to interest rates for credit cards and term loans, and an additional FOC with respect to steering. Recall that, because of data limitations, we observe the same interest rate for both small-size and large-size term loans. However, we allow for marginal costs to be different across small- and large-size term loans. Therefore we have four unknown marginal costs vectors: mc^{CC}_{jlm}, mc^{TL}_{jlm}, $mc^{\overline{TL}}_{jlm}$, and mc^{γ}_{jlm}. We also do not observe steering γ_{jm}. At this stage, our system of FOCs is under-identified.

Step 2: We solve the under-identification problem in Step 1 by exploiting our demand estimation strategy. Variation in our data across products between banks and non-banks provides additional micro-moments, allowing us to recover estimates for γ_{jlm} (see Section 6.1). To generate an exactly identified system of equations, we use estimated demand elasticities and $\hat{\gamma}_{jlm}$. We also need to normalize one marginal cost to zero. We chose to normalize mc^{γ}_{jlm}=0, such that banks do not pay a cost for steering. Next, we solve the system of FOCS and recover estimates for mc^{CC}_{jlm}, mc^{TL}_{jlm}, and $mc^{\overline{TL}}_{jlm}$. Intuitively, once we solve the under-identification problem, we are effectively equating marginal revenues to marginal costs, and solving for the latter.

Step 3: We project estimated marginal costs on lender market shares for deposits and mortgages (see Equation 7). We include lender-time to account for time-varying unobserved lender characteristics affecting marginal costs. We also add zipcode-time fixed effects to control for unobserved characteristics of local markets. These regressions provide us estimates of costs synergies η_1 and η_2.

6.2.2 Identification

When estimating cost synergies, we use an instrumental variable approach to address endogeneity concerns of mortgage shares and deposit shares in marginal costs projections. As an instrument for mortgage share we use the share of jumbo mortgages (for each lender at the zip code level) interacted with a lender-type dummy. Similarly, for deposit shares we use as instrumental variable the share of senior depositors (above 65 years for each lender at the zip code level) interacted with a lender-type dummy.

7 Estimation Results

In this section we briefly discuss the estimates of our key parameters after implementing our estimation strategy and taking the model to the data.

7.1 Demand Estimates

Table 7 reports estimates for demand parameters. The estimate for α, capturing the effect of interest rates on product demand, is equal to 0.31. The implied elasticity is 2.62, which is in line with previous estimates for firm credit demand (e.g., Crawford, Pavanini and Schivardi 2018), and lower than the

Table 7: ESTIMATION RESULTS FOR DEMAND PARAMETERS

	α	λ	ψ	$\bar{\gamma}$	σ	$\mu^{\hat{q}}$	$\sigma^{\hat{q}}$
Estimates:	0.31	0.16	1.47	0.23	0.27	9.42	1.36

Note: The table report estimates for parameters in Equation (5) and the estimated mean and variance of the (optimal) loan size distribution.

elasticities found for consumers mortgage demand (e.g., Benetton 2018, Buchak et al. 2018, Robles-Garcia 2019). This result perhaps suggests additional frictions in the less-standardized corporate lending.

The nesting parameter σ is 0.27, which suggest a higher sensitivity between term loans and credit card within banks than other product pairs. Finally, estimated fixed effects for lender types (part of the β parameter) show that firms have a preference for Top 4 lenders, and dislike non-banks relative to other banks, all else equal. We find a positive large effect of the credit card dummy (also part of the β parameter), which captures the popularity of credit cards relative to term loans, all else equal.

We find that the optimal loan size distribution has an average of 9.42 and a standard deviation of 1.36. This is equivalent to an average loan size of $31K and a standard deviation of $71K. The distortion between the optimal and observed loan size distributions is captured by parameter λ, which is equal to 0.16. This estimate implies that getting a loan $1K higher than the optimal amount is equivalent to paying a 50 basis points higher interest rate.

The average steering parameter, γ, is equal to 0.23. The additional costs that banks impose of small term loans generates the same disutility equivalent to a 74 basis points higher interest rates. Finally, the estimate for ψ is 1.47, which confirms that credit cards are not an optimal product when borrowing large amounts. Obtaining a 1% greater loan size through a credit card corresponds to a utility equilivalent 4.74% increase in interest rate. In other words, moving from a $10k to an $11k credit card loan (a 10% increase in size) is equivalent to increasing the interest rate on a credit card from 10% to roughly 15% (a 47 percent increase in rate).

7.2 Supply Estimates

Table 8 reports estimates for marginal costs across lenders and products. Top 4 banks face 9.3 average marginal costs for credit cards, and 1.04 and 4.8 for large and small term loans, respectively. Other banks have a similar cost structure as the Top 4. Average marginal costs for credit cards are 8.2, and large and small term loans have average marginal costs of 0.3 and 4.3. Other banks face lower costs in the market for large loans. Non-banks have average marginal costs for credit cards and term loans equal to 6.2 and 0.94, respectively. On average, non-banks have lower costs for credit cards and term loans. It is important to highlight that Top 4 banks have higher average marginal costs across all

Table 8: ESTIMATES FOR MARGINAL COSTS AND MARK-UPS

	MARGINAL COSTS					MARK-UPS				
	MEAN (1)	SD (2)	P10 (3)	P50 (4)	P90 (5)	MEAN (6)	SD (7)	P10 (8)	P50 (9)	P90 (10)
TOP 4 BANKS										
Credit Cards	9.3	1.5	7.6	8.8	11	3.3	0.41	2.9	3.3	3.9
Large Term Loans	1.04	0.98	-0.43	1.2	2.2	4.7	0.91	3.6	4.5	6
Small Term Loans	4.8	0.81	3.6	4.9	5.6	0.89	0.54	0.29	0.78	1.7
OTHER BANKS										
Credit Cards	8.2	0.43	7.9	8.2	8.6	2.9	0.2	2.7	2.8	3.1
Large Term Loans	0.3	0.82	-0.7	0.21	1.6	4.3	0.62	3.6	4.3	5.2
Small Term Loans	4.3	0.53	3.7	4.2	5.2	0.31	0.25	0.076	0.26	0.56
NON-BANKS										
Credit Cards	6.2	0.37	5.7	6.2	6.6	3.9	0.35	3.6	3.8	4.3
Term Loans	0.94	0.44	0.46	0.74	1.7	3.6	0.064	3.5	3.6	3.7

Note: Columns (1)-(5) report summary statistics of estimated marginal costs. Columns (6)-(10) show summary statistics for estimated mark-ups. Both are computed as rates.

products.

Table 8 also shows estimates for mark-ups across lenders and products. Small term loans are the least profitable product for Top 4 banks with a mark-up of 0.89. Credit cards and large term loans for Top 4 banks have mark-ups of 3.3 and 4.7, respectively. Other banks face similar mark-ups as Top 4 banks. Therefore, both Top 4 banks and other banks have incentives to promote their credit cards and large-size term loans, and discourage firms taking up small-size term loans. On the other hand, non-banks find credit cards and term loans equally profitable.

Table 9 reports estimates for cost synergies. Our estimates show that a large local market share for mortgages reduces the cost of originating both credit cards and small term loans. The effects are statistically significant and large in magnitude. Perhaps surprisingly, we find that a high deposit share has a smaller effect on marginal costs than the share of mortgages. The banking literature has focused mostly on cost complementarities between assets and liabilities (i.e., between loans and deposits). However, our results on costs synergies show that an important component of cost complementarities can originate across different type of assets. In our case, cost synergies are strongest between corporate loans and household mortgages, creating a bridge between household and small business markets via financial intermediaries' multi-product incentives.

Table 9: ESTIMATES FOR SYNERGIES IN MARGINAL COST PROJECTIONS

PANEL A. MORTGAGE SYNERGIES

		CREDIT CARDS		SMALL LOANS		LARGE LOANS	
	1ST STAGE	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Synergies							
Mortgage Share		-0.540^{***}	-1.477^{***}	-0.287^{***}	-0.776^{***}	0.071	0.207
		(0.045)	(0.100)	(0.020)	(0.047)	(0.129)	(0.254)
IVs							
Jumbo × Top-4	1.514^{***}						
	(0.067)						
Jumbo × Other Bank	0.976^{***}						
	(0.072)						
Jumbo × Non-Bank	0.676^{***}						
	(0.063)						
ZIP × TIME FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LENDER × TIME FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.880	0.993	0.990	0.999	0.999	0.820	0.820
OBSERVATIONS	2,061	2,061	2,061	2,061	2,061	2,061	2,061

PANEL B. DEPOSIT SYNERGIES

		CREDIT CARDS		SMALL LOANS		LARGE LOANS	
	1ST STAGE	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Synergies							
Deposit Share		-0.179^{***}	-0.305^{***}	-0.116^{***}	-0.1626^{***}	-0.194^{***}	0.108
		(0.026)	(0.061)	(0.012)	(0.029)	(0.073)	(0.174)
IVs							
Senior × Top-4	0.578^{**}						
	(0.228)						
Senior × Other Bank	2.811^{***}						
	(0.185)						
Senior × Non-Bank	0.330^{**}						
	(0.163)						
ZIP × TIME FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LENDER × TIME FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.762	0.992	0.994	0.999	0.999	0.821	0.809
OBSERVATIONS	2,061	2,061	2,061	2,061	2,061	2,061	2,061

Note: All variables are at the zip code-year level. The dependent variable in Column (1) of Panel A (B) is mortgage (deposit) share of a lender in a zip code. Dependent variables in Columns (2)-(7) are estimates of marginal costs for credit cards, and large and small loans. *Mortgage Share* denotes a lender's share in the mortgage market. *Deposit Share* denotes a lender's share in the deposit market. *Jumbo* refers to the share of jumbo mortgages. *Senior* represents the share of depositors above 65 years. Robust standard errors are in parentheses (with *** p<0.01, ** p<0.05, * p<0.1).

8 Counterfactuals

In this section we use our estimated model to simulate counterfactual scenarios. The results from the demand and supply estimation show that there is an important trade-off from having multi-product banks. On the one hand, banks steer firms to high-markup products, which may not be optimal from the firm point of view and generates quantity and product distortions. On the other hand, the presence of synergies across different products lowers marginal costs for multi-product banks, which are partly pass-through to firms via lower interest rates. Moreover, firms have a preference for multi-product lenders. We aim to quantify these channels with three counterfactual exercises.

We also use our model to explore the role of non-banks and regulation of banks. We simulate: (i) a counterfactual in which we remove the non-banks; and (ii) a counterfactual in which banks have no regulation in this market (that is, they are like non-banks). In the rest of this section we discuss in detail each set of counterfactuals and the key results.

8.1 Removing Steering

In column (2) of Table 10 we explore the equilibrium effects of removing banks' ability to steer firms into higher mark-up products. Removing steering does not change marginal costs for lenders. However, it does generate an heterogeneous response in rates across lender types. Top 4 banks decrease their rates for term loans by almost 10%, while other banks increase their rates for term loans. An interesting result is that, without steering, profits for both Top 4 and other banks increase relative to the baseline. This finding suggests that lenders face a prisoner's dilemma when it comes to steering. Both types of lenders would like to commit not to steer, such that they are both better off in the non-steering equilibrium. However, if one lender unilaterally decide not to steer, it is optimal for its competitors to steer. Firms' surplus increases 1% relative to the baseline. The effect on firm surplus is driven by both a decline in interest rates in term loans by the Top 4 and a better product match (due to lack of steering). Overall, the positive effect on firms' surplus and the gains in lenders' profits result in positive welfare effects. In this counterfactual (and in the remaining ones below), the effects on firm welfare are relatively small. The intuition behind this result is that steered firms are closest to indifferent.

8.2 Removing Cost Synergies

Column (3) of Table 10 shows the equilibrium effects of eliminating synergies for multi-product banks. We implement this counterfactual by setting to zero all the coefficients capturing synergies in Table 8. Eliminating synergies increases marginal costs for credit cards of Top 4 and other banks by over 4% and 8%, respectively. Banks also see an increase in their costs of providing small loans. However, the marginal costs for large loans decreases by almost 4% for Top 4 and 12% for other banks. Both types of lenders pass-through some of this increase in marginal costs for credit cards to

Table 10: COUNTERFACTUALS I: STEERING VS. COST SYNERGIES

	Baseline (1) Level	No Steering (2) %Δ	No Synergies (3) %Δ	Remove Both (4) %Δ	Remove Non-Banks (5) %Δ	Homogeneous Entities (6) %Δ
Bank Steering						
Top 4	0.50	-100%	-41%	-100%	113%	33%
Other Banks	0.19	-100%	-189%	-100%	82%	160%
Marginal costs						
Top 4 Credit Cards	9.28	0.00%	4.26%	4.26%	0.21%	-4.16%
Top 4 Large Loans	2.69	0.00%	0.00%	0.00%	-0.63%	0.32%
Top 4 Small Loans	5.60	0.00%	4.55%	4.55%	-0.25%	-9.21%
Other Bank Credit Cards	8.53	0.00%	8.37%	8.37%	0.09%	-5.08%
Other Bank Large Loans	1.24	0.00%	0.00%	0.00%	-0.93%	0.86%
Other Bank Small Loans	4.40	0.00%	9.07%	9.07%	-0.01	-11.33%
Non-Bank Credit Cards	6.63	0.00%	0.00%	0.00%	–	0.00%
Non-Bank Loans	0.98	0.00%	0.00%	0.00%	–	0.00%
Rates						
Top 4 Credit Cards	12.05	0.07%	1.52%	1.56%	34.00%	-1.40%
Top 4 Large Loans	5.78	-9.67%	-9.21%	-5.79%	-10.19%	-7.83%
Top 4 Small Loans	5.78	-9.67%	-9.21%	-5.79%	-10.19%	-7.83%
Other Bank Credit Cards	11.00	0.08%	4.82%	4.79%	23.97%	-2.97%
Other Bank Large Loans	4.52	8.22%	8.25%	10.73%	-0.39%	-10.63%
Other Bank Small Loans	4.52	8.22%	8.25%	10.73%	-0.39%	-10.63%
Non-Bank Credit Cards	10.03	0.01%	0.05%	0.04%	–	-0.01%
Non-Bank Loans	4.30	0.00%	0.01%	-0.01%	–	0.00%
Lender Profits						
Top 4	11,387	0.09%	-5.11%	-5.03%	32.13%	5.61%
Other Bank	6,457	0.22%	-3.22%	-3.20%	6.76%	2.20%
Non-Bank	4,351	-0.02%	0.01%	0.01%	–	-0.01%
Firm Surplus						
Utility	1.00	0.41%	-0.36%	-0.13%	-84.68%	0.74%

Note: As baseline, we use estimates for markets after 2013 (i.e., post-regulation).

firms via higher interest rates. The effect on interest rates for term loans is, however, heterogeneous across lenders. Top 4 decrease interest rates by 4.5%, while other banks increase them by 8%. Non-banks do not change their pricing strategy substantially. In this scenario, Top 4 and other banks reduce steering by 57% and 236%, respectively. Both lender types have less incentives to steer away from small loans. Profits for Top 4 banks fall by 5%. Other banks are also adversely affected by the removal of synergies with a reduction of almost 3% in profits. Non-banks see their profits increase slightly. Firm surplus falls by 0.36% relative to the baseline. This fall in firm welfare results from worse product matching and higher interest rates.

8.3 Removing Both Synergies and Steering

Column (4) of Table 10 study the effect of jointly removing steering and synergies. In this scenario, higher marginal costs dominate and all lenders increase their rates relative to the baseline. Profits for Top 4 and other banks fall 5% and 2.7%, respectively. Firm surplus decrease by approximately 0.13%, as a result of higher prices. Our results suggest that cost synergies for multi-product firms are more relevant for firm surplus than concerns about multi-product banks steering.

8.4 Removing Non-Bank Competitors

In most of our counterfactual scenarios, prices and market shares of non-banks remain fairly constant. However, non-banks play a key role disciplining banks and preventing them from steering and increasing rates. To quantify this effect, we simulate a counterfactual in which we remove non-banks. Column (5) in Table 10 shows the results. We find that interest rates for credit cards of Top 4 and other banks increase by 34% and 24%, respectively. Rates for term loans go down by 10% for Top 4 and 0.4% for other banks. Both types of lenders incur more steering, with Top 4 increasing steering by 113% and other banks by 82%. The overall effect on firm surplus is an 85% decrease. Profits, on the other hand, increase 32% for Top 4 and 7% for other banks. We find these results consistent with our view that non-banks compete with banks in this market, and we need to account for them.

8.5 Homogeneous Regulation Across Entities

In a final counterfactual we use our model to simulate an equilibrium with banks being "regulated" as non-banks. We assume that the fixed effect associated to the other banks (relative to the excluded category of the non-banks) capture the effect of regulation. We then subtract this fixed effects from the marginal costs of banks and compute the new equilibrium. Column (6) in Table 10 shows results from this counterfactual. Qualitatively, estimates are intuitive. Marginal costs for banks go down, and part of this fall is pass-through to firms via lower interest rates. However, banks are able to capture most of the gains from less regulation. Bank profits increase significantly, more than 5% for Top 4 and 2% for other banks, while firm surplus only slightly. The reason is that banks still have incentives (and the ability) to steer firms to higher mark-up products (independently of regulation).

9 Discussion

Previous work on financial intermediation has emphasized differences in the liability structure of banks and non-banks. This paper highlights the importance of also considering differences on the asset side. In particular, we show that, because banks have wider scope than their competitors, they benefit from cost synergies across different products in their balance sheets. We find that asset-asset synergies are quantitatively more important than deposit-to-loan cost complementarities. Banks also enjoy additional market power (relative to their non-bank competitors), which grants them the ability to steer firms into more profitable products. Counterfactual simulations show that the benefits of wider scope are larger than the potential costs of market power and steering. However, the ability to steer customers may limit the welfare gains for customers following reduction in marginal costs.

A key policy implication of our results is the need for regulation to account for the multi-product nature of financial intermediaries. Policies that regulate credit activities heterogeneously across entities (e.g., banks and non-banks) and product types (e.g., credit cards and term loans) can generate distortions and have unintended consequences in other parts of the banks' balance sheets. For example, in this paper we show that there is a link in a bank's balance sheet between consumer and corporate products via cost synergies. Regulation affecting some products but not others can have significant spillovers into other sectors of the economy through the multi-product lending channel.

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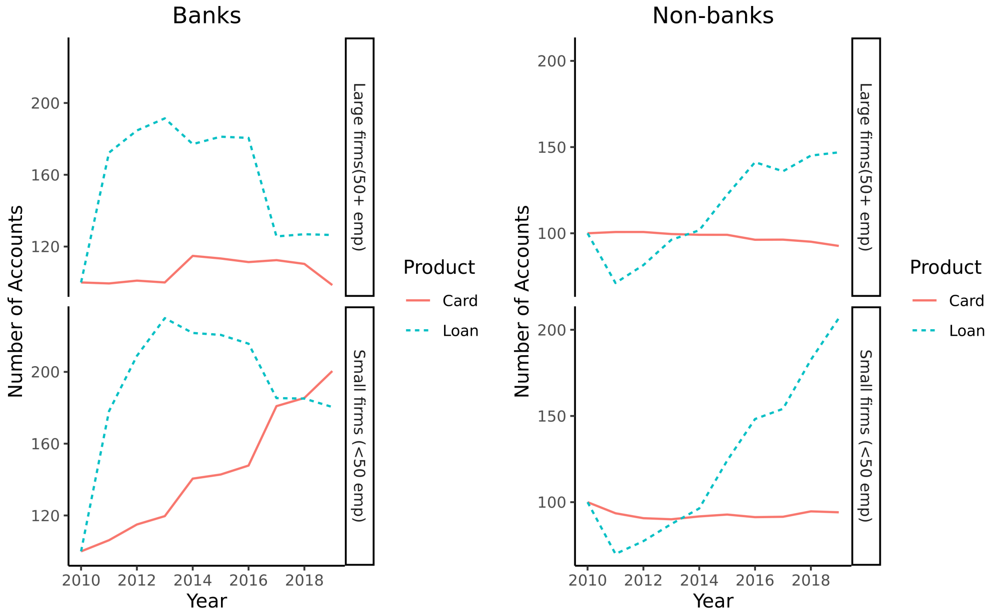
Appendix A Additional Facts

Figure A.1: Lender Specialization By Firm Size



Notes: Similarly to Figure 1, this figure shows the changes in the number of products originated by the largest banks (left plots) and non-banks (right plots) relative to 2010 (normalized to 100). The dashed lines represent term loans, and the solid lines represent credit cards. Top (bottom) graphs illustrate changes for large (small) firms defined as more (less) than 50 employees. We dropped 2008 and 2009 from our sample to avoid noise driven by the aftermath of the financial crisis.