Revolving Credit to SMEs: The Role of Business Credit Cards *

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Abstract

Small businesses in the US rely on business credit cards to meet their financing needs. Using a large dataset from a credit reporting agency we document new facts on firms borrowing via business credit cards: average utilization is almost 30%, is significantly higher for smaller and riskier firms, and is correlated with delinquencies. Simultaneously, interest rates on card balances are twice as high as those on term loans. We develop a structural equilibrium model of firms' demand for credit cards, their utilization, and their default choice, accounting for correlation between ex-post utilization and default, as well as bank competition with non-banks. Our model helps rationalize firms' demand for card borrowing as a hedge against cash flow volatility, and enables us to evaluate whether the high rates charged on cards reflect a high cost of lending due to the correlation of utilization and delinquency or high markups. Our estimation suggests high rates primarily reflect the latter. In counterfactual analyses, we explore the provision of business credit cards under stress scenarios featuring concurrent increases in firms credit card utilization and lenders costs. We find that absent large shocks to funding costs, lender profits increase as increased revenue through higher utilization more than offsets the accompanying increases in delinquency and lending costs. Finally, we use the model to explore the equilibrium impact of proposed bank capital rules that add a portion of undrawn credit card balances to bank risk-weighted assets. Such rules tend to reduce bank credit provision, push lending outside the regulated banking sector, while modestly decreasing firm surplus, especially among the smallest, most card-dependent firms.

Keywords: Small business lending, credit cards, revolving credit, market power, liquidity, competition, capital regulation.

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1 Introduction

Access to external finance is a key determinant of firms ability to invest, grow and create jobs. However, binding financial constraint and the lack of credit availability are a pervasive phenomenon, especially for the smallest businesses (Evans and Jovanovic, 1989; Whited and Wu, 2006; Rauh, 2006; Adelino et al., 2017). The tightening of bank lending standards after the global financial crisis has further limited financing options for small businesses (Bord et al., 2018; Chen et al., 2017), which have increasingly obtained loans from non-bank financial intermediaries (Gopal and Schnabl, 2020).

We focus on firm external financing obtained through business credit cards. In contrast to conventional wisdom that business credit cards are primarily a transaction product, they represent an important source of external finance for small businesses in the US.[1] The 2023 Small Business Credit Survey of the Federal Reserve Bank asked small businesses *"Which of the following forms of financing, if any, does your business regularly use or carry an outstanding balance on?"*[2] As shown in the left panel of Figure 1, more than 55% of respondents indicate that they borrow through business credit cards. The second most popular product is a term loan (53%), followed by credit lines (34%). It also also worth nothing that only 13% of the businesses respond that they do not use external financing. That is: most small businesses access external financing, and business credit cards is the dominant financial product through which they do it.

Business credit cards are particularly important for the smallest firms. The right panel of Figure 1 shows the response to the same question broken down by the size of the respondent measured by the number of employees. For the smallest firm (less than 5 employees) credit cards are the most important source of external financing, while credit lines have a much smaller share. Credit cards have a similar role for firms with less than 20 employees, with their importance declining as firm size increases. On the other hand, term loans—and even more so credit lines—become more relevant as sources of external finance for larger firms. As a result, while the typical large firm borrows via term loans and/or draws down on credit lines, the typical small firm borrows via term loans (even if to a lower extent than larger firms) and/or draws down on credit cards.

An important feature of revolving credit like credit cards or lines of credit is that ex-ante, the lending relationship creates the right to draw on the line ex-post. This contractual feature potentially makes a revolving credit product like a credit card expensive for lenders provide because utilization and delinquency may be positively correlated ex-post. This positive correlation may arise either due to ex-ante adverse selection, wherein firms that are observably riskier are also more likely to demand more credit, or due to ex-post shocks, where a negative shock to the firm's business may induce it to

[1] According to a study by the Chase institute *"In 2019, there was $368 billion in small business commercial and industrial loans outstanding, and over 46 percent of this amount was for loans less than $100,000. The majority of loans in this size category were small business credit cards (U.S. Small Business Administration 2020)."* (https://www.jpmorganchase.com/institute/all-topics/business-growth-and-entrepreneurship/small-business-use-of-credit-cards). For additional evidence on the role of credit cards as the primary source of funding for small businesses in the US for 2023. (https://quickbooks.intuit.com/r/small-business-data/index-annual-report-2023/).

[2] Respondent can choose all options that applies to them.

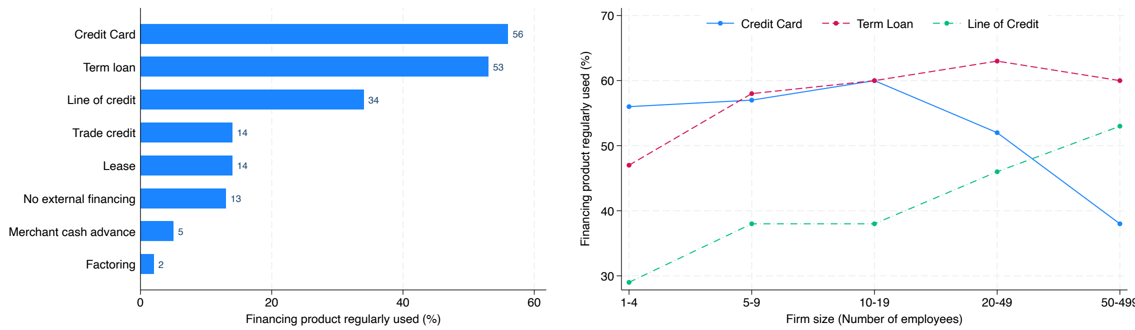

Figure 1: CREDIT CARD AS SOURCE OF EXTERNAL FINANCING FOR (SMALL) BUSINESSES
Note: The left panel shows the response to the following question from the 2023 Small Business Credit Survey of the Federal Reserve Banks: "Which of the following forms of financing, if any, does your business regularly use or carry an outstanding balance on?" The right panel shows the response to the same question broken down by firm size and only reports the three most popular products: credit cards, term loans, and credit lines.

engage in short-term borrowing to make up for cash flow shortfalls and ultimately cause an inability to repay what it borrows. The resulting correlation between utilization and delinquency means that the contract obligates the lender to provide credit precisely in the states of the world in which it is least likely to be paid back. In anticipation, these products may therefore be very costly for lenders to provide. While in our paper we do not attempt to separately identify whether this correlation arises from ex-ante adverse selection or ex-post correlated shocks, the resulting correlation, which we refer to as correlated utilization and delinquency, may drive many of the dynamics in this market.

With this survey evidence as motivation, our paper provide the first in-depth, firm-level analysis of the use of business credit cards as borrowing products.[3] Utilizing data from a business credit reporting agency, we begin by documenting new empirical evidence around business credit card limits, utilization, performance, and pricing. With these facts as motivating evidence, we develop and estimate a structural model in which firm demand credit cards, utilize them for borrowing, and potentially default. On the supply side, banks and non-banks set interest rates to maximize profits, accounting for default risk and correlated utilization and delinquency.

Our model helps rationalize why small businesses rely on credit cards for financing. We find evidence that, similar to the literature on credit lines, e.g., Greenwald et al. (2020) and DeMarzo and Fishman (2007), firms use business credit cards in order to hedge cashflow volatility. Additionally, we use our model to examine whether the high rates lenders charge reflect costs attributable to adverse selection, or merely high markups. We find that while credit card utilization is correlated with default, making this type of revolving credit expensive for lenders to provide, this force alone is insufficient to explain the high rates charged on cards. Rather, markups appear to explain the majority of high rates.

We next use our model to examine several counterfactuals. We first study how simultaneous shocks to borrower demand, delinquency, and lender funding costs, e.g., shocks approximating COVID-19 or the 2008 global financial crisis, impact firm borrowing and lender profitability. We

[3]We largely set aside the role of credit cards as transaction products.

find that due to high markups, lenders tend to benefit from these shocks even when accompanied with increases in default. Increased utilization, however, can be costly to the lender if is accompanied by large negative shocks to bank funding costs, which was the case during the 2008 crisis but less-so during COVID-19. Finally, we examine the counterfactual impact of new capital requirements under Basel III "Endgame" which add a portion of card borrowers' undrawn limits to risk-weighted assets. We find that rates increase, demand and utilization decrease, particularly among banks, who experience large losses in profits. Overall, firm surplus declines by roughly 3.85%, with stronger declines among the smallest firms that are most reliant on credit cards as a source of external financing.

Our paper begins by utilizing a large, borrower-level business credit panel between 2014 and 2019. Our dataset has three key advantages over existing, commonly used data considering small business borrowing. First, unlike Y-14Q data, our data shows credit relationships for the *very smallest* firms, with a median borrowing limit of $16,000 and an average credit card utilization of around 26%. As shown in Figure 1, observing the behavior of very small firms is critical in understanding the importance of business credit cards as a source of firm financing. Second, the scope of our data extends to all firms and lenders, and not only the highly selected sample of firm that, e.g., borrow through the SBA, or with banks, e.g., as would be reported in the Y-14 data. Finally, unlike public data recording secured transactions, our data allows us to observe not only the existence of a lending relationship, but also its size, utilization, and ultimate performance.

With this data, we first present four motivating facts around business credit card lending. First, we document that the average limit on business cards is roughly $16 thousand with an average utilization rate of around 26%. The distribution is highly bimodal, with a mass of firms carrying zero balances and using the cards for transactions only, while a large fraction of firms report positive balances and often max out their credit limits. Additionally, smaller firms and riskier firms have lower limits but higher utilization on average. Additionally, firms in industries that have higher cash flow volatility have higher limits and higher utilization rates, suggesting that firms obtain business credit cards partially to hedge cashflow risk. On the supply side, we find that banks, as opposed to non-banks, provide greater limits and bank borrowers have greater utilization rates. This finding is in line with the findings Hanson et al. (2015) on banks' advantages in providing credit lines due to their access to cheap, stable funding.

Second, we document that the average 60+ day delinquency rate on business credit cards is roughly 1.5% over our time sample. We document that small firms, risky firms, and firms in industries with higher cash-flow volatility have higher delinquency rates. Importantly, we find that delinquencies increase monotonically with credit card utilization, and that unobserved factors that drive credit card utilization are positively correlated with unobserved factors driving credit card delinquency. This last relationship provides evidence suggestive of asymmetric information or exposure to correlated ex-post shocks. For example, the evidence is consistent with the idea that firms, obtaining a credit card, may receive a negative demand shock which prompts the firm to borrow on the card in the short term while being ultimately unable to repay the balance. This relationship hints that business credit cards may be a particularly expensive product for lenders to provide, because ex-post, the states of the world in which firms are most likely to borrow are the states of the world in which firms are least likely to be able to repay.

Third, we examine credit card pricing. As is commonly the case with credit panels, we do not directly observe interest rates, so we supplement our data with branch-level product pricing from RateWatch. Utilizing this data, we document that the average interest rate is roughly 13%, which is significantly higher than the average rate charged on term loans during the same time period. While we do not directly observe interest payments, external sources confirm that 30-50% of card users carry outstanding balances on which they pay interest.[4] We then present evidence that credit card pricing is roughly uniform within lender:[5] The majority of variation in rates is across lenders, followed by variation over time. Variation across geographical markets is fairly small.

Finally, putting the facts around utilization, delinquency, and rates together, we examine the net interest income coming from credit card borrowers. We find first that the median net interest income, accounting for delinquency, is positive across all (non-zero) ranges of utilization. As greater utilization implies larger balances on which to charge interest, we find that net interest income increases with utilization until approximately a utilization rate of 75%, after which point the net interest income decreases as delinquency rates rise. However, the median firm with a 100% utilization rate still generates a positive net interest income for lenders. Across the risk spectrum, we find an inverse-U shape in median net interest income. Very low-risk firms generate a low net interest income because they tend to carry near-zero balances. Very high-risk firms generate a low net interest income because while they carry high balances, they are highly likely to be delinquent in their payments. Medium risk firms generate high net interest incomes because they carry high balances but still have low delinquency rates.[6]

These facts raise a number a questions. First, why, despite their high rates, do small firms borrow with credit cards? Our results are consistent with literature considering the role of credit lines in firm borrowing, namely, that firms obtain revolving credit in order to insure against future cashflow risk. This is consistent with our findings relating firm credit limits and utilization to industry cashflow volatility.

Second, why are credit card interest rates so high? One explanation is that a revolving credit line is a particularly expensive form of credit to provide to very small firms. Another explanation is that lenders exercise significant market power and are therefore able to charge high markups. The

[4] See https://www.jpmorganchase.com/institute/all-topics/business-growth-and-entrepreneurship/small-business-use-of-credit-cards and https://www.indinero.com/wp-content/uploads/2016/02/Access-to-Capital-Survey.pdf.

[5] This provides comfort that our branch-level pricing data accurately captures the rates that borrowing firms actually pay.

[6] This mirrors the results for consumers in Agarwal et al. (2015), where the highest risk (lowest credit score) consumers earn close to zero net profits due to high charge-off rates, high-to-moderate risk consumers are the most profitable with high balances and moderate charge-offs, and moderate-to-low risk consumers providing little interest income because they carry low balances. Their paper also measures interchange fee income, which makes higher-credit score consumers (who are mostly transactors) once again become profitable.

unconditional default rate on credit cards is 1.5%, which appears on its face insufficiently high to give rise to the large cost difference between credit cards and term loans observed in the data. However, as our motivating facts show, there is a strong correlation between utilization and default, likely arising out of adverse selection or ex-post common shocks. Given this relationship, it is plausible that the delinquency rate on high-balance cards is high enough to explain the interest rate on balances without there being high markups, but this remains a quantitative question.

Third, are lenders who have extended credit cards negatively exposed to an aggregate shock, similar to the global financial crisis or COVID-19 where simultaneously, (1) credit card utilization rises, (2) credit card delinquencies increase, and (3) bank funding costs increase? The concern is that having set out borrowing terms ex-ante, when such a shock occurs, will small firms draw down their credit card limits and become delinquent more in expectation, thus causing lenders to lose money precisely when they are most vulnerable? As above, the extent to which such a shock increases utilization (positive for banks) while increasing funding costs and delinquencies (negative for banks) is a quantitative one.

To directly address the second and third questions, we develop a model to explicitly account for the interaction of utilization and default as well as the industrial organization of lending to small business. Our model expands on standard IO models of financial intermediation and is similar to Crawford et al. (2018). In our model, firms make a discrete choice among differentiated credit card offers and the outside option of a term loan. Having made their discrete choice, firms choose their utilization rate and whether or not to default on the card. Importantly, the utilization and default decision are driven by correlated shocks, which allows our model to capture the idea that firms may be exposed to negative shocks that both lead them to borrow more to cover cash-flow shortfalls while simultaneously being unable to repay what they borrow.

Taking demand as given, lenders set borrowing rates to maximize expected profits. As lenders are differentiated from the point of view of borrowers, lenders are able to extract markups. Additionally, as the utilization and default shock occur after the lending relationship is formed, lenders cannot contract on these shocks and instead must set pricing ex-ante in anticipation of them occurring. In that way, these correlated shocks enter the lender's ex-ante pricing decision.

We estimate the model from the same microdata that generated our stylized facts. As in the reduced form data, there is a significant correlation between credit card utilization and delinquency, and this correlation partially explains why credit card interest rates are so high. However, we find that the majority of the rates are attributable to high markups. Intuitively, borrowers appear to be relatively insensitive to credit card rates, either because they do not expect to utilize the cards for borrowing, or because other contractual features (e.g., points or rewards) are more salient when borrowers are making their card decision.

With the estimated model, we explore a number of counterfactual analyses. In a first set of counterfactuals, we examine the profitability implication of shock inducing firms to draw down their credit card limit in times of overall market stress. We find that even after accounting for default increasing by 3pp (more than two times the baseline default rate), there is a much larger increase in interest income, on the order of 20% due to increased utilization. A shock like COVID- 19 which might increase utilization, but with limited impact on bank costs and default, is very profitable for banks. Intuitively, shocks that increase utilization dramatically increase the profitability of lending directly by increasing the size of balances on which interest is collected, and marginally increasing defaults does not offset this effect. A shock like 2008, in contrast, which caused greater increases in bank funding costs and default has a much more negative impact on bank profitability, first because the net interest spread between fixed credit card rates and adjustable funding costs narrows, and second because defaults directly decrease the size of the interest repayments.

In a second set of counterfactuals, we explore a proposed change in the capital regulation of undrawn balances. The proposal (often refereed to as Basel III "Endgame,") plans to link capital risk weights to the manner in which the customers use the credit cards. Most notably, we study the equilibrium effect on prices, demand, default, lenders profits and firms welfare of introducing a credit conversion factor (CCF), which effectively treats a portion of the undrawn balance as though it were partially drawn. We find that rates increase, demand and utilization decrease, particularly among banks, which loose market shares to non-banks. Hence, while the policy proposal improves banks capital position if a *potential* credit exposure becomes a *realized* one, this risk is shifted to non-banks. Overall, banks profits decline by almost 9% and firm surplus declines by roughly 3.85%, as a result of higher credit card, with stronger declines among the smallest firms that are most reliant on credit cards as a source of external financing.

Related Literature. Our paper is mostly related to the growing literature studying with a combination of granular micro-data and structural modelling the role of frictions, market structure and regulation in retail financial markets. Recent papers have studied markets for retail deposits (Egan et al., 2022; Xiao, 2020; Albertazzi et al., 2022), insurance (Koijen and Yogo, 2016; Barbu, 2022), mortgages (Buchak et al., 2018a; Benetton, 2021; Benetton et al., 2021; Robles-Garcia, 2022), personal loans (Cuesta and Sepúlveda, 2021), corporate lending (Crawford et al., 2018, Ioannidou et al. (2022)), and consumer credit cards (Nelson, 2018; Galenianos and Gavazza, 2020; Matcham, 2022).

Our structural model is closest to Crawford et al. (2018), who study corporate lending in Italy, and Matcham (2022), who studies consumer credit cards in the UK. In contrast to both papers, we focus on business credit cards in the US. Furthermore, in counterfactual analysis we explore the effect of concurrent increases in business credit card utilization and lenders costs, similar to the ones observed in the global financial crisis and the Covid-19 pandemic, as well as proposed changes in bank capital regulation to risk-weight undrawn balances via a credit conversion factor. Given these counterfactual analyses, our paper speaks to both the recent literature on the role of credit line drawdowns during crises (Acharya et al., 2023, Cooperman et al., 2023, Greenwald et al., 2020) and the large literature on the effects of risk-weighted capital regulation on credit provision and the substitution between banks and non-banks (Behn et al., 2016; Jiménez et al., 2017; Buchak et al., 2018b; Irani et al., 2021).

Finally, our paper related to the large literature studying credit cards as borrowing products. The majority of this literature has focused on consumer credit cards, due to data availability.[7] Notable exceptions that study business credit cards are Agarwal et al. (2015), who consider business credit cards as the not-treated group in a difference-in-difference of regulation of consumer credit cards; Berger et al. (2022), who studies the role of relationship lending for both both term loan and business credit cards; and Fonseca and Wang (2022), who study the substitution between personal and corporate credit. We complement this works by: (i) providing novel facts on business credit cards limits, utilization, and delinquencies; and (ii) developing a structural model of firms demand for credit card, utilization and default choice, accounting for possible adverse selection/correlated shocks, as well as for banks competition with non-banks.

2 Setting and Data

2.1 Setting

We briefly discuss some important aspects business credit cards in the US.

Product characteristics. Business credit cards, like consumer credit cards, are complex products with many features. Ru and Schoar (2016) use granular data on consumer credit card offers and document the presence of multiple attributes such as rewards, low introductory teaser rates, different interest rates for different uses, and late fees. Additionally, they highlight how lenders both highlight attractive features and hide unattractive features. Our analysis abstracts from most of this complexity to focus on credit card limits and imputed card rates for purchases, as we discuss below. While we therefore miss some of the product characteristic richness, the strength of our data lies in our ability to observe credit card limits, utilization, and performance, for a large sample of small and medium sized businesses.

While a more in-depth analysis of businesses choice of credit cars exploring the multi-dimensionality of the product is a promising area for future research,[8] given our focus on business credit cards as a source of external finance rather than on a transaction product, the combination of limit, balance, delinquency and APR is likely to capture the main characteristics of interest. For example, Stango and Zinman (2016) show that for consumer credit cards the balance-weighted APR constitutes more than 80% of borrowing costs.

Lenders of business credit cards have a claim against the assets of the business, and therefore, there is limited liability by default against the business owner. However, business credit cards will

[7] See Ausubel (1991), Gross and Souleles (2002), Stango and Zinman (2016); Nelson (2018), Gathergood et al. (2019), Keys and Wang (2019), Galenianos and Gavazza (2020), Kuchler and Pagel (2021), Grodzicki (2023) among many others.

[8] Such a dataset would require to match a dataset on business choices – similar to the one we use in this paper – with a dataset containing the full set of products offered to each business with their detailed characteristics. For an example of such a dataset see Han et al. (2018) on consumer credit cards.

often require a personal guarantee.[9] This personal guarantee will often not encompass the entirety of the guarantor's assets, and so in comparison to a personal credit card, business credit cards—even those with a personal guarantee—typically offer a limited form of limited liability. In a similar spirit, business credit bureaus sometimes report business credit card activity on personal credit reports, although these reporting practices vary across lenders.[10] Hence, delinquencies on business credit cards can both become the personal liability of the owner-operator as well as affecting his or her personal credit score.

Regulation. With respect to borrowers, business credit cards do not benefit from the same level of borrower protection as do personal credit cards. For example, the Credit Card Accountability Responsibility and Disclosure Act of 2009 does not cover small business credit cards (Agarwal et al., 2015). Similarly, the Truth in Lending Act only applies to business cards in limited situations. Specifically, only the provisions regarding the issuance of credit cards and liability for unauthorized use apply to credit cards with a business purpose. Like consumer credit cards, there are no interest rates limits, and state-based usury laws generally do not apply.

From the credit card providers' side, business credit card portfolios are subject to risk-weighted capital requirements. Following the 2017 Basel framework, for credit cards holders that are transactors—customers that pay their balance in full at each scheduled repayment date—the risk-weight is 45%. In contrast, for credit card holders that maintain balances and meet certain eligibility criteria (e.g., aggregate limit below $1 million), the risk-weight is 75%. A 2023 proposed changed to the Basel framework would raise both risk weights by 10 percentage points and add a 10% credit conversion factor (CCF) on undrawn credit.

Financing. Most lenders finance credit cards using a combination of on-balance sheet financing and securitization. Many large banks, such as JPMorgan Chase, Bank of America, and Wells Fargo, hold a significant portion of their credit card receivables on their balance sheets. This approach allows them to earn interest income and fees while maintaining control over the customer relationship and managing credit risk internally. Other banks, such as Citigroup, Capital One, and Discover make more extensive use of securization of credit card receivables. For example, Citigroup has issued asset-backed securities (ABS) backed by credit card receivables through its Citibank Credit Card Master Trust since 1988; Capital One uses the Capital One Multi-asset Execution Trust (COMET); and Discover engages in securitization of its credit card receivables through its Discover Card Execution Note Trust (DCENT).[11]

[9] As an example for the personal liability on a Chase business credit card see: https://sites.chase.com/services/creatives/pricingandterms.html/content/dam/pricingandterms/LGC56288.html. There are some business cards not requiring personal guarantees (See: https://www.bankrate.com/credit-cards/business/business-credit-cards-with-no-personal-guarantee/) and corporate cards issued to a corporation with significant assets and credit history also do not require personal guarantees.

[10] See: https://www.bankrate.com/credit-cards/business/how-does-my-business-credit-card-impact-my-personal-credit-score/.

[11] See https://www.citigroup.com/global/investors/fixed-income-investor-relations/credit-card-securitization for Citi-

2.2 Data

The primary dataset for our analysis is from a major US commercial credit reporting bureau on bank-firm credit relationships from 2014 to 2019. The bureau collects information from participating lenders on their lending relationships with firms.[12] The data has a panel structure, with information on firms' credit products over time, with snapshots every six-months. The dataset covers both banks and non-bank lenders, and includes information on term loans, credit cards, lines of credit, and leases. For each period-firm-lender type-product pair, we observe the number of trades (how many open accounts there are), total balances, limits, and whether the balance is greater than 60 or 90 days delinquent. At the firm-time level, we observe firm characteristics such as its zip code, a proprietary risk-score (analogous to FICO for consumers), the age of the firm, and the number of employees.

Table 1 shows summary statistics for our key variables. The average (median) firm has, on average, 1.3 (one) product for each snapshot. The average limit is $25 thousand, with a minimum of zero[13] and a maximum of about $180 million, while the average balance is about $10 thousand. The fraction of delinquent firm is about 1.8% and the average risk score is approximately 64 (out of 100, with 100 being the safest).[14] The provider defines high-risk firms as those having a risk score less than or equal to 25. 14% of firms are high risk. Roughly 70% of firms in our sample have fewer than 10 employees, and only 5% have 50 or more employees. As these statistics demonstrate, an advantage of our data is its coverage of credit relations of *very* small businesses. Greater than 80% of bank-firm relationship are credit card relationships rather than term loans or other products. Finally, highlighting another advantage of our dataset in contrast to data that reports only bank lending, about 35% of bank-firm relationship are from non-bank lenders.

We also report a measure of firm cash flow volatility, which we construct following the standard approach in Bates et al. (2009). For each firm-year, we compute the standard deviation of cash flow to assets for the previous 10 years and then average the firm cash flow standard deviations each year across each two-digit SIC code. The average cash flow volatility is about 0.04, with a standard deviation of 0.02.

Panels B and C of Table 1 report key variables for credit card and term loan relationships specifically. The average credit card limit is about $16 thousand, with a minimum of zero and a maximum of roughly $100 thousand. The average balance is about $3.8 thousand. The average utilization rate of credit cards is about 26%. The fraction of delinquent firm on credit card is about 1.6%. While outside evidence on business credit cards is relatively limited, we can compare our data to work based

group; https://investor.capitalone.com/abs-reporting/capital-one-multi-asset-execution-trust-comet for Capital One; and https://investorrelations.discover.com/investor-relations/debt-investors/discover-credit-card-abs-reporting/default.aspx for Discover.

[12] According to the data provider, the set of reporting lenders covers most of the relevant market. We discuss how moments of the variables in our data compare to the same moments from other data sources covering business credit cards (e.g., the Federal Reserve's supervisory Y-14M dataset) below.

[13] Likely reflecting closed or temporarily revoked lines.

[14] Unlike FICO scores, which fall between 300 and 850, this proprietary business risk score is reported on a 1-to-100 scale.

on confidential data from a sample of bank lenders in Berger et al. (2022). Our average limit of \$16 thousands and delinquency rate of 1.6% are in line with Berger et al. (2022), which report \$14 thousand and 1.6% for average limit and delinquency respectively.[15] Our data show higher average utilization than in Berger et al. (2022), which report average utilization on business credit cards of 4%, but our average and median utilization rates are in line with evidence for consumer credit cards (Gross and Souleles, 2002; Han et al., 2018; Fulford and Schuh, 2024).[16]

Term loans comprise about 19% of the bank-firm relationships. As expected, the average limit on a term loan is higher than on a business credit card, at about \$75 thousand. Reported balances (and therefore utilization) for term loans decreases over time as the firm repays the loan. The fraction of delinquent firm on term loan is about 2.4%.

Panels D and E of Table 1 report key variables for banks and non-banks focusing on credit cards only. Some notable differences between the two types of credit card providers stand out. First, bank-firm credit card relationships have higher limits on average (\$19 thousand for banks vs \$9 thousand for non-banks) as well as higher balances (\$5 thousand for banks vs \$1 thousand for non-banks). Second, as a result of a relative larger gap in balances compared to limits, banks have somewhat higher utilization. Average credit card utilization is approximately 27% for banks and about 23% for non-banks. Third, delinquencies on credit cards are similar for banks and non-banks.

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. We discuss the variation in this data in relation to our facts in Section 3.

[15] See Table 1 panel B for credit limits and Table B3 Panel B2 for delinquencies in Berger et al. (2022).

[16] See Table 1 panel B in Berger et al. (2022), Table 1 in Han et al. (2018), and Figure 1 in Fulford and Schuh (2024).

Table 1: SUMMARY STATISTICS

	Observations	Mean	Std. Dev.	Minimum	Median	Maximum
Panel A: Full sample						
Number	11,914,594	1.28	0.55	1.00	1.00	3.00
Limit ($.000)	11,914,594	25.63	109.35	0.00	13.13	180,000.00
Balance ($.000)	11,914,594	10.93	71.27	0.00	1.21	90,000.00
Utilization (%)	11,914,594	31.81	35.09	0.00	15.34	100.00
Delinquency (%)	11,914,594	1.84	13.44	0.00	0.00	100.00
Risk-score	11,914,594	63.79	27.41	1.00	70.00	100.00
Risk: High	11,914,594	0.14	0.35	0.00	0.00	1.00
Risk: Medium	11,914,594	0.15	0.36	0.00	0.00	1.00
Risk: Low	11,914,594	0.71	0.46	0.00	1.00	1.00
Employees: 1-9	11,914,594	0.69	0.46	0.00	1.00	1.00
Employees: 10-49	11,914,594	0.25	0.44	0.00	0.00	1.00
Employees: 50+	11,914,594	0.05	0.22	0.00	0.00	1.00
Credit card	11,914,594	0.80	0.40	0.00	1.00	1.00
Non-bank	11,914,594	0.35	0.48	0.00	0.00	1.00
Cash-flow volatility	11,914,594	0.04	0.02	0.01	0.04	0.10
Panel B: Credit card						
Limit ($.000)	9,572,421	15.72	16.23	0.00	10.70	100.00
Balance ($.000)	9,572,421	3.81	7.71	0.00	0.73	100.00
Utilization (%)	9,572,421	25.97	32.34	0.00	10.15	100.00
Delinquency (%)	9,572,421	1.56	12.38	0.00	0.00	100.00
Panel C: Term loans						
Limit ($.000)	1,932,151	74.31	123.09	0.00	39.35	1,200.00
Balance ($.000)	1,932,151	45.40	94.18	0.00	21.26	1,200.00
Utilization (%)	1,932,151	60.02	34.10	0.00	66.67	100.00
Delinquency (%)	1,932,151	2.43	15.41	0.00	0.00	100.00
Panel D: Credit card - Banks						
Limit ($.000)	6,441,535	19.16	17.75	0.00	14.85	100.00
Balance ($.000)	6,441,535	5.03	8.84	0.00	1.46	100.00
Utilization (%)	6,441,535	27.15	31.54	0.00	12.96	100.00
Delinquency (%)	6,441,535	1.57	12.42	0.00	0.00	100.00
Panel E: Credit card - Non-banks						
Limit ($.000)	3,130,886	8.66	9.11	0.00	6.00	100.00
Balance ($.000)	3,130,886	1.32	3.46	0.00	0.24	100.00
Utilization (%)	3,130,886	23.53	33.79	0.00	6.14	100.00
Delinquency (%)	3,130,886	1.54	12.30	0.00	0.00	100.00

Note: The Table shows the results the main variable from a major US commercial credit reporting bureau on bank-firm credit relationship. Panel A reports summary statistics for the full sample; Panel B for credit cards; and Panel C for term loans. Panel D and E report data for credit cards only. Panel D for bank lenders; and Panel E for non-bank lenders.

3 Facts On Business Credit Cards

In this section we exploit our rich data to document several facts about business credit card limits, utilization, default, pricing, and profitability.

3.1 Credit Card Accounts, Limits, and Utilization

We begin by documenting patterns in business credit card limits and utilization. Beginning with the extensive margin of whether a firm has *any* credit card relationship, we estimate a linear probability model regressing whether a firm has a credit card on firm observables. The coefficients, presented in Figure A2 in the online appendix show that smaller firms and firms with higher cash flow volatility are more likely to have credit cards. This confirms the earlier intuition that credit cards serve a cash flow hedging need for small firms, playing similar role to credit lines for larger firms.

Turning to the intensive margin, Figure 2 shows credit card limits (left panel) and utilization (right panel). As the figure shows, the average business credit card limit is about \$16 thousand. The vast majority of business credit cards have limits below \$20 thousand. The distribution is somewhat skewed, with the median limit is roughly \$11 thousand and the 75th percentile is roughly \$21 thousand. The distribution of credit card limits shows some bunching at salient round numbers such as 5, 10, 20, 25, 50 and 100.

In terms of utilization, shown on the right panel, the average utilization rate (balance divided by limit) of business credit cards is about 26%. Again, the distribution is highly skewed, with the median utilization rate being roughly 10%. This utilization rate is comparable, though somewhat higher, than firm credit line utilization, whose long-term average stands around 17% (Acharya et al., 2023). A possible explanation of this higher utilization rate relative to credit lines is that, consistent with Figure 1, smaller firms use credit cards, and these firms possess fewer alternative sources of external finance.

There is a large fraction (slightly above 25%) of observations with zero utilization and a small fraction (slightly above 5%) of observations with 100% utilization. More than 25% of firms have more than 40% utilization. The bimodal distribution of utilization with peaks at 0% and 100% is in line with the dual function of credit cards as a payment and a credit product. While we do not directly observe revolving balances on which borrowers pay interest, our result on utilization resemble the fact that a sizable share of (especially small) businesses consistently revolve credit card balances.[17]

We next study what drives the variation in business credit card limits and utilization? We begin by exploring the role of firm size and risk. Figure 3 shows average credit card limits (left) and utilization (right) by firm employment. The figure shows that credit card limits increase with firm size group up to up to firms with 50-99 employees, and decline thereafter. The average credit card limit for firms with fewer than 5 employees is less than \$15 thousand, and increases to roughly \$17.5 thousand for firms with 50-99 employees. The decline in credit card limit for firms with 100 or more employees may reflect a substitution into other products, e.g., credit lines, for borrowing purposes rather than credit cards. This interpretation is consistent with the relationship between balances and firm size shown in the left panel of Figure A3 in the Appendix. As this figure shows, credit card balances

[17]See for example the report from the JPMorgan Chase Institute here: https://www.jpmorganchase.com/institute/all-topics/business-growth-and-entrepreneurship/small-business-use-of-credit-cards.

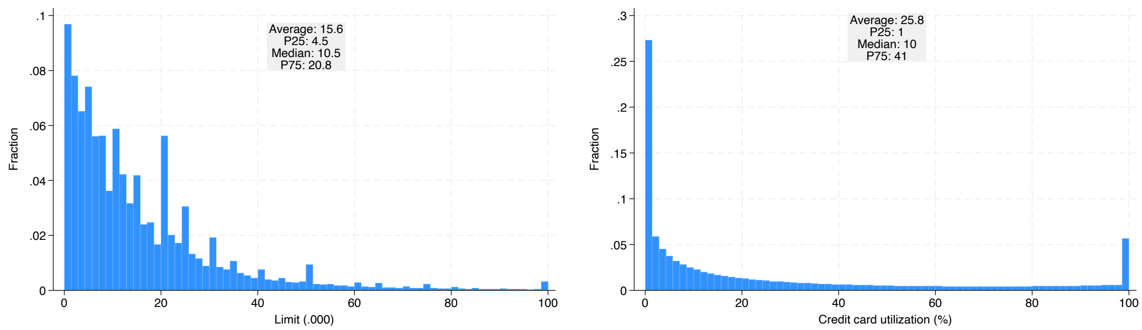

Figure 2: CREDIT CARD LIMIT AND UTILIZATION
Note: These figures show credit card limits (left) and utilization (right). They also report average, 25th percentile, median and 75th percentile of limit and utilization.

increase with firm size, reaching a peak for firms with 10-19 employees before declining for larger firms.

In consequence, the while there is a strong positive relationship between firm size and credit limit, the relationship is much weaker for card balances. For example, the average limit for a business with 50-99 is almost \$3 thousand larger than the average limit for a business with fewer than 5 employees, which corresponds to an almost 20% increase relative to the average limit. In contrast, the average balance for a business with 50-99 employees is only about \$400 larger than the balance of a business with fewer than 5 employees (\$4 thousand vs \$3.6 thousand). This difference corresponds to only a 4% increase relative to the average balance.

The right panel of Figure 3 shows that utilization monotonically decreases with firm size. For firms with fewer than 10 employees, representing roughly 70% of the observations in our data, the average utilization is more than 26%. Moving to firms with 10 to 49 employees, the average utilization rate declines to about 24% and drops even further, to below 23%, when looking at firms with 100 or more employees. This stark pattern is in line with credit cards being an important borrowing product particularly for smaller firms with less alternatives available (e.g., credit lines, terms loans, or capital markets).

Next, we explore the relation between firm risk, captured by the proprietary risk-score, and credit limits (utilization) in the left (right) panel of Figure 4. The riskiest firms have the lowest credit limit. For example, firms with a risk-score between 1 and 5 (the highest risk bin) have an average limit of about \$8 thousand. The limit increases with an improving risk score. Firms in the high-medium risk category have an average limit of roughly \$14 thousand. Upon reaching the medium risk category—a risk score of roughly 30—the average limit is roughly constant at \$16 thousand for the remaining risk scores. This (weakly) increasing relation between risk-score and credit card limit is in line with previous work documenting risk-based pricing with credit limits for consumers in the US and the UK (Agarwal et al., 2018; Matcham, 2022).

The right panel of Figure 4 shows a strong negative relation between risk-score and utilization.

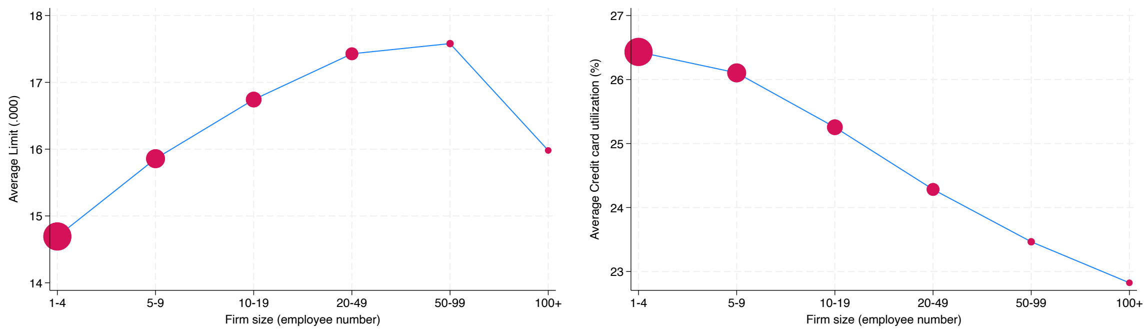

Figure 3: FIRM SIZE, LIMIT AND UTILIZATION
Note: The left figure shows the relationship between firm size groups and credit limits. The right figure shows the relation between firm size groups and utilization. The size of the circle is proportional to the number of observation in the specific firm size group.

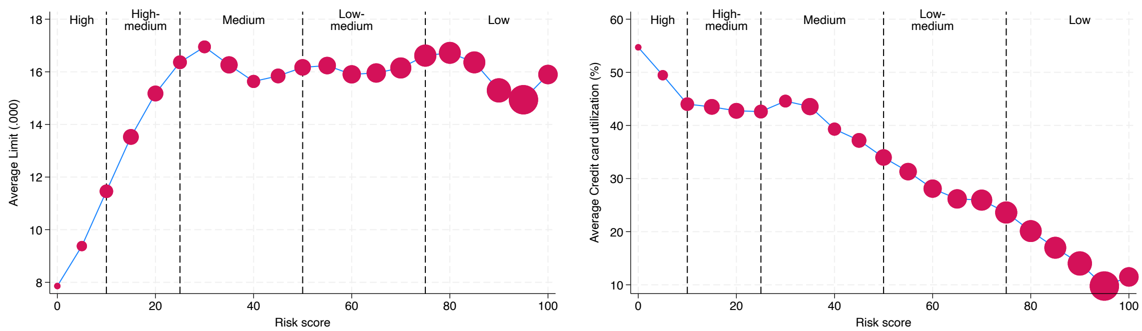

Figure 4: RISK-SCORE, LIMIT AND UTILIZATION
Note: The left figure shows the relation between risk-score and credit limits. The right figure shows the relation between risk-score and utilization. The size of the circle is proportional to the number of observation in the specific risk-score bin. The vertical dash black lines correspond to the thresholds that are used to segment the firms into five risk categories: High (1-10); High-medium (11-25); Medium (26-50); Medium-low (51-75); Low (76-100). For more details see: https://www.bci2experian.com/wp-content/uploads/2017/01/2013-06-Enhanced-Risk-Assessment.pdf

Firms in the highst risk bin, with a risk-score between 1 and 5, have average utilization rates above 50%. Utilization decreases to around 40% for firms with medium-high risk. This is due to a contemporaneous increases in limits as well as balances (see the right panel of Figure A3 in the Appendix). Finally, in contrast to the limits, which are flat for risk scores about 30, utilization rates decrease consistently for scores above 30. In consequence, firms in the medium risk category have an average utilization of about 35%, firms in the low-medium risk category have an average utilization of 25%, and firms in the lowest risk category have have an average utilization of 15%. Given the stable limits, the decline in credit card utilization is driven by a decrease in balances (see the right panel of Figure A3 in the Appendix).

Finally, in Tables 2 and 3 we explore several determinants of credit card limits and utilization in a regression framework. Table 2 Columns (1)-(3) show that variation over time, zip code, and risk-score has limited explanatory power for credit limits, where including these fixed effects in regressions gives

R^2s of between 1% and 3%. As Figure 4 shows, while risk scores have some explanatory power for the limits of the riskiest firms, they do not have much predictive power for the limits for other firms. Column (4) shows that firm fixed effects have the highest explanatory power, with an R^2 of more than 70%. In other words, most of the variation in credit limits are across firms and due to firm-specific factors outside of time, location, and risk.

In the last two columns of Table 2 we combine several different determinants of credit card limits. Within time and zipcode (Column (5)), we find that firms with a high risk have about a \$2 thousand lower credit limit than firms with medium and low risk. This difference corresponds to a 13-16% decrease relative to the mean limit of \$16 thousand. Firm with 10-49 employees have about a \$3 thousand higher credit limit than firms with fewer than 10 employees, which corresponds to a 20% increase relative to the mean limit, while firms with 50 or more employee have about a \$4 thousand higher credit limit than those with fewer than 10 employees, or a 25% increase relative to the mean limit. The relation between limit and firm cash-flow volatility is more ambiguous perhaps as a result of conflicting demand and supply side forces, where firms with high cashflow volatility demand higher credit limits as a hedge, but lenders are less willing to supply high credit limits due to concerns over delinquency, which we return to shortly.

Column (6) shows that variation in risk within firm (i.e., including firm fixed effects) has economically small effect on credit limits.[18] The interpretation here is that there is relatively little within-firm variation in risk that is associated with within-firm changes in limits. Finally, banks have higher credit limit than non-banks by about \$10 thousand, or almost 65% of the average credit card limit. This effect persist also within firm, suggesting that is it not driven exclusively by clientele differential selection across banks and non-banks. Rather, even among firms that have both bank and non-bank credit card providers, the limit on the bank-provided credit card is larger. The fact that banks are potentially more important provider of credit card as borrowing products (See also the results later in Table 3) than non-banks is in line with the work by Hanson et al. (2015), as the provision of contingent credit is facilitated by the availability of stable funding.

Table 3 repeats the preceding analysis using utilization as the dependent variable. Column (1) shows that variation over time has very limited explanatory power, with an R^2 below 1%, while zip code fixed effects capture about 2% of the variation in utilization. Risk-score fixed effects have a much higher explanatory power with an R^2 of approximately 14%. It is possible that this relationship is the mechanical result of carried balances being an imput into the (proprietary) risk score combined with persist differences in utilization across firms. As was the case with credit limits, column (4) shows that firm fixed effects have the highest explanatory power, with an R^2 of more than 60%.

In the last two columns of Table 3 we combine several different determinants of credit card utilization. Within time and zip, we find that firms with high (low) risk have a 4-percentage-point (20-percentage-point) higher (lower) credit card utilization as compared to firms classified as medium

[18]We omit size (as jumps between employee size buckets are rare within-firm) and cash flow volatility (as cash flow volatility is measured at the industry level and therefore is time-invariant for firms).

Table 2: WHAT EXPLAINS CREDIT CARD LIMITS?

	INDIVIDUAL FIXED EFFECTS				COMBINED	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk: High					-2.06***	-0.08***
					(0.03)	(0.01)
Risk: Low					0.40***	-0.08***
					(0.02)	(0.01)
Employee: 10-49					3.10***	
					(0.03)	
Employee: 50+					4.16***	
					(0.05)	
Cash-flow volatility: Low					0.31***	
					(0.02)	
Cash-flow volatility: High					0.43***	
					(0.02)	
Bank (dummy)					10.65***	10.58***
					(0.02)	(0.03)
TIME F.E.	Yes	No	No	No	Yes	Yes
ZIPCODE F.E.	No	Yes	No	No	Yes	No
RISK F.E.	No	No	Yes	No	No	No
FIRM F.E.	No	No	No	Yes	No	Yes
R^2	0.01	0.03	0.01	0.71	0.13	0.75
R^2 ADJUSTED	0.01	0.03	0.01	0.64	0.13	0.69
Y MEAN	15.72	15.72	15.72	15.78	15.72	15.78
Y SD	16.23	16.23	16.23	16.25	16.23	16.25
OBSERVATIONS	9,572,421	9,571,599	9,572,421	9,165,104	9,571,599	9,165,104

Note: The Table shows the estimates of several regressions of credit card limits on different sets of variables. The dependent variable is credit card limit in thousands of dollars. The explanatory variables which vary as specified in the different columns are: a categorical variable for firm risk; a categorical variable for firm size measured by the number of employees; terciles of firm cash-flow volatility; zip code fixed effects; time fixed effects; firm fixed effects; a dummy for credit cards offered by banks. Standard errors are clustered at the firm level.

risk, echoing the results in the right panel of Figure 4. We also confirm the results from Figures 3 that utilization decreases monotonically with firm size. For example, we find that firms with 50 or more employees have roughly a 3-percentage-points lower credit card utilization than firms with fewer than 10 employees. Given an average utilization of 26%, this corresponds to a 12% relative lower utilization.

When adding firm fixed effects in column (6) the effect of risk is lower in magnitude, but still statistically and economically significant, in contrast to the within-firm result for credit limits in Table 2, which showed a more limited role for risk score after controlling for firm fixed effects. That is, within a firm, the firm's becoming riskier is associated with an increase in its utilization. Finally, we find that utilization is about 2.5-3 percentage points higher for banks than non-banks, which correspond to 11% increase relative to the average utilization. The result is robust to controlling for firm fixed effects.

Table 3: WHAT EXPLAINS CREDIT CARD UTILIZATION?

	INDIVIDUAL FIXED EFFECTS				COMBINED	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk: High					4.24***	2.63***
					(0.06)	(0.05)
Risk: Low					-20.29***	-7.54***
					(0.05)	(0.03)
Employee: 10-49					-1.32***	
					(0.04)	
Employee: 50+					-3.22***	
					(0.09)	
Cash-flow volatility: Low					-0.22***	
					(0.04)	
Cash-flow volatility: High					0.28***	
					(0.04)	
Bank (dummy)					3.00***	2.39***
					(0.04)	(0.06)
TIME F.E.	Yes	No	No	No	Yes	Yes
ZIPCODE F.E.	No	Yes	No	No	Yes	No
RISK F.E.	No	No	Yes	No	No	No
FIRM F.E.	No	No	No	Yes	No	Yes
R^2	0.00	0.02	0.14	0.62	0.12	0.63
R^2 ADJUSTED	0.00	0.02	0.14	0.54	0.12	0.55
Y MEAN	25.97	25.97	25.97	25.81	25.97	25.81
Y SD	32.34	32.34	32.34	32.16	32.34	32.16
OBSERVATIONS	9,572,421	9,571,599	9,572,421	9,165,104	9,571,599	9,165,104

Note: The Table shows the estimates of several regressions of credit card utilization on different sets of variables. The dependent variable is credit card utilization defined as the ratio of the balance over the limit. We re-scale utilization by multiplying it by 100. The explanatory variables which vary as specified in the different columns are: a categorical variable for firm risk; a categorical variable for firm size measured by the number of employees; terciles of firm cash-flow volatility; zip code fixed effects; time fixed effects; firm fixed effects; a dummy for credit cards offered by banks. Standard errors are clustered at the firm level.

Fact 1—Accounts, Limits and Utilization: *Small firms and firms with greater cashflow volatility are more likely to have business credit cards. The average limit on a business card is roughly \$16 thousand with an average utilization rate of 26%. Small firms and risky firms have lower limits and higher utilization rates. Variation in limits and utilization is mostly driven by unobservable across-firm heterogeneity.*

3.2 Credit Card Delinquency

We next explore variation in delinquencies and delinquencies' relation to the documented variation in credit card limit and utilization. We begin by examining what explains variation in delinquencies in Table 4. Columns (1) and (2) show that variation over time and across zipcodes has very limited explanatory power, with an R^2 around 1%. Credit-score fixed effect have a higher explanatory power with an R^2 of approximately 7%. As expected, the majority of the variation in delinquency is explained by firm fixed effects, which explain almost 70% of the overall variation. The large unexplained variation across firms in both utilization and delinquencies will be an important feature in the economics of providing business credit cards and will be modeled explicitly in our structural model in Section 4.

In the last two columns of Table 4, we include the other observable firm covariates, together with credit limit and utilization. When including time and zip fixed effects, with other controls, we find that a high credit limit is negatively associated with delinquency, while high utilization is positively associated with delinquency. We interpret the negative coefficient on credit limits as supply driven, where lenders offer lower limits to riskier firms, consistent with the results shown in the left panel of Figure 4. We interpret the positive coefficient on utilization as capturing correlated shocks that lead to both increased utilization and a decreased ablity to repay. The effect is statistically and economically significant, and the point estimate of utilization is larger than the one of credit limit. Most notably, an increase in utilization by 10 percentage points generates a 0.4 percentage point change in delinquency. Given the average delinquency rate of 1.5%, this represent an increase by more than 25% in delinquency.

Column (6) of Table 4 includes firm fixed effects, and therefore exploits variation only within firm over time. The coefficient on limits turns positive, which rules out an interpretation where lenders mechanically reduce limits when the firm becomes delinquent. It is possible, rather, that the typical firm follows a path where its limit grows over but eventually happens to become delinquent in one of its accounts. The coefficient on utilization remains positive and strongly statistically and economically significant. An increase in utilization by 10 percentage points generates a 0.3 percentage point change in delinquency, which correspond to about 20% of the mean.

While we are mostly focused on the effect of credit limit and utilization on delinquency, other variables in Table 4 show interesting patterns. As expected, firms with high (low) risk are more (less) likely to be delinquent on their credit cards than firms with medium risk. Small (those with fewer than 10 employees) firms are more likely to be delinquent on credit cards than larger firms, even after controlling for credit card limits and utilization. Given an average delinquency rate of 1.5%, small firms are about 27% more likely to default than medium firms with 10-49 employees and 50% more likely to default than large firms with more than 50 employees.[19] Finally, we find that firms with high (low) cash-flow volatility are more (less) likely to be delinquent on their credit cards than firms with medium cash-flow volatility. This is consistent with firms with volatile cash flows turning to credit cards as flexible products when borrowing needs arise, and potentially becoming delinquent on them later on because these borrowing needs in fact arise from negative shocks to the firm.

Turning to the lender side, we find that credit cards issued by banks have higher delinquencies that credit cards issued by non-banks. Bank credit cards are 8 basis points or about 5% more likely to be delinquent than non-bank credit cards. While in column (5) of Table 3 we are controlling for a rich set of firm characteristics, it could still be that banks serve firms that are riskier based on

[19]Figure A4 in the Online Appendix shows the relation of delinquencies with firm size and risk using finer bins.

Table 4: WHAT EXPLAINS CREDIT CARD DELINQUENCIES?

	INDIVIDUAL FIXED EFFECTS				COMBINED	
	(1)	(2)	(3)	(4)	(5)	(6)
Limit ($000)					-0.01***	0.02***
					(0.00)	(0.00)
Utilization (%)					0.04***	0.03***
					(0.00)	(0.00)
Risk: High					5.33***	0.74***
					(0.03)	(0.02)
Risk: Low					-0.14***	0.04***
					(0.01)	(0.01)
Employee: 10-49					-0.38***	
					(0.02)	
Employee: 50+					-0.70***	
					(0.03)	
Cash-flow volatility: Low					-0.10***	
					(0.02)	
Cash-flow volatility: High					0.07***	
					(0.02)	
Bank (dummy)					0.08***	-0.35***
					(0.02)	(0.03)
TIME F.E.	Yes	No	No	No	Yes	Yes
ZIPCODE F.E.	No	Yes	No	No	Yes	No
RISK F.E.	No	No	Yes	No	No	No
FIRM F.E.	No	No	No	Yes	No	Yes
R^2	0.01	0.01	0.07	0.69	0.06	0.69
R^2 ADJUSTED	0.01	0.01	0.07	0.62	0.06	0.62
Y MEAN	1.56	1.56	1.56	1.51	1.56	1.51
Y SD	12.38	12.38	12.38	12.19	12.38	12.19
OBSERVATIONS	9,572,421	9,571,599	9,572,421	9,165,104	9,571,599	9,165,104

Note: The Table shows the estimates of several regressions of credit card delinquency on different sets of variables. The dependent variable is credit card delinquency defined as as a 60-days past due. We re-scale delinquency by multiplying it by 100. The explanatory variables which vary as specified in the different columns are: a categorical variable for firm risk; a categorical variable for firm size measured by the number of employees; terciles of firm cash-flow volatility; zip code fixed effects; time fixed effects; firm fixed effects; a dummy for credit cards offered by banks. Standard errors are clustered at the firm level.

unobservable characteristics (e.g., they have lower unobserved cash buffers). In column (6) we find that, after controlling for firm fixed effects, delinquencies are lower for banks than non-banks. The point estimate is large at 35 basis points (or about 23% relative to the mean). This effect could be due to: (i) selection within firm over time across banks and non-banks; (ii) firm with two cards deciding to default first on the non-banks card.[20]

Next, we examine more granular variation in both credit card limits and utilization as well as possible non-linear effects on delinquencies. For limits, we create 8 bands ($≤1, 1-5, 5-10, 10-20,

[20] In unreported regression with firm-time interacted fixed effects we find that the coefficient on bank dummy decreases further to about 10 basis points, suggesting that there could be some selection within firm over time. For example, a firm might first take a credit card with a non-bank, and switch to a bank after showing its creditworthiness. Exploring this further as well as differential incentive to default could be an interesting avenue for future work.

20-30, 30-40, 40-50, >50 thousand), while for utilization we create 10-percentage-points utilization bins rounding the continuous utilization to the nearest multiple of 10. Figure 5 shows the coefficients on these binned limits (left panel) and utilization (right panel) with analogous controls and fixed effects from Table 4 Column (5). We find that delinquencies for credit cards with limits up to \$5 and \$10 thousand have higher delinquencies than credit card with limits up to \$1 thousands, although the differences are borderline statistically significant. This relation between credit limit and delinquency could be driven by lenders offering relatively lower limits to riskier firms, in line with the evidence in the left panel of Figure 4. Credit cards with limit up to \$20 thousand and above have similar delinquencies to credit cards with limits below \$1 thousands. Overall, controlling for risk-score and other observable firm characteristics, credit limits do not appear to have a strong direct correlation with delinquencies.

The right panel of Figure 5 shows that the relation of utilization with delinquency is monotonic and strongly convex. Firms with a utilization up to about 30% have 40-80 basis points higher delinquencies than firms with zero utilization, all else equal. Firms with utilization around 40% to 60% have between 100-basis-points to 150-basis-points higher probability to be delinquent, which correspond to a 100% increase relative to the mean. For firms with utilization of 80% the increase is more than 2 percentage points relative to the mean, while for firms with utilization of 90% the increase is more than 3 percentage points. Finally, firms that fully utilize their credit card balance have an increase in delinquency rate of almost 6 percentage points, which corresponds to more than 3.5 times the average default rate.

The strong positive relation between utilization and delinquencies could arise from two factors. First, firms that are ex-ante riskier utilize their cards more and are less likely to be able to repay them, or similarly, firms receive ex-post negative shocks that lead them to utilize their cards more while also being less likely to be able to repay. This is an adverse selection or correlated shock interpretation of these results. Second, over time, lenders may increase credit limits to better firms who maintain roughly constant balances, leading their utilization and delinqueny rates to be lower, all else equal. This is a lender supply interpretation of these results. To rule out the latter explanation, we reestimate the same linear probability model of delinquency from the right panel of Figure 5 on the subset of firms whose credit limit is unchanged throughout our sample period. Figure A5 in the online appendix shows that the results are very similar to the ones in the full sample. These findings corroborate the adverse selection or correlated shock interpretation discussed above.

Finally, we provide some evidence for the possible presence of asymmetric information between the firm and the lender or correlated ex-post shocks to utilization and ability to repay. We follow the empirical literature based on a correlation test between the unobservable component of demand and the unobservable component ex-post outcomes, such as accidents in the insurance literature (Chiappori and Salanie, 2000), or default in the credit market literature (Crawford et al., 2018). In our case, we examine delinquency. We proceed by estimating the following seemingly unrelated regression:

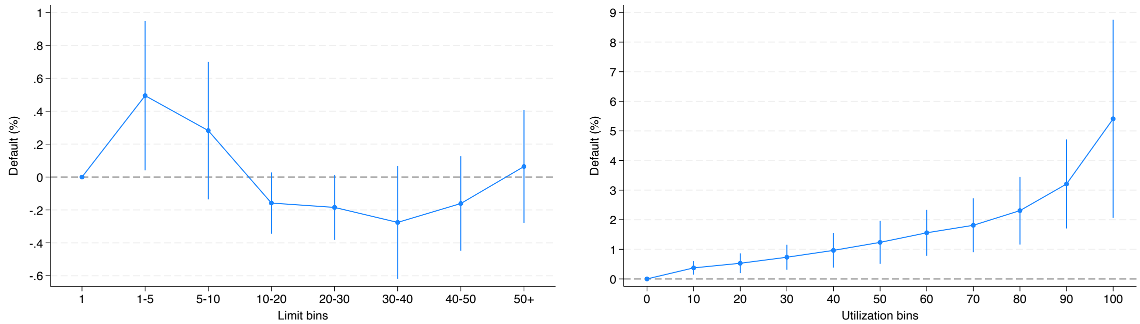

Figure 5: CREDIT LIMIT, UTILIZATION AND DELINQUENCY
Note: The left figure shows the point estimates and 95% confidence interval on the effect of credit card limits by group on delinquency. The right figure show the point estimates and 95% confidence interval on the effect of 10-percentage-points utilization bins on delinquency. A delinquent credit card is defined as a 60-days past due. We rescale delinquency by multiplying it by 100. Standard errors are clustered at the firm level.

$$
\begin{aligned}
y_i &= X_i\beta + \epsilon_i \\
f_i &= X_i\beta + \eta_i,
\end{aligned} \tag{1}
$$

where y_i is the credit card limit or utilization, f_i is a dummy equal to one if the firm is delinquent on the credit card, and X_i contains a set of firm characteristics (size, risk-score, time, location, industry) plus a dummy for bank-issued credit cards. We specify the distribution of the residuals ϵ_i and η_i as joint normal and estimate their correlation coefficient ρ. Table 5 report the results for a random 5% subsample of the full dataset.

Column (1) shows that the correlation between the residual of the credit limit equation and the delinquency equation is negative and small in magnitude. This suggests that to the extent that there is a correlation between seeking a high limit and the likelihood of ex-post default, lenders are able to screen and provide lower limits to riskier firms.

Turning to utilization, column (3) of Table 5 shows that the correlation between the residual of the credit utilization equation and the delinquency equation is positive and large in magnitude. A Breusch–Pagan test for independent equations strongly rejects the hypothesis that the disturbance covariance matrix is diagonal. Because the nature of the contract is that lender and borrower set the *limit* up front, but the borrower chooses *utilization* ex-post, this positive correlation is likely demand-driven. That is, the positive correlation between credit card utilization and default provides suggestive evidence of asymmetric information between borrowing firms and lenders or correlated ex-post shocks that drive both utilization and delinquency.

Columns (2) and (4) of Table 5 report the estimate of the correlation in residuals not controlling for firm risk-score. We find that the correlation between the credit utilization equation and the delinquency equation increases from 0.11 to 0.15, a 36% increase. This result shows that risk scoring can help mitigate possible adverse selection or in the prediction of correlated ex-post shocks in the business credit card market, in line with previous work on consumer borrowing (Adams et al., 2009;

Table 5: CORRELATION BETWEEN UNOBSERVABLES OF DEMAND AND DELINQUENCY

	Intensive Margin: Credit Card Limit		Intensive Margin: Credit Card Utilization	
	(1)	(2)	(3)	(4)
CORRELATION BETWEEN UNOBSERVABLES	-0.02	-0.03	0.11	0.15
BREUSCH-PAGAN CHI-SQUARED	190	411	5774	10265
TIME F.E.	Yes	Yes	Yes	Yes
BANK F.E.	Yes	Yes	Yes	Yes
FIRM SIZE F.E.	Yes	Yes	Yes	Yes
FIRM LOCATION F.E.	Yes	Yes	Yes	Yes
FIRM INDUSTRY F.E.	Yes	Yes	Yes	Yes
FIRM RISK F.E.	Yes	No	Yes	No
DEP. VAR. (MEAN)	15.72	15.72	25.95	25.95
OBSERVATIONS	478,621	478,621	478,621	478,621

Note: The Table shows the estimates for the correlation coefficient on the residuals of the seemingly unrelated regression model given by equation (1). Standard errors are clustered at the firm level.

Einav et al., 2012).

Fact 2—Delinquency and Correlation with Utilization: *The average delinquency rate for business credit cards is about 1.5%. Small and especially risky firms with high cash flow volatility are more likely to be delinquent. Delinquencies increase monotonically with credit card utilization but the relationship between limits and delinquencies is weaker. Unobservable factors driving credit card utilization are positively correlated with credit card delinquencies, providing suggestive evidence of asymmetric information or correlated ex-post shocks to utilization and delinquency.*

3.3 Credit Card Pricing

As we discussed in Section 2, our main dataset does not contain information on prices. We address this limitation by studying rates for loans and credit cards from RateWatch. RateWatch data is reported at the branch-time level, and thus our measure of rates thus varies jointly across lenders, over time, and across geographical markets, but not at the firm level. Table 6 reports the results of several specifications to understand the determinants of variation in rates for small business credit. Several results are notable.

First, and not surprisingly, business credit cards have significantly higher interest rates than term loans, controlling for lender, state and time fixed effects. On average, credit card rates are almost 6.5 percentage point higher term loan rates. While there could be several explanation for the higher rates on business credit cards relative to term loans, a higher *unconditional* delinquency rate is an unlikely one. As we show in Table 1 delinquencies are higher on term loans than on credit cards. As we explore in our model, however, due to the correlation between utilization and delinquency it is possible that delinquencies, conditional on having large balances, explains the pricing difference.

Table 6: BUSINESS CREDIT CARDS AND TERM LOAN RATES

	ALL	CREDIT CARDS					TERM LOANS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Credit card (dummy)	6.40***										
	(0.36)										
Bank (dummy)						0.57*					0.64**
						(0.32)					(0.25)
LENDER F.E.	Yes	Yes	No	No	No	No	Yes	No	No	No	No
STATE F.E.	Yes	No	Yes	No	No	Yes	No	Yes	No	No	Yes
YEAR-MONTH F.E.	Yes	No	No	Yes	No	Yes	No	No	Yes	No	Yes
LENDER × YEAR-MONTH F.E.	No	No	No	No	Yes	No	No	No	No	Yes	No
R^2	0.87	0.71	0.09	0.10	0.91	0.19	0.65	0.18	0.05	0.54	0.24
R^2 ADJUSTED	0.86	0.70	0.08	0.10	0.87	0.18	0.63	0.17	-0.01	0.14	0.18
Y MEAN	12.11	12.52	12.52	12.52	12.68	12.52	5.42	5.42	5.42	5.17	5.42
Y SD	2.83	2.34	2.34	2.34	2.22	2.34	0.91	0.91	0.91	0.79	0.91
OBSERVATIONS	16,306	15,356	15,379	15,381	5,715	15,379	944	952	952	106	952

Note: The Table shows the estimates of several regressions of interest rates from RateWatch on different set of variables. The dependent variable is the APR in percentage points. The explanatory variables which vary as specified in the different columns are: a dummy for credit cards; a dummy for banks; lender fixed effects; state fixed effects; time fixed effects. Standard errors are clustered at the firm level.

Second, columns (2) to (6) in Table 6 focus on credit cards only. The average interest rate on business credit cards in our sample is about 12.5%, which is very similar to that reported by Berger et al. (2022) using Federal Reserve's supervisory data. [21] We find that the majority of the variation in rates is across lenders (R^2 of 70%), followed by variation over time (R^2 of 10%) and then across states (R^2 of 9%). The limited explanatory power of geography is consistent with the literature documenting uniform pricing in other banking products, such as mortgages (Hurst et al., 2016), deposit accounts (Granja and Paixao, 2021) and consumer credit cards (Stango and Zinman, 2016). Since in our rates data we do not have variation across firms, state fixed effects likely capture different distribution of firm risk across locations.

Notably, column (6) of Table 6 shows that banks have significantly higher business credit card rates than non-banks (the omitted category). On average the rate on credit card by banks is almost 60 basis points higher than the rate on credit cards by non-banks. Given an average rate on business credit cards of 12.9%, banks products have a 5% higher rate in relative terms. Like the differential above for credit card relative to term loans, there could be several explanations for the higher rates on bank business credit cards relative to non-bank business credit cards. However, a higher unconditional delinquency rate is perhaps an unlikely one, since delinquencies on business credit cards are similar for bank and non-bank issuers (See Panels D and E of Table 1).

Third, while the main novelty of our paper is the analysis of business credit cards, we also look at relatively more studied term loans in columns (7) to (11) of Table 6. The majority of the variation in

[21] Table 1 Panel B in Berger et al. (2022) report an interest rate on business credit card of about 11%.

term loan rates is also across lenders (R^2 of 65%), followed by across states (R^2 of 18%), and then over time (R^2 of 5%). Column (11) shows that banks have also significantly higher term loan rates than non-banks. On average, the rate on bank term loans is about 65 basis points higher than the rate on non-bank term loans, which corresponds to an 11% increase higher rate relative to the mean.

Overall, variation across lenders is more important for business credit cards than it is for term loans. This is consistent with credit cards being a more homogeneous product, relative to term loans, that are more likely tailored to firm-specific financing needs. To further explore these differences, we estimate for both business credit cards and term loans a specification with interacted lender-time fixed effects. The results are presented in columns (5) and (10) for credit cards and term loans, respectively. Interacted lender-time fixed effects explain more than 90% of the variation for credit cards, while only about 55% for term loans. While the comparison with other specifications is complicated by the different sample sizes, the more limited residual variation within lender-time across states with credit cards relative to term loans is again consistent with the more standardized nature of the former product relative to the latter.

Fact 3—Pricing: *Business credit cards have about 6-percentage-point higher interest rates than term loans. The majority of variation in business credit cards rate is across lenders, followed by variation over time, while variation across geographical market is small. Lender-time fixed effects explain 90% of the variation in credit card rates.*

3.4 Credit Card Net Interest Income

Finally, we explore credit card net interest income, which synthesizes the previous facts concerning utilization, delinquency, and rates. We define net interest income as the expected revenue after delinquency less a rough measure of funding costs, assumed to be banks' overnight wholesale funding rate. For a borrower i, the net interest income is given by:

$$NII_i = r_i \times Balance_i \times (1 - Delinquent_i) - f_i \times Balance_i, \tag{2}$$

where r_i is the interest rate on the credit card; and f_i is the proxy for funding costs. Note that this definition does not capture other costs of providing cards, such as the costs involved in underwriting or servicing the loans.

Figure 6 shows average net interest income as defined above. The left figure shows the average for all card borrowers by utilization. Observe that net interest income is identically zero for card holders with zero utilization, and increases as balances grow. Average net interest income peaks around \$1,400 per year for borrowers with 80-90% utilization, and decline thereafter by about half for borrowers with 100% utilization, as higher delinquency accompanies full utilization. However, for no utilization rate is the average net interest income negative.

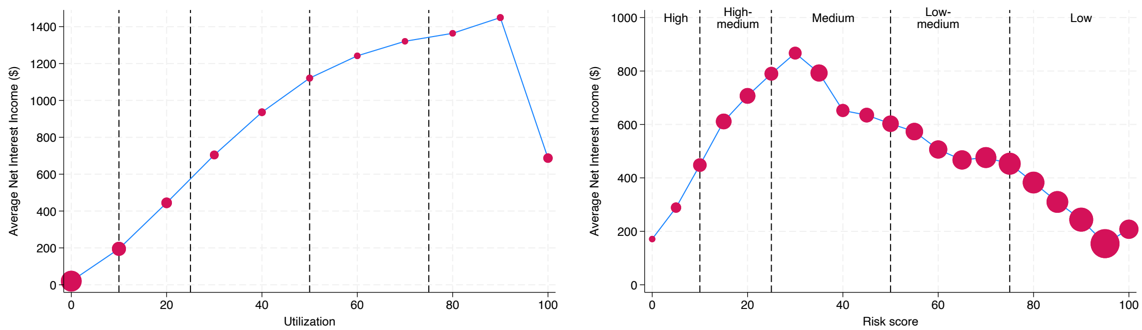

Figure 6: CREDIT CARDS NET INTEREST INCOME

Note: The left figure shows the average net interest income by 10-percentage-points utilization bins. The right figure shows the average net interest income by risk-score. The size of the circle is proportional to the number of observation in the specific utilization and risk-score bin. The vertical dashed black lines correspond to the thresholds that are used to segment the firms into five risk categories: High (1-10); High-medium (11-25); Medium (26-50); Medium-low (51-75); Low (76-100). For more details see: https://www.bci2experian.com/wp-content/uploads/2017/01/2013-06-Enhanced-Risk-Assessment.pdf

The right figure in Figure 6 shows the average net interest income by risk score. Net interest income is lowest for the highest risk firms (risk scores between 0 and 10) and for the lowest risk firms (risk scores between 75 and 100), and peaks for medium risk firms. This inverse-U shape arises from the fact that both utilization and delinquency increase with firm risk (Figures 4 and A4). That is, the highest-risk firms have high utilization but are the most likely to become delinquent on their balances, while the lowest-risk firms tend to not carry balances on which lenders can charge interest. Our result for business credit cards mirrors the results for consumers in Agarwal et al. (2015), where the highest risk (lowest credit score) consumers earn close to zero net profits due to high charge-off rates, high-to-moderate risk consumers are the most profitable with high balances and moderate charge-offs, and moderate-to-low risk score consumers providing little interest income because they carry low balances (their profitability comes mainly from interchange fees).

Two important features emerge from this analysis. First, over most of the range of borrower card utilization, increased utilization leads to higher average net interest income, even accounting for the fact that default also rises with utilization. In the extreme, borrowers with 100% utilization rates still provide positive net interest income to lenders. Second, the average borrower has non-negative net interest income across all risk types, even the most observably risky borrowers.

Fact 4—Net Interest Income: *The median net interest income accounting for delinquency on business credit cards is positive across all (non-zero) ranges of utilization. Net interest income increases with utilization until approximately 90% and then declines as delinquency rates spike with full utilization. Average net interest income is positive but low for the highest- and lowest-risk borrowers and peaks for middle risk borrowers.*

4 The Model

In this Section we present a model of firm demand and lender supply of credit cards. Our model follows the work by Crawford et al. (2018) and Ioannidou et al. (2022) for firm credit, and Matcham (2022) for consumer credit cards. We adopt their model to our context in line with the empirical facts presented in Section 3 and the richness of our sample, which allows for variation in some structural parameters across firms with different characteristics.

As an overview, firms make a discrete choice among credit card offers from differentiated lenders that vary in (endogenous) rates and other (exogenous) characteristics. Having formed a lending relationship, firms then choose how much to utilize the card and whether to become delinquent on the balance. Importantly, these decisions are linked through a (potentially correlated) shock, which captures ex-ante adverse selection (wherein firms that are more likely to experience negative shocks demand to borrow in greater quantities) or ex-post correlated shocks (wherein firms receive negative real shocks ex-post which cause them to borrow more in states of the world where default is more likely). Regardless of its source, lenders anticipate this relationship and set ex-ante prices accordingly.

4.1 Credit Demand

In each market m and period t there are I_{mt} firms, indexed by i, choosing to open a credit card among J_{mt} lenders, indexed by j. First, the firm makes the discrete choice among the J_{mt} offers to open a credit card from a lender j. The utility for firm i choosing lender j is given by:

$$u_{ijmt}^{D} = \bar{\alpha}_0^D + \alpha^D r_{jmt} + \beta^D X_{jmt}^D + \xi_{jmt}^D + \eta^D Y_{ijmt}^D + \epsilon_i^D + \varepsilon_{ijmt}^D, \tag{3}$$

where r_{jmt} is the interest rate; X_{jmt}^D are other observable determinants of market-level demand for lender j at time t; ξ_{jmt} are unobservable market-level determinants of demand for lender j; Y_{ijmt}^D are observable determinants of firm-level demand for lender j at time t; ϵ_i^D captures unobservable firm-level demand for credit cards from any bank; and ε_{ijmt}^D capture unobserved shocks to firm i demand for bank j.

Second, conditional on having a credit card from lender j, firm i decides how much to borrow on it. Firms make this utilization choice to maximize the following indirect utility:

$$u_{ijmt}^{U} = \bar{\alpha}_0^U + \alpha^U r_{jmt} + \beta^U X_{jmt}^U + \eta^U Y_{ijmt}^U + \epsilon_i^U, \tag{4}$$

where X_{jmt}^U are observable determinants of market-level utilization for lender j at time t; Y_{ijmt}^U are observable determinants of firm-level utilization; and ϵ_i^U captures firm-level utilization propensity that is known by the firm, but unobserved to the bank (and the econometrician).

With equation (4) we capture the difference between: (i) firms choosing a credit card as a borrowing products; and (ii) firms choosing a credit card for only transaction functions. The literature often refer to the former as "revolvers" and the latter as "transactors". In our data we cannot observe the balance that is rolled over month by month, but we observe both the limit and the balance. Thus we use the ratio of balance over limits as a measure of credit card usage as a borrowing product.

Third, conditional on having product j and making a utilization choice, firm i decides whether to pay the interest (if positive) or default. In particular, we assume that the firm chooses to default if its utility from doing so is greater than zero, where the utility is given by the following:

$$u_{ijmt}^F = \bar{\alpha}_0^F + \alpha^F r_{jmt} + \beta^F X_{jmt}^F + \eta^F Y_{ijmt}^F + \epsilon_i^F, \tag{5}$$

where X_{jmt}^F are observable determinants of market-level default for lender j at time t, Y_{ijmt}^F are observable determinants of firm-level default, and ϵ_i^F captures firm-level default propensity that is known by the firm, but unobserved to the bank (and the econometrician).

We assume that firm unobservable determinants of demand and default follows a multivariate normal distribution given by:

$$\begin{pmatrix} \epsilon_i^D \\ \epsilon_i^U \\ \epsilon_i^F \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_D^2 & 0 & 0 \\ 0 & \sigma_U^2 & \rho_{UF}\sigma_U \\ 0 & \rho_{UF}\sigma_U & 1 \end{pmatrix}\right), \tag{6}$$

where σ_D^2 captures heterogeneity in firms' unobservable preferences for credit cards (akin to a random coefficient on a dummy for the inside goods); σ_U^2 captures heterogeneity in firms' unobservable utilization propensity; and ρ_{UF} measures the correlation between the unobservable firm propensity to borrow on the credit card and to default on it.

We differ from Crawford et al. (2018) in three ways. First, interest rates vary at the product-time-market level, but not across firms. This choice is driven by the level of variation in our rates data as well as commonly reported practices in credit card pricing.[22] Second, we set the correlation between unobservable demand propensity and default to zero and we focus instead on the correlation between unobservable utilization propensity and default. This modelling choice is justified by our context, most notably particular contractual feature of a revolving credit line that naturally links ex-post utilization with ex-post default as discussed in Section 3, as well as the fact that firms also demand credit cards for transaction reasons. Third, we allow the correlation between unobservable utilization propensity and default (ρ_{UF}) and the unobservable utilization propensity (σ_U^2) to vary based on firms' characteristics such as risk and size.

As we have noted previously, a positive correlation in the data between unobservable firm utilization and default propensity ($\rho_{UF} > 0$) is consistent with both: (i) ex-ante adverse selection; (ii) ex-post firm-specific shocks. In the case of the former, firms that ex-ante have a higher propensity to borrow on the credit card are also more likely to default. In the case of the latter, firms are ex-post

[22] If data at the firm level on rates are available our model could allow for that and the estimation follows the steps discussed in Crawford et al. (2018).

(after choosing the credit card) hit by a shock that increase both utilization and default (for example a negative cash-flow shock). We do not attempt to distinguish these alternate mechanisms and instead focus on how the resulting correlation impacts lender pricing decisions and the equilibrium consequences of shocks to utilization or funding costs for equilibrium credit card provision.

4.2 Credit Supply

On the supply side, we assume that lenders take consumer demand, utilization, and delinquency as given and compete in a Bertrand-Nash fashion by setting interest rates on their credit cards. Lender j's expected profit from offering a credit card to firms in market m at time t is given by:

$$\Pi_{jmt} = \sum_{i \in I_{mt}} \left[r_{jmt} q_{ijmt} (1 - f_{ijmt}) - mc_{jmt} q_{ijmt} \right], \tag{7}$$

where q_{ijmt} is expected borrowing quantity by firm i for lender j, given by the product of the discrete choice and the utilization choice, f_{ijmt} is the probability that firm i defaults on lender j, and mc_{jmt} is lender j's marginal cost in market m and time t.[23]

Taking the derivative of (7) with respect to the interest rate, we obtain the lender's first order condition:

$$\sum_{i \in I_{mt}} q_{ijmt}(1 - f_{ijmt}) + \sum_{i \in I_{mt}} \frac{\partial q}{\partial r_{ijmt}} (r_{jmt}(1 - f_{ijmt}) - mc_{jmt}) - \sum_{i \in I_{mt}} \frac{\partial f}{\partial r_{ijmt}} r_{jmt} q_{ijmt}, \tag{8}$$

where the first term captures the increase in profits net of default from higher rates on inframarginal borrowing; the second term captures the decrease in credit demand from higher rates, which is due to both lower extensive margin market share and lower intensive margin utilization; the third term captures the increase in default from higher rates. The increase in rates increases expected default in two ways. First, directly if α^F in the default equation (5) is positive. Second, indirectly if a higher rate increases the expectation of ϵ_i^U and $\rho_{UF} > 0$ (i.e., if firms who have high utilization when rates are higher tend to be riskier). Solving (8) for the interest rate (r_{jmt}) gives:

[23] Reflecting the fact that borrowers may not pay interest on the entire balance q_{ijmt}, we consider an extension where the lender receives a fraction $\lambda \in (0, 1]$ of the revenue $\lambda r_{jmt} q_{ijmt}(1 - f_{ijmt})$, while still paying the full cost of financing the balance, $mc_{jmt} q_{ijmt}$. In short, such an extension does not impact lender markups or profitability as these are pinned down by borrower sensitivity to rates, which is implied by the data and the (same) estimated demand system. Rather, the firm's first-order condition implies that lender marginal costs are lower by a factor of $1/\lambda$. The intuition is as follows: Suppose borrowers pay interest on their entire balance ($\lambda = 1$) and lenders optimally set a rate equal to $r\%$, observed in the data. This, together with markups implied by borrower demand, implies a particular marginal cost of providing the balance. In contrast, if borrowers pay interest only on a portion of the balance ($\lambda < 1$), and lenders still optimally set a rate equal to $r\%$ as observed in the data, lender optimization behavior implies that the marginal cost of providing the balances must be lower (or otherwise they would charge higher rates).

$$r_{jmt} = \overbrace{\frac{mc_{jmt}}{\sum_{i \in I_{mt}}(1 - f_{ijmt}) - \sum_{i \in I_{mt}} \frac{\partial f}{\partial r_{ijmt}} \frac{q_{ijmt}}{\frac{\partial q}{\partial r_{ijmt}}}}}^{\text{Effective marginal cost}} - \overbrace{\frac{\sum_{i \in I_{mt}}(1 - f_{ijmt}) \frac{q_{ijmt}}{\frac{\partial q}{\partial r_{ijmt}}}}{\sum_{i \in I_{mt}}(1 - f_{ijmt}) - \sum_{i \in I_{mt}} \frac{\partial f}{\partial r_{ijmt}} \frac{q_{ijmt}}{\frac{\partial q}{\partial r_{ijmt}}}}}^{\text{Effective markup}}. \tag{9}$$

Our supply-side model captures the key aspects driving lender profits from net interest income on credit cards. On the other hand, in our model a firm that is a pure "transactor" yields zero expected profits for lenders, since its utilization is zero (and $q_{ijmt} = 0$). While lenders are likely to profits from credit cards in other ways (e.g., net transaction margin, other fees), charges from interest rate payments account for the majority of lenders profits from credit cards. For example in the case of consumer credit cards Evans and Schmalensee (2005) shows that in 2001 charges from interest accounted for 70% of US lenders revenues from credit cards (with interchange fees and cash-advances doing the rest). More recent work from the Federal Reserve confirms this finding, showing that in 2022 the credit function made up approximately 80% of credit card profitability, and that net interest margin on revolving balances has increased in recent years.[24] Thus, while our model ignores the fee-income aspect of business credit cards, we both capture the key source of revenue and the main economic question—firms borrowing with credit cards—that we aim to explore in our analysis.

5 Estimation and Results

In this section we first discuss our estimation approach before presenting the structural parameters and measures of model fit.

5.1 Estimation

Demand side. For the structural estimation we focus on credit cards with positive utilization, given the focus of our analysis on credit cards as borrowing products. This choice is also in line with the assumption on the outside option, which we define as choosing a term loan. The structure of our data means that we do not observe firms taking no credit (or they would not be in the credit panel), so we do not model borrowers' extensive margin choice of not borrowing at all.

Our data contains information on the lender type (top 4 largest banks,[25] other banks, credit unions, other non-depository institutions) from which each individual firm borrows, but we do not observe an individual lender identifier. Hence, in the estimation of the model we assume a fixed number of lenders within each type and that lenders are identical within type following Buchak et al. (2018b),

[24] See https://www.federalreserve.gov/econres/notes/feds-notes/credit-card-profitability-20220909.html.
[25] JP Morgan, Bank of America, Citibank, and Wells Fargo.

among others. For example, the top-4 banks are assumed to be observably identical, compete independently, and are each idiosyncratically differentiated from one another. Due to this data structure, we do not observe the exact number of lenders offering business credit cards in each market over time. Therefore, we follow common practice in the literature and focus on the firms that account for the majority of the market (Egan et al., 2017; Xiao, 2020; Benetton, 2021), and assume that there are 25 lenders in total in each market.[26]

Our demand estimation of the structural model proceeds in several steps. We first estimate firms' discrete credit demand given by equation (3). We use a two-step method based on maximum simulated likelihood and instrumental variables (Berry et al., 1995; Crawford et al., 2018). In the first step, we use firm level choice of term loans and credit cards across different lender types to estimate the demand parameters and recover the mean utilities (δ_{jmt}) using the contraction mapping method. The mean utilities are given by:

$$\delta_{jmt} = \bar{\alpha}_0^D + \alpha^D r_{jmt} + \beta^D X_{jmt}^D + \xi_{jmt}^D. \tag{10}$$

We assume the error term ε_{ijmt}^D in equation (3) is distributed as a type I extreme value. Based on this assumption the probability that firm i chooses to borrow from lender j in market m at time t is given by:

$$P_{ijmt}^D = \int \frac{\delta_{jmt} + \eta^D Y_{ijmt}^D}{1 + \sum_k \exp(\delta_{kmt} + \eta^D Y_{ikmt}^D))} f(\epsilon_i^D) d\epsilon_i^D, \tag{11}$$

where $f(\epsilon_i^D)$ is the density of $f(\epsilon_i^D)$ and the 1 in the denominator is the normalized utility of taking the outside option. Hence, in the first step we estimate the mean utility δ_{jmt} and the structural parameters η^D and σ^D.

In the second step, we regress the mean utilities on characteristics and (instrumented) rates to recover the structural demand parameters α_0^D, α^D and β^D. To account for a possible correlation between endogenous rates (r_{jmt}) and unobservable market-level determinants of product-specific demand (ξ_{jmt}^D), we adopt an instrumental variable strategy. In particular, we instrument the interest rate on credit cards for lender j in market m at time t with: (i) the interest rate on credit cards for lender j at time t in other markets; and (ii) the deposit rate for lender j in market m at time t. Since non-banks do not offer deposits, we replace the deposit rate with the federal fund rate. Conceptually, these instruments are cost shifters uncorrelated with local demand. In the first case, the instrument picks up lender-specific operating costs that predict lender marginal cost in market mt. In the second case, the deposit rates capture funding costs that must be (partially) passed through to borrowers.

In the last step, we estimate simultaneously firms' credit card utilization (equation (4)) and default (equation (5)) to account for the variance-covariance matrix of the error system given by equation

[26] The CFPB surveyed in 2023 about 150 credit card issuers. The top 30 credit card companies represented about 95 percent of credit card debt, and the top 10 dominate the marketplace (See: https://www.consumerfinance.gov/data-research/research-reports/credit-card-data-small-issuers-offer-lower-rates/).

(6). In this case we use data on firms utilization and default to estimate all the utilization parameters ($\bar{\alpha}_0^U; \alpha^U; \beta^U; \eta^U; \sigma^U$), the default parameters ($\bar{\alpha}_0^F; \beta^F; \eta^F$); and the correlation between utilization and default (ρ_{UF}). We set the effect of interest rate on default to zero ($\alpha^F = 0$), following work in household finance on consumer credit cards (Nelson, 2018; Matcham, 2022). Hence our approach accounts for unobservable shocks linking utilization and delinquency, but abstracts from a more careful study of moral hazard, i.e., firms defaulting strategically due to high rates. The assumption is also in line with the large body of evidence in household finance that liquidity shocks drive default, rather than the long-term value of debt (Ganong and Noel, 2020a,b).[27]

Given the assumption on the distribution of the error terms in equation (6), the probability to observe a utilization level U_{ijmt} for firm i, conditional on getting a credit card, is given by:

$$P^U_{ijmt|D=1} = \phi_{\epsilon_i^U}\left(\frac{U_{ijmt} - \bar{\alpha}_0^U - \alpha^U r_{jmt} - \beta^U X^U_{jmt} - \eta^U Y^U_{ijmt}}{\sigma_U}\right), \tag{12}$$

where ϕ is the PDF of a standard normal distribution. The probability of observing firm i delinquent F_{ijmt}, conditional on getting a credit card from lender j and using an amount U_{ijmt}, is given by:

$$P^F_{ijmt|D=1,U} = \Phi_{\epsilon_i^F|\epsilon_i^U}\left(\frac{\bar{\alpha}_0^F + \alpha^F r_{jmt} + \beta^F X^F_{jmt} + \eta^F Y^F_{ijmt} + \mu_{\epsilon_i^F|\epsilon_i^U}}{\sigma_{\epsilon_i^F|\epsilon_i^U}}\right), \tag{13}$$

where ϕ is the CDF of a standard normal distribution, and:

$$\epsilon_i^F|\epsilon_i^U \sim N(\frac{\rho_{UF}}{\sigma_U^2}\epsilon_i^U, \sigma_F^2 - \frac{\rho_{UF}^2}{\sigma_U^2}). \tag{14}$$

Since our interest rate data are the bank-time-market level, it is unlikely that they are correlated with firm-specific utilization and default unobservable (ϵ_i^U and ϵ_i^F). Additionally we include market and time fixed effects, lender type fixed effects, as well as firms characteristics such as risk-score and size. For this reason we use the actual interest rate in the likelihood function of the utilization and default choices rather than the instrumented interest rate we use in the extensive margin demand estimation.

Supply side. Having estimated the demand side of the model, the supply side estimation is standard. We obtain lenders marginal cost of offering credit cards by inverting the first order conditions given by equation (9). We observe interest rates r_{jmt} in the data and we use our estimated demand parameters to predict at the firm-lender-market-time level demand ($\widehat{q_{ijmt}}$) and default ($\widehat{f_{ijmt}}$); as well as the sensitivity of demand ($\widehat{\frac{\partial q}{\partial r_{ijmt}}}$) to the interest rate. We then sum across firms and invert the first-order-conditions and solve for the only unobservable variable left, which is the lender-time-market level marginal costs (mc_{jmt}).

[27] Additionally, in our own setting we find no empirical positive relationship between interest rates and delinquency.

5.2 Parameters Estimates

Table 7 presents the estimates from the structural model. Column (1) reports the results from the demand equation. The coefficient on interest rate is negative and significant, as expected. A higher interest rate has a negative impact on demand for credit card from a given lender. To give a better sense of the magnitude of the estimate we compute the own and cross-elasticities. The average own-elasticity is about 1.2, which implies that a 10% increase in rates reduced the lender market share by about 12%. Our demand elasticities are similar to the ones in previous work on firm credit demand (Crawford et al., 2018) and lower than the ones estimated for household credit card demand (Nelson, 2018; Matcham, 2022). One explanation for the lower rate elasticities for business credit cards compared to households credit cards could be that business credit cards are a less standardized product than consumer credit cards, hence non-rate characteristics might play a more important role in the borrower's decision.[28] Another possible reason is that because some businesses initially demand the card for payment purposes, they do not anticipate borrowing and are therefor not sensitive to the rate. They only borrow following a shock. Finally, the own-elasticities are larger for non-banks than for banks, suggesting possible selection of more price-sensitive customers to non-bank lenders.

Relative to firms with a medium level of risk (the omitted category), firms with very high and high risk are less likely to have a credit card; firms with low risk are also less likely, but firm with very low risk are more likely to have a credit card. The smallest firms with fewer than 5 employees have the highest demand for credit cards. The demand for credit cards monotonically decrease with firm size up until firms with up to 100 employees. A high utility for credit cards as borrowing products for the smallest firms is in line with banks shying away from providing customized term loans with very small amounts, and opting instead to serve the smallest business customers with more standardized business credit cards. Firms with high cash-flow volatility have a higher demand for credit cards, which is consistent with their demanding revolving products in order to meet liquidity shocks. Finally, we estimate a large and significant unexplained heterogeneity in demand for business credit cards as borrowing products.

Table 7 Column (2) reports the estimates for the utilization choice. A higher interest rate is associated with significantly lower utilization. Most notably, a one-percentage-point higher interest rate is associated to approximately a 0.5 percentage-point lower credit card utilization. This translate to an average elasticity of utilization to interest rate by about 0.25, which is similar to the findings of Matcham (2022) for households credit card utilization in the UK. In line with our facts of Section 2, we find that utilization monotonically increases with firm risk, monotonically decreases with firm size, and monotonically increases with firm cash-flow volatility. Hence, our model is able to capture rich and economically sensible patterns of firm-level credit card utilization.

Column (3) of Table 7 shows the estimates for the delinquency choice. Again in line with the

[28] As we already discussed in Section 2 business credit cards have several features. The interest rate is often presented as a wide range, with the final rate depending on borrower creditworthiness. This features combined with the presence of low (zero) introductory rates complicates comparison among credit card products, potentially affecting rates sensitivity.

facts presented in Section 2, we find that delinquency monotonically increases with risk and decreases with firm size. Both firms with high and low cash-flow volatility have higher delinquencies than firm with medium cash-flow volatility. For both the utilization and delinquency choice, the effects from differences in observable risk are economically larger than the effect from differences in observable firm size and our proxy for cash-flow volatility.

Importantly, we find a positive and highly statistically significant correlation in the unobserved shocks for utilization and delinquency. Thus, firms with an unexpectedly high utilization of their credit card are also unexpectedly more likely to be delinquent on their credit card. The correlation is about 0.06. Our estimates are lower than what Crawford et al. (2018) find for firm credit in Italy. One reason for the difference could be the presence of more sophisticated risk scoring approaches by lenders in the US small business credit card market in the 2014-2019 compared to the Italian corporate loan market in 1988-1998, studied by Crawford et al. (2018). We explicitly test this hypothesis by re-estimating our structural model without the fixed effects capturing firm risk scores. Table A1 in the online appendix shows the results. The correlation between credit card utilization and delinquency almost doubles, increasing to 0.11, while the other parameter estimates are relatively unaffected, broadly in line with the hypothesis that better risk scoring reduces the correlated impact of these ex-post shocks.

Table A2 in the online appendix reports some measures of the fit of the model. We focus on the key variable of interest: predicted credit card demand, utilization, and delinquencies on the firm side; and predicted marginal costs and markup on the lender side. Overall, the model predicts means well. We also account for most of the dispersion in the data with the predicted credit card demand, but the model ability to capture the large variation in utilization and delinquencies observed in the data is more limited. We estimate marginal costs and effective marginal costs of about 4.3 and 4.4 percentage points on average. In consequence, accounting for default increases effective marginal costs by about 10 basis points during our estimation period. This relatively small difference in costs is in line with the low average default rate observed in the data. Given the observed rates in the data, we calculate that the average effective markup is about 8 percentage points. This large markup is the combined result of relative inelastic own-firm demand and relative low default rates, even after accounting for the fact that higher-utilization borrowers are significantly more likely to default.

We allow for further heterogeneity in our model by estimating some structural parameters flexibly across firms in two dimensions, risk and size, in line with the facts presented in Section 2. Figure 7 shows the estimates capturing unobservable variation in utilization and its correlation with delinquencies across risk groups. Allowing for variation in the structural parameters across observable risk score categories reveal interesting patterns. Firms classified as very-high risk have the highest correlation between unobservable utilization and delinquency. The difference is both statistically and economically significant. The point estimate is almost 0.14, which is more than twice the point estimates for the very-low risk group of firms. Additionally, we find that the standard deviation of utilization monotonically increases with firm risk. Firms classified as very-high risk score have the

Table 7: STRUCTURAL ESTIMATES

	Demand	Utilization	Default
	(1)	(2)	(3)
Interest rate	-10.855	-0.556	
	(1.433)	(0.009)	
Risk: Very high	-0.607	0.154	1.319
	(0.057)	(0.009)	(0.041)
Risk: High	-0.176	0.046	0.562
	(0.035)	(0.005)	(0.033)
Risk: Low	-0.285	-0.136	-0.207
	(0.021)	(0.003)	(0.020)
Risk: Very low	0.181	-0.272	-0.538
	(0.020)	(0.002)	(0.030)
Employee: 5-9	-0.261	-0.011	-0.111
	(0.025)	(0.003)	(0.023)
Employee: 10-19	-0.446	-0.028	-0.119
	(0.029)	(0.004)	(0.031)
Employee: 20-49	-0.579	-0.037	-0.211
	(0.035)	(0.005)	(0.058)
Employee: 50-99	-0.525	-0.029	-0.202
	(0.067)	(0.009)	(0.174)
Employee: 100+	-0.447	-0.058	-0.424
	(0.082)	(0.011)	(0.114)
Cash-flow volatility: High	0.188	0.004	0.107
	(0.020)	(0.003)	(0.017)
Cash-flow volatility: Low	0.120	-0.003	0.079
	(0.022)	(0.003)	(0.028)
Covariance Matrix			
	$\sigma_D = 0.941$		
	(0.028)		
		$\sigma_U = 0.307$	
		(0.001)	
		$\rho_{UF} = 0.064$	$\sigma_F = 1.000$
		(0.005)	
Fixed effects			
Time × Market	Yes	Yes	Yes
Time × Lender Type	Yes	Yes	Yes
Observations	1175887	38936	38936

Note: The Table shows the results from the structural estimation of the demand and default model. All coefficients are estimated in the first stage, with the exception of the interest rate for the demand equation that is estimated in the second stage. Standard errors are in brackets. First-stage standard errors are calculated by the inverse of the Information matrix. Second-stage standard errors are computed with 200 bootstrap replications.

highest standard deviation for unobservable utilization, which is approximately 0.36. Again, the difference with firms with lower risk is both statistically and economically significant. For example, firms with low and very-low risk score have a standard deviation of utilization of about 0.32 and 0.26, respectively.

Table 8 reports the estimates of some structural parameters by firm size. Columns (1) and (2) show the baseline estimates using the full set of firm and bank controls and fixed effects as in Table 7. The correlation between credit card utilization and delinquency is highest for the smallest firms at

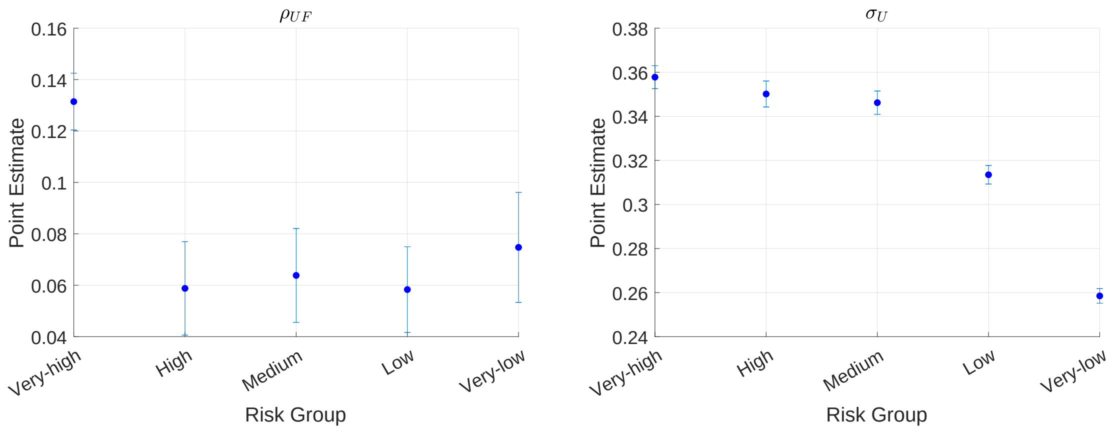

Figure 7: STRUCTURAL ESTIMATES BY FIRM RISK

Note: The left figure shows the point estimates and 95% confidence interval on the parameter capturing the correlation between utilization and delinquency (ρ_{UF}). The right figure shows the point estimates and 95% confidence interval on the parameter capturing the unobservable variation in utilization (σ_U). Standard errors are calculated with the inverse of the Information matrix.

almost 0.07. The correlation declines for firms with 5-9 employees to 0.06 and even further to 0.034 for firms with 10-19 employees. Interestingly, the correlation then rises again to about 0.06 for firms with 20 or more employees, perhaps suggesting additional negative selection for these relatively larger firms that still choose to borrow on credit cards. The standard deviation of unexplained utilization is relatively stable around 0.3, and slightly higher for the largest firms.

Columns (3) and (4) of Table 8 report the estimates without the risk-controls, and columns (5) and (6) show the difference between these estimates with the baseline estimates. Removing credit risk controls has the largest effect of the smallest firms. For firms with fewer than five employees, not controlling for risk score almost doubles the correlation between utilization and default, which increases by 0.058 (from 0.069 to 0.127). For firms with more than 50 employees, not controlling for risk score increases the correlation between utilization and default by less than half relative to the smallest firms (i.e., by 0.024, from 0.059 to 0.083). Similarly, not controlling for risk score, increases the unexplained variation in utilization the most for the smallest firms and the size of the increase monotonically decreases with firm size. For example for firms with 5-9 employees the standard deviation of unexplained utilization increases by 0.022, while for firms with 50 or more employees the increases is less than a third at 0.007. Hence, the main takeaway from Table 8 is that risk score matters especially for the smallest firms. The interpretation is that these smallest firms are the most opaque and also the firms where detailed officer screening through soft information is the least valuable simply due to the small expected borrowing amount. Thus, the harder information contained in the risk-score is most consequential among this subset of firms.

Table 8: STRUCTURAL ESTIMATES BY FIRM SIZE

	Baseline		No Risk Score		Δ	
	ρ_{UF}	σ_U	ρ_{UF}	σ_U	ρ_{UF}	σ_U
	(1)	(2)	(3)	(4)	(5)	(6)
1-4	0.069	0.300	0.127	0.336	0.058	0.036
	(0.007)	(0.002)	(0.005)	(0.002)		
5-9	0.060	0.309	0.107	0.331	0.047	0.022
	(0.010)	(0.002)	(0.009)	(0.002)		
10-19	0.034	0.308	0.084	0.327	0.050	0.018
	(0.010)	(0.002)	(0.006)	(0.002)		
20-49	0.061	0.308	0.102	0.321	0.041	0.013
	(0.010)	(0.002)	(0.005)	(0.002)		
50+	0.059	0.319	0.083	0.326	0.024	0.007
	(0.009)	(0.002)	(0.008)	(0.002)		

Note: The Table shows the results from the structural estimation of the demand and default model by firm size. The reported coefficients are estimated in the first stage. Standard errors are in brackets. First-stage standard errors are calculated by the inverse of the Information matrix. Columns (1) and (2) show the baseline estimates using the full set of firm and bank controls and fixed effects as in Table 7. Columns (3) and (4) show the estimates without the risk-controls. Columns (5) and (6) show the differences between the baseline estimates and the estimates without the risk-controls.

6 Counterfactuals

In this section we present the results of several counterfactual exercises using our estimated model. We begin by considering how delinquencies and lender profits respond to large unexpected shocks in the spirit of a COVID-19 shock or 2008 Global Financial Crisis shock, in which utilization, delinquency, and lender marginal costs changed quickly and dramatically. We then explore how proposed bank capital regulation under Basel III "Endgame," which adds capital risk weights to the *undrawn* portion of the revolving line, is likely to impact credit card lending.

6.1 Credit Card Lending Under Stress

We first explore how delinquencies and profits respond to shocks to: (i) firm credit card utilization; (ii) lenders marginal costs; and (iii) both. The goal of this set of counterfactuals is to provide a quantitative contribution to the debate on banks as providers of contingent credit under stress scenarios.

Among others, Acharya et al. (2023) and Cooperman et al. (2023) study the drawdowns on credit lines and bank performance during the global financial crisis (GFC) and the COVID-19 outbreak. Both papers emphasize how during the GFC, large drawdowns on credit lines coincided with increasing costs for banks, while during the COVID-19 outbreak, drawdowns were channeled back to banks as deposits, thus leaving the banking system largely unaffected. We complement these studies by: examining business credit cards rather than lines of credits; and more importantly, providing a quantitative model that accounts for competition among lenders as well as realistic correlation between utilization, default and profitability. As Figure 1 shows, credit card are the small firm counterpart of credit lines. Therefore, understanding the impact of shocks to credit card utilization and lenders marginal costs has important implications for small firms access to external finance and liquidity management. Although our quantitative analysis concerns business credit cards in particular, the lessons here apply more broadly to other revolving and contingent lending contracts.

In our counterfactual analysis, we fix contracts ex-ante (i.e., extensive margin relationships and interest rates are held fixed) and vary the size of the utilization shock, lender marginal costs, and the correlation between utilization and default. By fixing contracts ex-ante, we simulate a scenario in which borrowers and lenders and hit by an unexpected shock and do not have a chance to renegotiate new terms. That is, lenders have made commitments to borrowers and must uphold their commitments. We interpret the utilization shock increase as reflecting a deterioration in real economic conditions (e.g., COVID-19 shutdowns) that increase the firms' demand to make liquid draws to pay workers or suppliers. We interpret the increases in lender marginal costs as large bank funding shocks coming from, e.g., financial market instability. We interpret increases in the correlation between utilization and default as representing an increase in "shock-driven" credit draws relative to draws for, e.g., investment. We discuss how we discipline the size of these shocks below.

Figure 8 shows how delinquency and lender profits vary as we change these parameteres. Changes in delinquencies are shown down the left-side subplots. Changes in lender profits are shown down the right-side subplots. The counterfactual change in credit card utilization versus the baseline is reported on the y-axis of each figure in percentage points (pps). The counterfactual lender marginal cost is reported on the x-axis in basis points (bps). We vary the correlation between utilization and default going down the panels, starting from the baseline and increasing it.

Before delving into the counterfactuals that most closely resemble the GFC or Covid-19 events, we discuss some general patterns focusing on the top panels of Figure 8. Credit card delinquencies are not affected by changes in marginal costs, since rates are kept fixed, but increase with credit card utilization, due to the estimated positive correlation between unobservable utilization and delinquencies. In the baseline, a 10pp increase in utilization (which is about a 33% increase relative to the average utilization) is associated to a 0.4pp increase in delinquencies (which is about a 20% increase relative to the average delinquency rate). Lenders profits from credit card lending decrease with higher marginal costs, as expected. For example, a 100 bps increase in marginal costs (which is about a 25% increase relative to the average marginal cost) decreases lender profits by approximately 12% at the baseline level of utilization.

Although higher delinquencies accompany higher utilization, we find that lenders profits increase with higher utilization, holding marginal costs constant. For example, a 10pp increase in utilization is associated to an almost 30% increase in profits, at the baseline level of costs. Intuitively, the increase in revenue from collecting interest on a larger balance more than offsets the decrease in revenue from higher delinquencies. This is true even for large values of ρ_{UF}, although the increases become much smaller when ρ_{UF} is high: For the baseline ρ_{UF}, increasing utilization by 5pp leads to a 14.5%

increase in profits. In contrast, for a ρ_{UF} that is five times the baseline value, the same increase in utilization increases lender profits by only 6%. Lender profits become materially lower only with direct increases in marginal costs, i.e., only when bank funding costs directly increase while lending rates are held constant. With the estimated model, we can explore joint changes in firms utilization and lenders costs. For example, the aforementioned 10pp increase in utilization increases lender profits, unless marginal costs increases at the same time by 200bps or more.

Through the lens of the model, we now explicitly compare our quantitative exercises to the changes observed during the GFC and COVID-19 pandemic. During the GFC, lenders experienced large increases in the costs of their external finance at the same time that firms drew down credit lines and delinquencies increased.[29] According to the Equifax Small Business Delinquency Index (SBDI), delinquencies in 2009 increased to more than 6%.[30] We approximate the GFC in the context of our model by looking at the bottom panels in Figure 8. Empirically, there was a utilization increase of about 5pp accompanied by an increase in delinquencies of about 4.6pp to 6.1pp (given pre-shock delinquencies around 1.5pp), which corresponds to the lower-left panel's 5pp increase in utilization. Given increase in marginal costs observed to be on the order of 300bps, our model suggests that bank profits on their business credit card lending fell by roughly 37%, but still remained positive.

In contrast, the COVID-19 pandemic was characterized by even larger firm drawdowns compared to the GFC, especially by firms below investment grades (Acharya et al., 2023; Greenwald et al., 2020).[31] However, crucially different from the GFC, banks were able to meet the liquidity demand due to a combination of ex-ante higher capital and liquidity buffer, ex-post policy interventions, household increase supply of deposits as well as firms drawing down for precautionary reasons and redepositing the money in the banking system (Levine et al., 2021; Cooperman et al., 2023). The increase in delinquencies was also more modest compared to the GFC. The same Equifax SBDI shows that delinquencies in 2020 increased to more than 3%, compared to 6% during the GFC. As a result of these different factors, the need of external finance for banks was limited and the cost of external finance for banks increased by less relative to the GFC.

The COVID-19 pandemic is well-captured by our model when looking at the middle panels in Figure 8. A utilization increase by about 15pp, which represents approximately a 50% increase relative to the mean utilization, lead to an increase in delinquencies by about 1.9pp to 3.4 (given pre-shock delinquencies around 1.5pp), in line with the observed increase in the data. Given an increase in marginal costs in the order of 100bps, our model suggests that bank profits on business credit card lending would have increased by about 23% absent programs like the PPP which obviated many small business's needs to draw down their credit cards. We can then simulate what would have happened if

[29] See Acharya and Mora (2015) and Ivashina and Scharfstein (2010), among others.

[30] See https://assets.equifax.com/marketing/US/assets/Equifax.MonthlyStrategicInsights.November2023.pdf.

[31] For example, Acharya et al. (2023) find that lower quality firms drawn down twice as much relative to higher quality firms, but both groups increased their drawdowns by a factor of two during the Covid-19 outbreak (see their Figures 4 and 5). These drawdowns were likely minimized for small firms by the passage of the PPP. In consequence, we interpret this counterfactual as a "no-PPP" counterfactual.

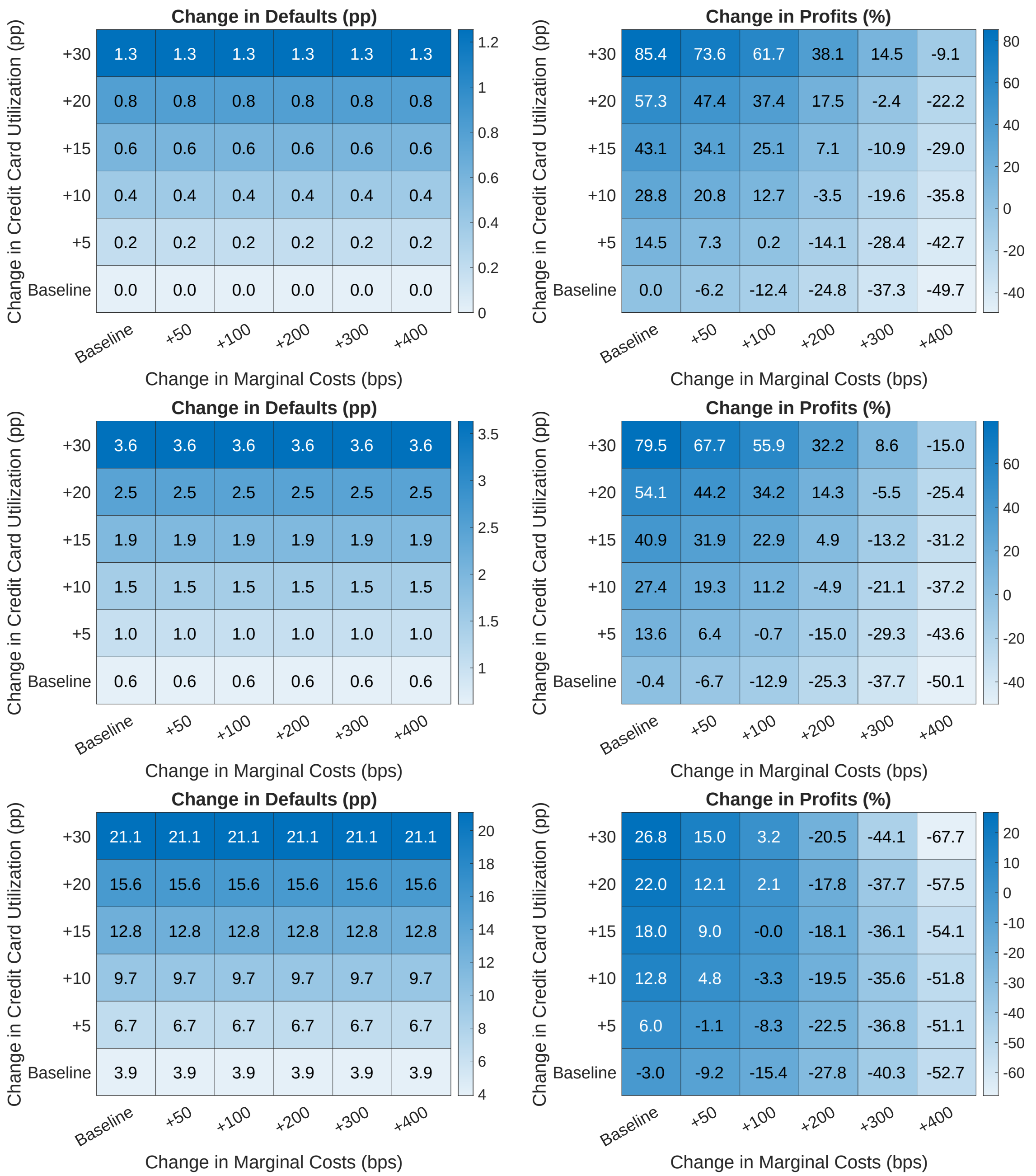

Figure 8: COUNTERFACTUALS: CREDIT CARD LENDING UNDER STRESS

Note: The top two panels show counterfactual firm delinquencies (left) and lenders profits (right) using the baseline ρ_{UF} for different level of firm credit card utilization and lenders marginal costs. The middle two panels show counterfactual firm delinquencies (left) and lenders profits (right) using a ρ_{UF} that is two times the baseline one for different level of firm credit card utilization and lenders marginal costs. The bottom two panels show counterfactual firm delinquencies (left) and lenders profits (right) using a ρ_{UF} that is five times the baseline one for different level of firm credit card utilization and lenders marginal costs.

the cost of lenders external finance was increasing to a larger extent. Given the increase in utilization and delinquencies, banks cost would have had to increase by about 300bps – similar to the increase observed during the GFC – for bank profits to decline during the COVID-19 pandemic.

6.2 Capital Regulation of Undrawn Credit Commitments

We now explore how a proposed change in the capital regulation of undrawn balances affects equilibrium credit card provision, as well as its differential impact on banks, which are subject to the regulation, and non-banks, which are not.

The proposal (often refereed to as the Basel III "Endgame,") plans to link capital risk weights to the manner in which the customers use the credit cards. Customers who use the card as a payment product (transactors) would receive a relatively lower risk weight (55%) than customers who use the card as a borrowing product (revolvers), who would receive an 85% risk weight.[32] The idea, consistent with our findings in this paper, is that borrowers with greater rates of utilization are riskier.

Importantly, current capital rules treat the undrawn credit (i.e., the difference between the limit and the balance) as having zero risk weight. However, because borrowers are free to draw down their limits ex-post—particularly when faced with a negative shock—this treatment of undrawn balances potentially understates the risk that banks face from undrawn credit card balances. The Basel III proposal attempts to address this issue with the addition of a so-called credit conversion factor (CCF), which effectively treats a portion of the undrawn balance as though it was actually drawn. The baseline proposal is for a 10% CCF.

The proposal works as follows. Consider a credit card revolver with a limit of \$15 thousand and a current balance of \$5 thousand. The \$5 thousand balance receives an 85% risk weight. The \$10 thousand undrawn is then treated as if it were 10% drawn, and that hypothetical balance receives an 85% risk weight. In total, the risk-weighted asset contribution of this account is therefore $\$5 \times 0.85 + \$10 \times 0.10 \times 0.85 = \$5.1$ thousand, which is \$0.85 thousand greater than it would be without the CCF rule. Thus, the CCF disproportionally affects cards with a high limit and low balance.

We explore this proposed changes through the lens of our model, by enriching banks profits to account for the additional capital cost on undrawn credit commitments. We modify profits from equation (7) as follows:

$$\Pi_{jmt} = \sum_{i \in I_{mt}} \left[\overbrace{r_{jmt} q_{ijmt}(1 - f_{ijmt}) - mc_{jmt} q_{ijmt}}^{\text{Profits as in equation (7)}} \overbrace{- CCF \times mc_{jmt} s_{ijmt}(1 - u_{ijmt})}^{\text{Regulation of undrawn commitments}} \right], \quad (15)$$

where CCF is the credit conversion factor, s_{ijmt} is the predicted discrete demand from firm i for credit card offered by lender j, and u_{ijmt} is the predicted utilization from i. Recall that total credit demand is the product of the discrete demand and the utilization choice (i.e., $q_{ijmt} = s_{ijmt} \times u_{ijmt}$).

[32] Customers with cumulative borrowing above \$1 million will have a risk weight of 110%, since they fall above the limit of regulatory retail exposure.

Hence, our flexible demand model is well suited to study regulation that depends on customers differential usage of credit cards. Observe also that marginal costs combine both financing/capital costs as well as non-financial production costs (e.g., the costs of originating and monitoring loans). Because we CCF impacts only the financing component of the marginal cost, we experiment with different levels of the CCF, which is equivalent to applying it to only a portion of the estimated marginal cost.

Table 9 shows the results. In column (1) we report the baseline estimates for the variables of interest: rates, demand, utilization, default, lender profits and firms surplus. Because the regulation impacts banks but not non-banks, we bread down several of these outcomes by lender type. The baseline results reflect many of the reduced form findings: Bank rates are somewhat higher than non-banks, banks have larger market shares and utilization, and lower delinquency rates. In terms of firms, the smallest firms obtain the highest consumer surplus from borrowing on cards, reflecting their lack of outside options in other external financing products.

Column (2) reports the results of the counterfactual with a CCF of 10%, which is the Basel III "Endgame" proposal. On average, interest rate increase by about 3%. The cost of providing credit cards directly increases for banks, and they raise rates by almost 5.8%. Non-banks, who are unaffected by the regulation, modestly decrease rates by less than 0.5% As a result of higher rates, demand for credit cards decreases at the extensive margin by roughly 1%. The average change masks a relatively large reallocation away from banks and toward non-banks. The average bank looses more than 4% market share, and the average non-bank gains about 3.6% in market share relative to the baseline. Hence, while the policy proposal improves banks capital position if a potential credit exposure becomes a realized one, this conversion risk is shifted to non-banks.

Average credit card utilization decreases by almost 1%, driven by a large decline (above 1.5%) for banks. Despite the lower utilization rate, default increases by almost 1%, again driven by the relatively large increase for banks. The joint decrease in utilization and increase in default for banks can be explained by the model selection mechanism. As banks increase rates, utilization goes down (given the downward sloping demand for utilization relative to rates). However, the firms that are taking credit card from banks at these higher rates are increasingly more risky, hence the increase in default. Changes in utilization and defaults for non-banks are small in magnitude (less than 0.05%). However, non-banks are now more exposed to "shock-driven" correlated increases in utilization and default, like the ones that we studied in Figure 8.

Finally, we compute lenders profits and firms surplus. Overall profits decline by about 4%, as a result of an almost 9% decrease in banks profits. Non-banks benefit from the regulation and experience an increase in profits by 3.6%, despite the lower rates, as a result of the large increase in market share. Firms surplus from access to credit card products decline since they now face even higher credit card rates and borrow less. However, the possibility to substitute away from more expensive banks credit cards toward relatively cheaper non-banks credit cards limits losses to around 3.9%. While surplus losses are fairly homogeneous across the firm size distribution, we find that the smallest firms experience the largest losses from higher bank rates, consistent with their being the most reliant on credit

Table 9: Counterfactuals: Capital Regulation of Undrawn Credit Commitments

	Baseline	Risk-weights for Undrawn Balances		
		Proposed: CCF=10%	Lower: CCF=5%	Higher: CCF=25%
		Δ %	Δ %	Δ %
	(1)	(2)	(3)	(4)
Rates	12.47	3.24	1.38	9.16
Banks	12.82	5.74	2.64	15.62
Non-banks	12.00	-0.44	-0.47	-0.34
Demand	3.15	-1.02	-0.51	-2.59
Banks	3.25	-4.15	-2.06	-10.64
Non-banks	3.02	3.63	1.79	9.35
Utilization	33.41	-0.97	-0.48	-2.53
Banks	33.70	-1.64	-0.81	-4.30
Non-banks	33.00	-0.02	-0.01	-0.04
Default	1.73	0.95	0.46	2.50
Banks	1.52	1.84	0.90	4.87
Non-banks	2.02	0.02	0.01	0.05
Lender Profit	0.08	-4.02	-2.03	-9.70
Banks	0.08	-8.99	-4.52	-22.08
Non-banks	0.08	3.64	1.80	9.39
Firm Surplus	1011.89	-3.85	-1.94	-9.39
1-4	1155.29	-3.90	-1.97	-9.51
5-9	920.94	-3.80	-1.92	-9.27
10-19	880.18	-3.78	-1.91	-9.22
20-49	860.89	-3.77	-1.90	-9.20
50-99	869.87	-3.79	-1.91	-9.24
100+	872.79	-3.79	-1.91	-9.25

Note: This Table shows the results of several counterfactual analyses in relation to the capital regulation of undrawn credit commitments. Column (1) reports the baseline estimates. Column (2) reports the counterfactual estimates with a credit conversion factor (CCF) of 10%, which is the one currently suggested in the so-called Basel III "Endgame" proposal. We also simulate the case with a lower CCF at 5% and a higher one at 25%, which are reported in columns (3) and (4), respectively.

cards for external financing.

We repeat the experiment for a smaller CCF (5% in Column (3)) and a larger CCF (25% in Column (4)). The results are qualitatively in line, though as expected are smaller for the lower CCF and larger for the larger CCF. To summarize our findings, the implementation of capital requirements on the undrawn portion of credit card, we find that rates increase, while demand and utilization decrease as a result, particularly for banks. Interestingly, while the regulation targets unutilized lines, because banks pass through higher costs through interest rates, firms in fact utilize credit *less*, and overall utilization rates decrease.

7 Conclusions

Business credit cards represent a major source of external financing for small businesses and often fill the role that a line of credit would for larger firms. Credit cards provide businesses with an insurance policy against ex-post shocks, enabling them to access liquidity in states of the world where it is most needed. However, it is potentially very costly for a lender to provide this contract, as ex-post demand for utilization may be highly correlated with ex-post propensity to default.

In this paper we provided several new facts around business credit cards using a novel small business credit panel. The average limit on a business card is roughly \$16 thousand with a 26% utilization rate. Firms in industries with high cashflow volatility are more likely to have credit cards and utilize them ex-post. Over our time period, the delinquency rate on cards is roughly 1.5%, and delinquency increases monotonically with utilization, providing suggestive evidence of asymmetric information or correlated ex-post shocks to utilization and delinquency, which would push breakeven rates on credit cards higher. Card rates are roughly 6% higher than term loan rates and are mostly set at the lender-month level. Finally, net interest income is positive in expectation across the spectrum of utilization rates and firm risk, but highest for medium risk firms who carry large balances but rarely default.

We then estimated a structural model of firm credit card demand, utilization, and delinquency. Reflecting the key facts in our data, our model allows for correlated unobservable shocks between utilization and delinquency. Our estimated model suggests that while this correlation leads to higher rates, the high rates charged on cards mostly reflect lender markups. We use our model to evaluate borrower delinquency and lender default in stress scenarios resembling the global financial crisis and COVID-19. Our counterfactual suggest that shocks to borrower utilization tend to increase lender profitability, as rising defaults are more than offset by increased revenue on larger balances. Lender profitability is only materially harmed when utilization shocks are also accompanied by large increases in funding costs. Additionally, we examine the counterfactual impact of new capital requirements under Basel III "Endgame" which add a portion of card borrowers' undrawn limits to risk-weighted assets, and find that rates increase, demand and utilization decrease, particularly among banks. Firm surplus declines by roughly 3.85%, with stronger declines among the smallest firms that are most reliant on credit cards as a source of external financing.

Overall, our results highlight that while business credit cards are *potentially* costly for lenders to provide, in normal times, they are highly marked-up and profitable products. Our paper is a first step in understanding the role that business credit cards play in the provision of external financing to the smallest firms and how these firms access credit more generally.

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Online Appendix

In this appendix we report additional results on the facts and structural model.

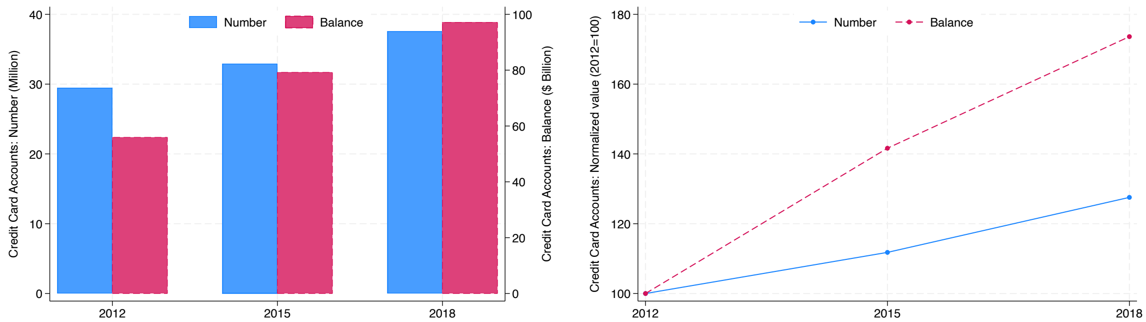

Figure A1: CREDIT CARD AS SOURCE OF EXTERNAL FINANCING FOR (SMALL) BUSINESSES
Note: The left panel shows the number and balance of business credit card accounts at reporting depository institutions. The right panel shows the number and balance of credit card accounts normalized to 100 in 2012. Source: 2019 2019 Federal Reserve Payments Study Detailed Data Tables.

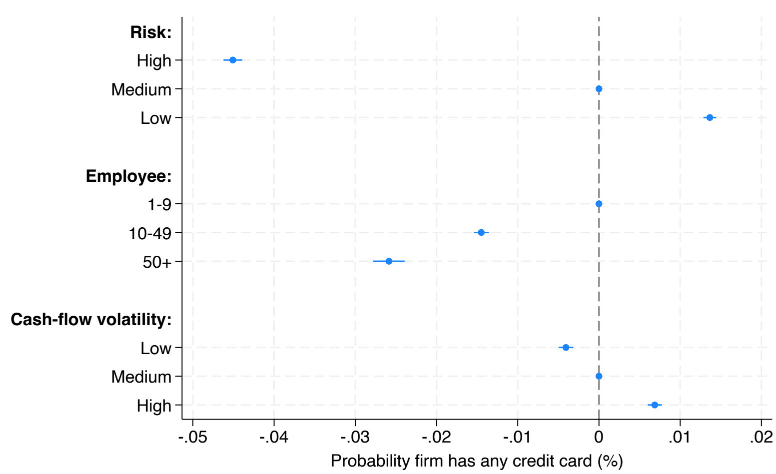

Figure A2: CREDIT CARD CHOICE
Note: The figure shows the point estimates and 95% confidence intervals from a linear probability model. The dependent variable is a dummy equal to one if the firm has any credit card. The explanatory variables are: a categorical variable for firm risk; a categorical variable for firm size measured by the number of employees; tercile of firm cash-flow volatility; zip code and time fixed effects. Standard errors are clustered at the firm level.

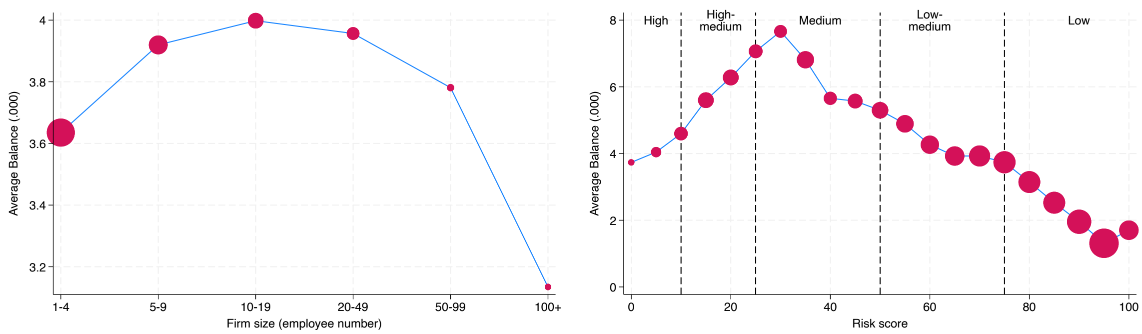

Figure A3: FIRM SIZE AND RISK: CREDIT CARD BALANCES

Note: The left figure shows the relation between firm size groups and credit balances. The right figure shows the relation between risk-score groups and credit balances. The size of the circle is proportional to the number of observation in the specific firm size group.

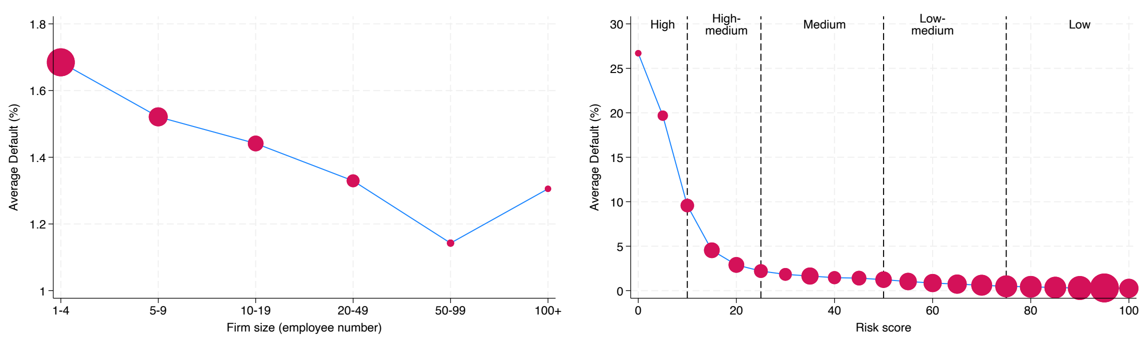

Figure A4: FIRM SIZE AND RISK: DELINQUENCY

Note: The left figure shows the relation between firm size groups and delinquency. The right figure shows the relation between risk-score groups and delinquency. The size of the circle is proportional to the number of observation in the specific firm size group.

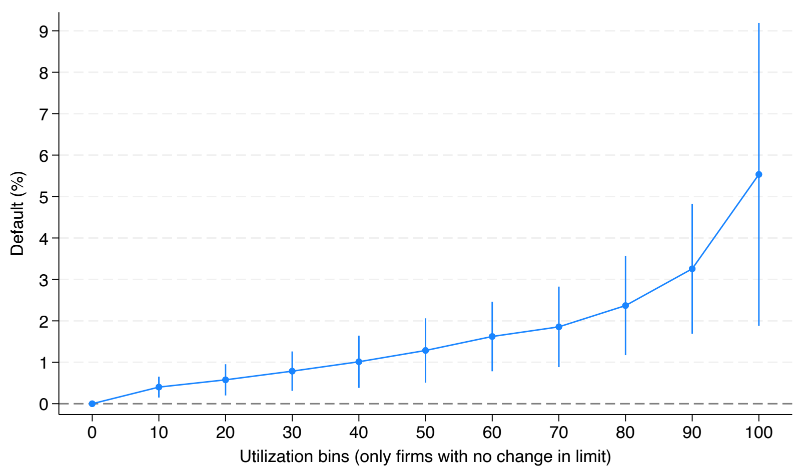

Figure A5: UTILIZATION AND DELINQUENCY: ONLY FIRMS WITH NO CHANGE IN CREDIT CARD LIMIT

Note: The figure shows the point estimates and 95% confidence intervals from a linear probability model. The dependent variable is a dummy equal to one if the firm has any credit card. The explanatory variables are: a categorical variable for firm risk; a categorical variable for firm size measured by the number of employees; tercile of firm cash-flow volatility; zip code and time fixed effects. Standard errors are clustered at the firm level.

Table A1: STRUCTURAL ESTIMATES - NO RISK CONTROLS

	Demand	Utilization	Default
	(1)	(2)	(3)
Interest rate	-10.869	-0.799	
	(1.435)	(0.009)	
Employee: 5-9	-0.266	-0.004	-0.077
	(0.025)	(0.004)	(0.019)
Employee: 10-19	-0.437	-0.026	-0.106
	(0.029)	(0.004)	(0.028)
Employee: 20-49	-0.567	-0.039	-0.199
	(0.035)	(0.005)	(0.037)
Employee: 50-99	-0.502	-0.024	-0.167
	(0.067)	(0.010)	(0.040)
Employee: 100+	-0.445	-0.046	-0.359
	(0.082)	(0.012)	(0.108)
Cash-flow volatility: High	0.184	0.010	0.099
	(0.020)	(0.003)	(0.018)
Cash-flow volatility: Low	0.121	-0.003	0.049
	(0.022)	(0.003)	(0.016)
Covariance Matrix			
	$\sigma_D = 0.966$		
	(0.028)		
		$\sigma_U = 0.333$	
		(0.001)	
		$\rho_{UF} = 0.113$	$\sigma_F = 1.000$
		(0.003)	
Fixed effects			
Time $\times$ Market	Yes	Yes	Yes
Time $\times$ Lender Type	Yes	Yes	Yes
Observations	1175887	38936	38936

Note: The Table shows the results from the structural estimation of the demand and default model. The difference with the estimates in the main text is that we remove the controls for firm risk. All coefficients are estimated in the first stage, with the exception of the interest rate for the demand equation that is estimated in the second stage. Standard errors are in brackets. First-stage standard errors are calculated by the inverse of the Information matrix. Second-stage standard errors are computed with 200 bootstrap replications.

Table A2: MODEL FIT

	Data	Model
	(1)	(2)
Demand	4.06	4.06
	(19.73)	(15.62)
Utilization	33.10	33.10
	(33.45)	(13.37)
Default	1.69	1.69
	(12.89)	(4.18)
Marginal Cost		4.34
		(1.88)
Marginal Cost (effective)		4.41
		(1.89)
Markup		8.06
		(0.52)

Note: The Table shows some measures of the fit of the estimated structural model. We report averages and standard deviation for several variables. Demand is the predicted lender-level demand for credit cards in percentage points. Utilization is defined as predicted balances over limits in percentage points. Default is predicted delinquencies in percentage points. Marginal cost, effective-marginal cost and markup are from equation (9).