Private Information and Price Regulation in the US Credit Card Market

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December 2019

Abstract

The 2009 CARD Act limited credit card lenders’ ability to raise borrowers’ interest rates on the basis of new information. Pricing became less responsive to public and private signals of borrowers’ risk and demand characteristics, and price dispersion fell by one third. I estimate the efficiency and distributional effects of this shift toward more pooled pricing. Prices fell for high-risk and price-inelastic consumers, but prices rose elsewhere in the market and newly exceeded willingness to pay for up to 30% of the safest consumers within some subprime groups. On net, average transacted prices fell and consumers captured roughly twice as much surplus on average. Total surplus inclusive of firm profits rose in the prime market. These surplus gains reflect both lower markups and the Act’s insurance value to borrowers who could retain favorable pricing after adverse changes to their default risk.

JEL Codes: D18, D22, D43, G21, G28, L13, L14, L51.

*Nelson: University of Chicago, Booth School of Business (Scott.Nelson@chicagobooth.edu), 5807 South Woodlawn Avenue, Chicago, IL 60637. This paper is a revised version of what served as the first chapter of my dissertation at MIT, and for their generous help at all stages of this project, I am deeply indebted to my dissertation committee: Antoinette Schoar, Jonathan Parker, and especially my committee chair Jim Poterba. For thoughtful discussions and suggestions, I thank Nikhil Agarwal, Alex Bartik, Vivek Bhattacharya, Ron Borzekowski, Ken Brevoort, Brian Bucks, Amy Finkelstein, Daniel Green, Daniel Grodzicki, Luu Nguyen, Richard Schmalensee, David Silberman, Daniel Waldinger, and Mike Whinston, as well as conference discussants Johannes Stroebel and Simcha Barkai, and seminar participants at the Columbia Junior Workshop in New Empirical Finance, Copenhagen Business School, Duke University, the European Summer Symposia in Financial Markets, the Federal Reserve Board, the Federal Trade Commission, Harvard Business School, Harvard Kennedy School, London Business School, London School of Economics, NBER Summer Institute (Household Finance), New York University, Northwestern University, the NYU Stern Household Finance Conference, the Federal Reserve Bank of Philadelphia, Queen Mary University of London, Princeton University, Stanford University, the University of California, Berkeley, the University of Chicago, University of Wisconsin-Madison Juniors Conference, the University of Texas at Austin, and the Wharton School. The views expressed herein are those of the author and do not necessarily reflect those of the Consumer Financial Protection Bureau or the United States. I am also grateful to Shaiya Ahmed, Michelle Kambara, Joe Remy, Stefano Sciolli, and Susan Singer for their support at the CFPB, to the Lynde and Harry Bradley Foundation for financial support at MIT, and to the National Science Foundation Graduate Research Fellowship for support under grant number 1122374.
1 Introduction

Lenders typically learn new information about their borrowers over time. What are the consequences of restricting how lenders use such information, and what does this reveal about the role of such information in credit markets?

I study these questions in the context of the US credit card market and the Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009. The CARD Act restricted lenders’ ability to discretionarily raise credit card borrowers’ interest rates over time and also restricted fees that could otherwise substitute for such interest rate increases. Lenders therefore became substantially less able to respond to new information by adjusting borrowers’ pricing.

Understanding the effects of the CARD Act price restrictions is important both because of these restrictions’ economic interest and because of the credit card market’s central role in the US consumer credit landscape. Among the estimated 85 million US households with credit cards, roughly 60% use credit cards for at least occasional borrowing, and credit card holders collectively have access to over $3 trillion in open credit lines. Reliance on credit cards for borrowing is especially pronounced for less credit-worthy consumers, for whom the share of accounts used for at least occasional borrowing exceeds 90%.1

In this paper, I quantify the distributional and efficiency consequences of the CARD Act price restrictions.2 I analyze two channels through which informational restrictions on pricing can influence credit market outcomes. First, if lenders learn over time about borrower demand, the CARD Act price restrictions may limit lenders’ ability to extract rents from inelastic borrowers. Second, such restrictions may also limit lenders’ ability to adjust prices for risk, which may exacerbate the effect of information asymmetries and induce either partial or complete market unraveling. Both channels matter in the short run and also dynamically: consumers face changes to their demand and risk over time and may value favorable pricing more in some states than in others. The interplay of these forces may cause interest rates to fall for some consumers and rise for others; total welfare may also either rise or fall.

I study these effects using two large administrative datasets. The first contains monthly account-level data from the near-universe of US credit card accounts. These data have detailed price measures, including both interest rates paid and fees incurred, as well as measures of outstanding consumer debt, new borrowing, and repayment. The second dataset is a large, randomly sampled panel of US consumer credit reports. These data reveal patterns not observable in the account data, including which consumers are not credit card holders at a given time.

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1See Bricker et al. (2017) and the Federal Reserve Bank of New York’s quarterly reports on consumer credit, together with estimates in this paper’s Appendix Table 1.
2The effects of the CARD Act are also the subject of a seminal paper by Agarwal et al. (2015b). While our studies are strongly complementary, my focus is on the distributional and efficiency implications of these effects – for whom, how, and why does welfare change in equilibrium under the Act’s pricing restrictions. Further discussion of the relationship between our two papers follows later in this section.
I first present new facts about how credit card pricing changed with the implementation of the CARD Act. I show that the class of interest rate increases restricted by the Act affected over 50% of borrowing accounts annually prior to the CARD Act, but this rate of incidence dropped to nearly zero once the Act took effect. The elimination of these interest rate increases had immediate effects on the price distribution: as lenders became unable to discretionarily raise some borrowers’ interest rates, price dispersion (as measured by the interquartile range of interest rates) on new cohorts of mature accounts dropped immediately by one third. The bottom of the price distribution was also compressed, albeit not immediately: within credit score, the bottom quartile of interest rates rose over time relative to the mean by over 100 basis points for most prime borrowers and by over 200 basis points for subprime borrowers. The credit score segments that saw the greatest increase in the left tail of the price distribution also experienced the greatest rates of consumer exit. This is consistent with (partial) market unraveling as the market shifted toward greater pooling.

I also describe the dynamic pricing of risk- and demand-relevant information after the CARD Act. Prior to the Act, interest rates were strongly responsive to changes in risk after origination, whereas after the Act, such “emergent” risk became nearly 75% cheaper for a borrower, relative to risk observable at origination. Lenders appear to face higher adverse retention of risky borrowers as a result. I find that the Act also restricted lenders from adjusting interest rates in response to new information about borrowers’ price sensitivity, and that lenders’ excess returns from inelastic borrowers then fell. These two reduced-form results underscore the importance of both demand- and risk-relevant information in studying the Act’s effects.

With these reduced-form results in mind, I develop and estimate a detailed structural model of the credit card market as a tool for studying the CARD Act price restrictions’ effects. The structural model features consumers who face changes in their risk and demand over time, differentiated lenders who acquire private information about borrowers, and flexible correlation between borrower demand and risk. I estimate the model on the pre-CARD-Act equilibrium observed in the market. I then impose the CARD Act price restrictions in the model and analyze their effects for different types of consumers and for total welfare when the market re-equilibrates. Consequently, this exercise quantifies one precise sense of the Act’s restrictions’ effects: the ceteris paribus effects holding consumer characteristics and other features of the pre-CARD-Act environment constant, rather than the effects of these restrictions in conjunction with other contemporaneous changes, such as the Great Recession and coincident regulation that both accompanied the Act.

In estimating the model, I estimate several key parameters related to the workings of the US credit card market that, to my knowledge, are not available in previous academic work. I use a novel source of quasi-experimental price variation – occasional, portfolio-wide repricing of existing accounts – to estimate borrowers’ sensitivities to price. I find that riskier borrowers are
less price elastic, consistent with the market being adversely selected. Other estimates on the
demand side of the model indicate that consumers’ set-up (or switching) costs for opening new
credit card accounts are relatively high, contributing to persistence in lending relationships even
when prices rise over time.

The results of imposing the CARD Act price restrictions in the model reveal several inter-
related effects. On net, the restrictions cause average transacted prices to fall throughout
the market and especially on subprime accounts, consistent with the results in Agarwal et al.
(2015b). At the same time, consumers who previously could access the cheapest credit within
their credit score segment tend to face higher prices and exit from borrowing. This type of partial
unraveling is especially pronounced among subprime consumers, and I estimate that prices newly
exceed willingness to pay for up to 30% of some subprime consumer types. Nonetheless, given
the effect of lower prices for consumers with the strongest demand for credit, consumer surplus
rises throughout the market. Among subprime consumers, the rise in consumer surplus is mostly
offset by a fall in lender profits; among prime consumers, total surplus rises.

Some of this surplus gain is due to the insurance value of these restrictions for consumers
whose credit scores deteriorate over time. This insurance is most relevant for superprime borrow-
ers. However, the Act’s insurance value also affects the interpretation of surplus gains among
subprime borrowers. The subprime borrowers who benefit most are those whose credit score has
recently fallen below prime, since these restrictions allow them to retain favorable pricing from
loans originated at prime scores. In contrast, subprime borrowers looking to open a new credit
card – for example, a young borrower or a long-time subprime consumer – feel the effects of
market unraveling more severely.

This paper makes a number of contributions relative to existing literature. In a seminal
paper, Agarwal et al. (2015b) also study how the CARD Act affected credit card pricing, finding
through a difference-in-differences strategy that the Act reduced the average, fee-inclusive cost
of credit card borrowing. They also estimate the effects of several non-price provisions of the
Act not studied here, such as the Act’s nudges for consumers to repay balances more quickly.
I complement their analysis by examining which consumers benefited from CARD-Act-induced
price decreases, and which consumers may have instead exited the market as they were pooled
with their peers; I also translate these price changes and exit patterns into estimates of consumer
and total surplus gains. Furthermore, I highlight the importance of reducing market power from
private information rents, and of the insurance value in the Act’s restrictions, as countervailing
forces that made it possible for the Act to increase surplus despite the Act making it more
difficult for lenders to price risk.

Other research on the CARD Act includes Keys and Wang (2019), who study the Act’s nudges

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3I follow the convention of referring to accounts with FICO scores below 660 as subprime, accounts with FICO
scores of 660 or above but below 720 as prime, and accounts with FICO scores of 720 and above as superprime.
If there appears no risk of confusion, I also at times use prime as an antonym for subprime.
for borrowers to pay more than their minimum required payment each month, Jambulapati and Stavins (2014) and Santucci (2015), who describe patterns of account closures and credit line changes coinciding with the Act and the Great Recession, Debbaut et al. (2016), who focus on the Act’s particular restrictions to protect young borrowers, and Han et al. (2017), who compare direct-mail offers for credit cards with those for other financial products before and after the CARD Act to conclude, consistent with my results on partial market unraveling among subprime accounts, that the Act partially curtailed supply among subprime credit cards. There is also a growing body of theoretical work focused on the CARD Act price restrictions in particular: Hong et al. (2018) and Pinheiro et al. (2016) examine pricing and welfare effects of repricing restrictions in a perfectly competitive setting, whereas lender market power plays a central role in my study.4

This paper also joins a long literature examining the competitiveness of, and sources of market power in, the credit card industry. After seminal work by Ausubel (1991) showed credit card lenders tended not to pass through changes in the cost of funds to their borrowers,5 a series of papers have explored whether and why the industry may be imperfectly competitive, including for reasons of search costs (Berlin and Mester (2004), Galenianos and Gavazza (2019)), consumer irrationality (Brito and Hartley (1995)),6 adverse selection (Stavins (1996)), and lender concentration (Herkenhoff and Raveendranathan (2019)). My work integrates many of these potential sources of market power in a single model – including switching costs across firms, adverse selection, and lender private information – and provides an estimation framework that helps identify their relative importance. My results on the particular importance of switching costs across firms join a growing recent literature on the role of switching costs in selection markets, including Handel (2013) and Illanes (2016).

I also provide new evidence on consumer demand for credit card borrowing and how consumers respond to changes in their credit terms. To date, much of the research on this front has focused on how spending or borrowing responds to changes in credit limits (Gross and Souleles (2002), Agarwal et al. (2018), Gross et al. (2019)), and how credit limits affect consumers’ holdings of cash on hand (Telyukova and Wright (2008), Fulford (2015)). In contrast to this work on credit limits, research on how borrowers respond to interest rates and fees has been more limited.7 To

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4The models of both Hong et al. (2018) and Pinheiro et al. (2016) feature ex-post market power after lenders acquire private information about their borrowers, as in Sharpe (1990). I study similar dynamics in a setting that features imperfect competition ex-ante, at the time of contract origination.

5See Grodzicki (2012) for evidence on how the patterns identified in Ausubel (1991) have become less pronounced in more recent data.

6Research on behavioral consumers in the credit card market has remained quite active, including work by Angeletos et al. (2001), DellaVigna and Malmendier (2004), Grubb (2009), Heidhues and Koszegi (2010), Meier and Sprenger (2010), Heidhues and Kőszegi (2015), Ru and Schoar (2016), and Kuchler and Pagel (2018). Related work focuses on how consumers learn over time how to avoid apparent mistakes with credit cards (Agarwal et al. (2008), Agarwal et al. (2009)) and how the probability of mistakes also falls as consumers face higher stakes, e.g. higher balances borrowed (Agarwal et al. (2015a)). However, for some contrasting evidence on this point, see Gathergood et al. (2019) and Ponce et al. (2017).

7The available evidence does find a nontrivial elasticity of borrowing with respect to interest rates, although this evidence tends to use price variation generated either by (1) the pre-scheduled expiration of promotional
help fill this gap, I estimate borrower price elasticities across a range of borrower risk types, and I also estimate primitives of a rich demand model – including switching costs, liquidity costs, and disutility from price – that predict how price elasticities change non-locally as pricing changes. Estimates of these primitives help not only for understanding the CARD Act price restrictions, but also for future research in consumer credit markets.

This paper is organized as follows. In Section 2, I provide background on the credit card market, the CARD Act and the two datasets that I use in my analysis. I also present summary statistics from these datasets to highlight key changes in the credit card market around the implementation of the Act. In Section 3, I report reduced-form analyses of how lenders used CARD-Act-restricted repricing prior to the Act and how the market responded to the implementation of the Act. I develop and estimate my model of the credit card market in Section 4. Section 5 presents results from using the model to study how the CARD Act’s pricing restrictions affect prices, borrowing and welfare in equilibrium. Section 6 concludes.

2 Background and Data

2.1 Institutional Background

2.1.1 The Credit Card Industry

Credit cards are well known as a means of transaction. For many households they are also an important source of credit. Credit cards provide over $3 trillion in open credit lines for unsecured borrowing, and survey estimates suggest that roughly 60% of US households that hold credit cards actively use credit cards to borrow, that is, they do not pay their balance due in full and hence incur interest charges (Bricker et al. (2017)). The importance of credit card borrowing is especially pronounced among less credit-worthy consumers, where the prevalence of at least occasional borrowing rises to roughly 85% among accounts held by near-prime consumers and over 95% for subprime consumers.

Prior to the CARD Act, lenders’ pricing strategies rested on two main sources of information. The first is consumer credit bureaus, which collect data on consumer borrowing history across a wide range of loan products and then use these data to predict consumers’ likelihood of future default, encoded as a credit score. This information is typically available to all firms in the market and so is best thought of as public information for the purposes of studying firm behavior.

The second key source of information for a lender is a consumer’s own credit card behavior after origination. Much of this information is private for the lender because it is not reported to interest rates (Gross and Souleles (2002)), which may predominantly affect a particularly price-sensitive subset of borrowers who serially shop for promotional rates, or (2) within-account interest rate changes over time (Alexandrov et al. (2017)), which, as I detail in Section 3.1, can arise endogenously as lenders respond to shifts in individual borrowers’ risk or demand.
consumer credit bureaus and is not otherwise observable to competitors, including a consumer’s purchase volume, shopping behavior, prevalence of borrowing, repayment rates, and monthly payment timing. This private information is generally learned through a relationship with a borrower after origination.

Prior to the CARD Act, lenders could use a number of price dimensions to respond to new information learned after origination. First, an account’s interest rate for borrowing, or annual percentage rate (APR), could change “at any time for any reason,” according to stock language included in nearly all credit card contracts. Roughly 52% of borrowers in pre-CARD-Act data experienced a discretionary increase in their card’s interest rate over the course of a year. Thus, lenders found it optimal to upwardly reprice the interest rate on many, but not all, borrowers as new information arrived over the course of lending to a consumer.

### 2.1.2 The Credit CARD Act

The CARD Act placed strong restrictions on how credit card pricing responds to borrower behavior. First, discretionary increases in interest rates on outstanding balances were almost completely eliminated; the two major exceptions that lenders were allowed have, in practice, proved to be exceptions that lenders rarely use. Second, over-limit fees, which were one of the most common contingent fees prior to the CARD Act, were likewise almost completely eliminated. Third, the other most prevalently used contingent fee, late fees, were effectively capped by a safe-harbor ceiling of $25 (or $39 for subsequent incidences within 6 months). On net, these restrictions strongly constrained lenders from adjusting prices in response to information revealed through borrower behavior over time, while placing little to no restriction on the interest rate set at the time of origination. While the CARD Act contained other, non-price regulations

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8See Consumer Action (2007) for details on the prevalence of these any-time-any-reason terms. Examples include “All terms, including the APRs and fees...may change based on information in your credit report, market conditions, business strategies, or for any reason”, and “We have the right to change the rates, fees, and terms at any time, for any reason...These reasons may also include competitive or market-related factors.”

9In addition to such discretionary interest rate increases, 36% of borrowers saw a promotional interest rate either be introduced or expire during the year. Promotional rates are especially common at the time of origination; prior to the CARD Act, 35% of originations included some kind of promotional rate, and among accounts used for borrowing, this share reached 71%. These rates were often offered below lenders’ costs; in particular, I estimate that 81% of promotional rates were a 0% APR, allowing interest-free borrowing. However, I estimate that 86% of consumers who borrowed during an introductory promotion were still borrowing on their card three months after the end of their promotion.

10Credit card pricing also responded to borrower behavior through behavior-contingent fees, such as fees for late payments or over-limit transactions. For an average account prior to the CARD Act, revenue from these fees was 32% as large as interest charges, and on subprime accounts it was 46% of interest charge revenue. All major categories of fees were contingent on one or more borrower behaviors revealed after origination, with the exception of annual fees, which made up less than 10% of all fee revenue in pre-CARD-Act data.

11These exceptions allow for the upward repricing of balances on accounts that are 60 or more days delinquent or of newly transacted (rather than already outstanding) balances. The post-CARD-Act data in Figure 1, Panel (a) show these exceptions are rarely used in practice.

12While in principle these fees are still permitted if borrowers opt-in to allow these fees, they have virtually disappeared from the market (see Appendix Figure 1).
as well, industry statements portray the restriction on interest rate increases as “the core, most important provision of the CARD Act” (American Bankers Association (2013)).

These interest rate repricing restrictions and over-limit fee restrictions took effect in February 2010, and late fee restrictions took effect in August 2010. These implementation dates followed a compressed period of policy debate surrounding the Act’s passage: in December 2008, as a precursor to the Act, the Federal Reserve issued a rule (originally scheduled to take effect in July 2010) that would have implemented a weaker version of the CARD Act interest rate repricing restrictions and fee restrictions; the CARD Act, introduced in Congress a month later in January 2009, superseded these restrictions and strengthened them to their present form; the Act was then passed and signed into law several months later in May 2009.

Given the Act’s staggered congressional debates, passage, and implementation, for much of my analysis I will focus on a pre-CARD-Act period stretching from July 2008 through June 2009, and a post-CARD-Act period from July 2011 through June 2014. I focus on these full-12-month periods, both beginning in July, in order to avoid overemphasizing any seasonality.

2.2 Data Sources and Summary Statistics

I use two main datasets in my analysis. One dataset contains the near-universe of US credit card accounts in a monthly account-level panel. The second dataset is a large random sample of consumer credit reports, showing all credit cards and other non-credit-card loans held by a panel of consumers over time. Both are anonymized, administrative datasets furnished by industry and maintained by the Consumer Financial Protection Bureau (CFPB).

2.2.1 CCDB Account-Level Dataset

The first dataset I use is the CFPB’s Credit Card Database (CCDB), a near-universe of de-identified credit card account data in a monthly panel from 2008 to present. The data include all open credit card accounts held by 17 to 19 large and midsized credit card issuers (lenders) under the supervisory authority of either the OCC or the CFPB, which together cover roughly 90% of outstanding general-purpose US credit card balances. For each account in each month, the data show totals of all aggregate quantities that would appear on a monthly account statement,

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13 Besides these price restrictions, the CARD Act also included a series of restrictions that sought to make credit card borrowing more predictable and transparent for borrowers. Lenders were banned, for example, from changing borrowers’ statement due dates from month to month, or from imposing a cutoff time on due dates that came before 5 PM. Lenders were also required to include additional information on account statements that emphasized how long it would take to pay off a balance at various monthly payment sizes. Changes in account terms were also required to be disclosed to borrowers with 45 days of advance warning rather than the previous 15 day limit. A full review of these restrictions is available in CFPB (2013).

14 A limited number of other provisions, including the requirement of earlier disclosure for account changes, took effect soon after the Act’s passage, in mid-2009.

15 A total of 6 lenders enter or exit at some point in the sample period. Evidence on the data’s coverage rate of overall industry balances is presented in CFPB (2013).
including total purchases in dollars, amount borrowed and repaid, interest charges and fees by type of interest or fee, payment due dates, and delinquencies.

These data represent a modest superset of the credit card data used in Agarwal et al. (2015b) and Agarwal et al. (2018), including 9 to 10 additional midsize issuers that cover an additional 17% to 23% of outstanding balances. An advantage of using this superset is the inclusion of a more diverse set of firms, especially issuers with relatively concentrated market shares in important submarkets such as subprime or super-prime accounts.

For reasons of panel balance and data availability, I restrict my analysis to a subset of CCDB lenders that hold over 88% of all credit card balances observed in the CCDB in 2008-2009. This subset includes all of the issuers studied previously in Agarwal et al. (2015b) and several additional issuers, including a large issuer with relative specialization in prime lending. Given the presence of some smaller and regional issuers in this sample, I also pool data from the smallest issuers into a single “fringe” issuer, as in Somaini (2019), when estimating my model.

2.2.2 CCP Borrower-Level Dataset

The second database I use is the CFPB’s Consumer Credit Panel (CCP), a large, randomly sampled panel of consumer credit reports showing all credit card accounts and other non-credit-card loans for a set of anonymized consumers over time. The non-credit-card-loans in these data include mortgages, auto loans, student loans, lines of credit, and installment loans held by a given consumer. The data also include non-loan items such as a measure of past loan applications, defaulted debts in collection, and public records such as bankruptcies.

The panel is a 1-in-48 random sample, drawn from one of the three nationwide consumer credit reporting agencies. This panel is observed quarterly beginning in 2004. The CCP therefore has the advantages of showing a large representative sample of consumers, following these consumers over a longer time frame than is available in the CCDB, and reporting all credit card and non-credit-card accounts for a given consumer. Additionally, the CCP makes it possible to study borrower entry and exit, as the dataset includes individuals not holding credit cards at any given point in time. Neither accounts nor account-holders can be linked between the CCDB and CCP.

2.2.3 Summary Statistics

Several summary statistics are helpful in motivating my analysis. For sake of brevity, statistics that may be familiar from prior work are placed in the appendix; the non-appendix results below are to my knowledge new and emphasize the equilibrium effects of the Act’s repricing restrictions. First, Figure 1 Panel (a) shows the prevalence over time of the type of interest rate increases restricted by the Act: that is, rate increases that were not caused by the expiration of a promotional interest rate or by changes in an indexed base rate and that did not coincide with a delinquency of 60 days or more. Forty-eight to fifty-four percent of borrowing accounts experi-
enced such a discretionary interest rate increase at least once a year before the CARD Act. The prevalence of interest rate increases then dropped sharply to nearly zero when the CARD Act repricing restrictions went into effect.\footnote{The nonzero occurrence of post-CARD-Act interest rate increases in this figure is due to the exception discussed in Section 2.1.2 for newly transacted (rather than already outstanding) balances. The post-CARD-Act data in Figure 1, Panel (a) show this exception is rarely used in practice.}

Panel (b) of the figure documents that this collapse in the prevalence of interest rate increases coincided with an immediate compression in the distribution of interest rates across accounts. The figure shows the interquartile range (IQR) of interest rates after controlling for origination FICO score, with one data point presented for each quarterly origination cohort.\footnote{I focus here on the age of accounts’ maturity, that is, the age by which all promotional teaser rates from the time of origination have usually expired, because a substantial amount of price dispersion emerges around the time of promotional rates expiring. In order to focus on within-FICO price dispersion, the IQRs plotted in the figure are for residual borrowing costs after partialling out FICO-score fixed effects, for accounts with less than 20 points change in FICO score since origination.} For cohorts reaching maturity before the Act’s repricing restrictions went into effect, these IQRs are consistently about 7.5 percentage points; for cohorts reaching maturity after these restrictions took effect, these IQRs fell sharply to around 5 percentage points.

Table 1 presents further evidence on which percentiles of the price distribution compressed with the implementation of the Act. In Panels (a) and (b), each column corresponds to a statistic of credit card pricing, and each row highlights a different market segment. The statistics presented are changes from pre-CARD-Act data (2008Q3 through 2009Q2) to post-CARD-Act data (2011Q3 through 2014Q2). Effective interest rates\footnote{The effective interest rates presented here are calculated by dividing total interest charges by the average amount borrowed and then annualizing. Because several APRs may be in effect on an account at any given time, for example, a promotional and a standard purchase APR, this measure of effective interest provides the arguably most representative average of these different APRs.} and fee-inclusive borrowing costs\footnote{To calculate a measure of the fee-inclusive price of borrowing, I sum interest charges and fee revenue on a given account, divide by the amount borrowed over a given period, such as a month or quarter, and then annualize. I refer to this measure as the fee-inclusive borrowing cost or price. This is the same price measure used previously in research on the credit card market, including Agarwal et al. (2015b) and CFPB (2013).} both compressed. The table shows increases of several hundred basis points in the 25th percentile of the distribution for most prime borrowers (credit scores at or over 660) or in the 10th percentile for most subprime borrowers (credit scores under 660), while the 75th and 90th percentiles usually fell, sometimes by hundreds of basis points, or at least rose by less than the lower tail.

Overall the table shows that most credit scores saw compression in both tails of the price distribution and that this compression was most pronounced among subprime consumers. Indeed, subprime consumers saw their IQRs of effective interest rates and of fee-inclusive borrowing costs both typically fall by over 500 basis points, while the very bottom of the subprime price distribution sometimes rose by over 300 basis points. The compression in the left tail of the distribution is suggestive of an equilibrium outcome whereby borrowers in the left tail faced higher prices as within-credit-score pooling increased.
The final panel of the table reports the share of consumers in each credit-score segment who hold a credit card and the share of active credit card accounts in each segment used for borrowing. The share of consumers who have any credit card at all fell by up to 10 percentage points in the subprime market, and on net, there was substantial consumer exit from the market in the same segments that saw increases in the low-cost left tail of the price distribution. While these patterns are only suggestive, they motivate my analysis of whether the Act led to partial market unraveling as a result of increased pooling.

3 Reduced-Form Evidence

The preceding summary statistics highlighted the sharp decrease in credit card price dispersion immediately after the CARD Act took effect. Which types of consumers faced relative price changes as this compression occurred? And how did credit card borrowing respond to these changes? In this section, I provide reduced-form evidence on these questions that also highlights two key forces influencing the CARD Act’s effects in equilibrium.

3.1 Risk Pricing and Adverse Retention

This subsection examines how the CARD Act affected the pricing of risk. I compare two types of risk treated differently under the Act: risk observable at the time of origination, which I term origination risk; and risk that becomes observable after origination, which I refer to as emergent risk. Whereas the Act restricted lenders’ ability to adjust pricing in response to emergent risk, the pricing of origination risk was unrestricted. Therefore one indication of how the Act affected the pricing of risk is how the relative pricing of these two types of risk changed with the implementation of the Act.

I first estimate the price gradient of origination risk as a linear relationship between interest rates $r_{i,0}$ and FICO scores at origination, FICO$_{i,0}$.

$$r_{i,0} = a + bFICO_{i,0} + e_{i,0}$$  \hspace{1cm} (3.1)

I plot this gradient in pre-CARD-Act data as the dashed line in Figure 2 Panel (a) against the left and bottom axes, along with an accompanying binscatter.\textsuperscript{20} There is a consistent relationship between price and risk throughout the FICO distribution: the average price of risk is roughly 32 basis points in annualized interest for every 10 FICO points of expected default risk.

\textsuperscript{20}A binscatter plots the conditional mean of the dependent variable at each percentile of the regressor, helping illustrate the shape of the relationship between the two across the distribution of the data. This can also be extended to regressions with controls by first partialling out controls from both the dependent variable and the regressor. See Stepner et al. (2013).
I then estimate the pre-CARD-Act price gradient of emergent risk using a similar model, where I estimate the relationship between interest rates and change in FICO since origination,

\[ r_{i,t} = \alpha_{\tau_{i,t}} + \alpha_{\text{FICO}_{i,0}} + \beta (\text{FICO}_{i,t} - \text{FICO}_{i,0}) + \epsilon_{i,t} \]  

(3.2)

This regression also includes fixed effects \( \alpha \) for origination FICO score, \( \text{FICO}_{i,0} \), which are included to absorb variation in interest rates \( r_{i,0} \) from the time of origination,\(^{21}\) as well as fixed effects for account age \( \tau_{i,t} \), which absorb average changes in interest rates over the life of an account due to, for example, promotional rates expiring over time. Given the presence of these fixed effects, the estimated coefficient \( \beta \) then shows the correlation between changes in FICO score since origination and changes in (average) interest rate since origination.

In the same figure I plot the estimate of \( \beta \) from this second regression with an accompanying binscatter. These are plotted on the opposite set of axes (right and top axes), which have the same scaling as the main axes for sake of comparability. The two gradients are nearly indistinguishable: for both origination risk and emergent risk, borrowers on average face a difference in price of about 30 basis points in annualized interest for every 10 FICO-point difference in risk. This points to the credit card market setting a consistent price of risk, on average, in the pre-CARD-Act data, regardless of whether the risk was evident at origination or emergent later.

Figure 2 Panel (b) re-estimates both of these price gradients in post-CARD-Act data. Here there is evidence of the CARD Act’s repricing restrictions causing a divergence between the two gradients: whereas origination risk is priced at 26 basis points annualized per 10 points of FICO score difference, lenders are only able to price risk that emerges after origination at less than a third of that rate, at 7 basis points per 10 FICO points.

The gap between these gradients weakens incentives for newly risky borrowers to attrite from borrowing and incentivizes newly safe borrowers to attrite. I look for evidence of such adverse retention by estimating the relationship between borrower retention and changes in FICO score since origination, using a specification similar to equation 3.2,

\[ A_{i,t} = \alpha_{\tau_{i,t}} + \alpha_{\text{FICO}_{i,0}} + \beta (\text{FICO}_{i,t} - \text{FICO}_{i,0}) + \eta_{i,t} \]  

(3.3)

where \( A_{i,t} \) is an indicator for attrition from borrowing, and, as in equation 3.2, the fixed effects \( \alpha \) control for age \( \tau_{i,t} \) since origination and FICO score at origination, \( \text{FICO}_{i,0} \). The equation is again estimated at a quarterly frequency. The \( \beta \) coefficient therefore captures how quarterly linear-probability hazards from borrowing to non-borrowing change as a function of FICO score differences since origination.

\(^{21}\)This specification is equivalent to a long-differences specification in price and risk (without controls for origination risk) if the above error terms \( \epsilon_{i,0} \) and \( \epsilon_{i,t} \) are independent. The long-differences specification cannot be estimated directly, as \( r_{i,0} \) is typically unobserved in the data for accounts originated prior to 2008. Results are robust to an alternative, first-differences specification, which can be estimated.
I estimate this attrition model separately in the pre-CARD-Act and post-CARD-Act data and show corresponding binscatters in Figure 2 Panel (c). The gap between the two plotted relationships shows the difference between attrition hazards at each credit score. The gaps show that borrowers who become safer over time become more likely to attrite from borrowing after the Act relative to before. Similarly, borrowers who become riskier over time become less likely to attrite than before the Act. The estimates imply that for every one percentage point in interest by which emergent risk is mispriced relative to origination risk, borrowers respond with a 0.7 percentage point change in the quarterly hazard of attrition from borrowing.

3.2 Price Elasticity Signals and Lender Returns

I provide evidence that some consumer behaviors provide lenders with private information about consumers’ price elasticities of borrowing demand – behaviors that I term price elasticity signals. To do so, I analyze heterogeneity in lender returns across accounts that exhibit different consumer behaviors in pre-CARD-Act data, and I identify which privately observed behaviors predict higher returns relative to returns on other, equally risky accounts that exhibit no such particular behavior. These higher returns, together with coincident price increases at the time of the privately observed behavior, suggest that lenders learn from such behaviors which accounts were relatively price-inelastic. The CARD Act then limited lenders’ ability to impose these price increases, and relative returns and pricing for affected accounts both fell.\textsuperscript{22}

My core finding in this exercise is that two of the most common causes of interest rate repricing the pre-CARD-Act data – transactions exceeding an account’s credit limit, and delinquencies of less than 30 days – were price elasticity signals in many FICO-score segments. In particular, delinquencies of less than 30 days predicted excess returns as high as 300 basis points annualized for some prime FICO scores, and transactions exceeding an account’s credit limit predicted excess returns as high as 100 basis points annualized for some subprime FICO scores. These signals typically are not reported to credit bureaus and remain private information for lenders.\textsuperscript{23}

To categorize borrower behaviors as price elasticity signals, I calculate the expected present discounted value of lender revenues minus default losses among accounts that exhibit a certain behavior \(s\) in period \(t = 0\), as a share of the expected present discounted value of balances lent on the same accounts. Concretely, this is an expected return on assets that I denote \(Y\) given an

\textsuperscript{22}Using ex-post returns to identify price elasticity signals is an appealing approach because such signals are otherwise inherently difficult for a researcher to identify. Lenders’ endogenous price responses to such signals can make the borrowers in question appear less, not more, likely to borrow than their peers. However even when these endogenous price changes lead to higher attrition, they still lead to higher ex-post returns if a behavior is indeed revealing of higher price inelasticity and if lenders optimally increase prices to maximize returns after observing such behaviors.

\textsuperscript{23}Delinquencies of less than 30 days are not reported to credit bureaus at all; over-limit transactions are in practice only reported if the end-of-billing-cycle balance remains over the credit limit \textit{and} if the lender chooses to report credit limits to the credit bureau, which some lenders do not.
observed behavior or signal $s$,

$$
\hat{E}[Y|s] = \frac{\sum_{t=0}^{T} \beta^t \sum_{t:b_0(i)=s} R_{it} - L_{it}}{\sum_{t=0}^{T} \beta^t \sum_{t:b_0(i)=s} B_{it}/T} \quad (3.4)
$$

where $b_t(i)$ is the behavior exhibited by consumer $i$ in period $t$, and respectively $R_{it}$, $L_{it}$, and $B_{it}$ are revenues, default losses, and revolved balances for that consumer. For a given signal $s$, I then compare these expected returns to the corresponding returns on equally risky accounts that do not exhibit any such particular behavior, in order to gauge whether $s$ predicts higher or lower relative returns. I classify $s$ as a price elasticity signal if, for a given FICO score,

$$
\hat{E}[Y|s] > \hat{E}[Y|0] \quad (3.5)
$$

where the behavior “0” on the right-hand-side of the inequality signifies that an account displayed no such particular behavior in that period.$^{24}$

I conduct this exercise for all behaviors that were typically included in pre-CARD-Act credit card contracts as causes for either a penalty fee or a change in interest rate: over-limit transactions, delinquencies in paying a monthly bill of various severity (less than 30 days, 30 to 60 days, and over 60 days), as well as preceding changes in FICO score or other credit report information. I take $T = 24$ to correspond to a 2-year horizon, which is a standard horizon over which to evaluate outcomes in consumer credit (Federal Reserve Board (2007)).

Table 2 shows the results of this exercise. The first column shows baseline expected return on assets, $\hat{E}[Y|0]$, as defined in expression 3.4; subsequent columns show differences relative to this baseline predicted by various consumer behaviors or signals $s$, as in expression 3.5. Each row corresponds to a different FICO-score segment. As shown in the first group of columns of the table, I find that two behaviors in particular predict higher expected returns and hence are classified as price elasticity signals in different credit score ranges: over-limit transactions not coinciding with delinquencies are generally price elasticity signals on subprime accounts, where they predict higher returns of as much as 76 basis points annualized; meanwhile, late payments of less than 30 days are generally price elasticity signals on prime accounts, where they predict higher returns of as much as 266 basis points annualized. These behaviors may be signals of price-inelastic demand for a number of reasons, including credit constraints, a higher cost of time, or borrower inattention.$^{25}$

$^{24}$Precisely, accounts with behavior “0” are those with no delinquency or default, no transactions in excess of their credit limit, and no change in FICO score of 30 or more points in the past quarter. This comprises roughly 72% of accounts each month in the pre-CARD-Act period I study.

$^{25}$As further evidence that late payments of less than 30 days may indicate inattention among some borrowers, I find that these payments are positively correlated with borrowers reporting having a credit card misplaced or stolen. Late payments of less than 30 days have been recognized by credit card lenders as revealing highly profitable accounts; see Lieber (2002).
The remaining columns of Table 2 show results for other behaviors not classified as price elasticity signals. Each other signal predicts greater losses over two years: for example, among subprime accounts with credit scores of 660-659, a late payment of 30-59 days predicts lower annual returns by 23.4 percentage points off a baseline return of 4.35%.

4 A Model of the Credit Card Market

In this section I develop and estimate a model of the credit card market. The model incorporates a key result from the preceding section: lenders learn new information about risk and demand over time and respond to this information by changing pricing. The model also has three other prominent features – heterogeneous price sensitivities, adjustment costs for consumers who switch lenders or pay off balances, and private information among lenders about borrowers. In subsection 4.1 I illustrate how the model is identified by the data and why the data motivate including these features. I then formally introduce the model in subsection 4.2, discuss estimation in subsection 4.3, and present model parameter estimates in subsection 4.4.

4.1 Credit Card Demand: Three Key Facts

4.1.1 Fact 1: Price Sensitivity of Demand

This subsection establishes that credit card borrowers are sensitive to price and illustrates the pricing variation I will use in model estimation. The source of pricing variation is, to my knowledge, novel: occasional, idiosyncratic repricing campaigns in the pre-CARD-Act period, where lenders are seen to increase interest rates on entire extant credit card portfolios at once. Former industry participants have confirmed in conversation that these repricing campaigns occur for a variety of reasons, sometimes at the discretion of an individual portfolio manager, sometimes in response to a bank-wide directive driven by, for example, bank-level cost shocks.

To use the most clearly exogenous pricing variation available from among the repricing campaigns in the data, I focus on a campaign where I can verify, using documents from one lender’s investor relations materials, that the lender in question undertook this campaign at a time when it was seeking to shrink its credit card portfolio in anticipation of acquiring another bank. This variation therefore appears to come from a cost shock – in particular, a change in the bank’s internal cost of capital in anticipation of the acquisition – rather than a demand shock, making it ideal pricing variation for identifying demand. The particular merger or acquisition was not consummated until several quarters after the repricing event in question, and I can find no evidence that other dimensions of the bank’s product quality, such as its product branding, changed in the months around this event.

To illustrate this particular repricing campaign, Figure 5’s left panel shows, in red, all nine
deciles of the APR distribution for this bank’s credit card portfolio over time; the bank in question is labeled as “Bank A.” All deciles of Bank A’s APR distribution shift upward by exactly 100 basis points in a month labeled as event time 0, after a preceding period with minimal price change. This campaign occurred more than a year before the implementation of the CARD Act and occurred at a time when, as shown by the figure’s dashed blue line, other lenders’ pricing was on average unchanged.

The right panel of Figure 5 then shows Bank A’s retention of its existing credit card borrowers around this price change, relative to competitors’ retention of their existing credit card borrowers. The retention rate for Bank A’s borrowers falls relative to other banks’ borrowers immediately after the repricing campaign, with the greatest difference in the first month and a sustained but lesser gap in subsequent months. This pattern appears clearly despite strong seasonal effects on borrowing that occur during this time period, as retention rates peak annually in or around the month labeled as event time 0.

To be precise about how the retention rates in the right panel of Figure 5 are estimated, first note that this comparison of retention rates can be done across consumer types, for example consumers with different credit scores, to recover heterogeneity in borrowers’ price sensivities. For types denoted $\theta$, the estimates in the right panel of Figure 5 are then taken from the regression,

$$\log Q_{j\theta t} = \alpha_{\theta j} + \alpha_t + \alpha_{A,t} + \beta_j t + \epsilon_{j\theta t}$$  \hspace{1cm} (4.1)

where $Q_{j\theta t}$ denotes retention rates among existing borrowers of type $\theta$ for lender $j$ in month $t$, i.e. the share of these borrowers who continue to borrow in the next period. The first two $\alpha$ terms in this equation implement a standard difference-in-differences design, while the $\alpha_{A,t}$ terms capture differences between Bank A and other, non-campaign banks. For sake of presentation, the $\beta$ term is included to account for different time trends among the included banks, though as I show later this does not substantially affect the model parameters ultimately estimated off of this variation.\footnote{See the discussion in section 4.3.2 and also Appendix Figure 3, which reproduces Figure 5 while excluding this $\beta_j t$ term.}

4.1.2 Fact 2: Persistence and Adjustment Costs

The previous subsection showed that price elasticities of borrowing demand are nonzero; this subsection shows evidence for two adjustment costs faced by credit card users that help explain why price elasticities are also not infinite. This evidence also highlights the consumer behaviors that help identify adjustment costs in the model. For sake of brevity, much of the evidence in
This section is presented in the appendix. The two adjustment costs I document are, first, a cost to opening an account with a new bank, which I term a setup cost, and second, a cost to paying off a balance owed, which I term a liquidity cost.

As evidence of such setup costs, I show that borrowers often face strong incentives to switch credit cards but nevertheless switch cards infrequently. First, as evidence of borrowers’ incentives to switch cards, Appendix Table 2 shows average interest rates available on newly originated accounts in the pre-CARD-Act period; the table follows the same formatting as the earlier Appendix Table 1. Here prices are shown for newly originated accounts to which a borrower transferred a previous balance at a promotional interest rate. Discounts relative to mature accounts appear throughout the FICO score distribution. For example, among FICO 740 consumers, the average cost of borrowing is roughly 600 basis points lower on newly originated accounts with promotional balance transfers, relative to mature accounts. Next, Appendix Figure 2 examines how frequently borrowers switch cards in the presence of these price incentives. To estimate these switch rates, I calculate the total number of balance transfers with promotional rates per quarter in the pre-CARD-Act period, and I compare this flow to the stock of consumers borrowing on mature accounts at non-promotional rates. The figure shows this rate across a range of FICO groups. Even on a quarterly basis, only 16% of prime consumers and less than 5% of subprime consumers respond to the price incentives shown in Appendix Table 2 by transferring balances to a new credit card, indicating that many consumers face some kind of adjustment cost in setting up accounts with new banks.

As evidence that borrowers face adjustment costs in paying off a balance owed, Appendix Table 3 examines persistence in credit card borrowing. The table shows that throughout the FICO score distribution, consumers are substantially more likely to borrow on a credit card in a given month if they also borrowed in the preceding month than if they did not borrow in the preceding month. This persistence appears both in a subsample of consumers with a demonstrated preference for borrowing – those consumers who borrowed on their credit card at least once in the past six months – and in the whole population of credit card holders, not just those who borrowed at some time in the past six months.

4.1.3 Fact 3: Lenders’ Private Information

This subsection presents evidence suggesting that lenders possess private information about their borrowers’ default risk and previews my strategy for recovering private information empirically. Previous research has shown lenders can learn private information from consumers’ purchase behavior on credit cards (Khandani et al. (2010)), and in Section 2.1.1 I discuss a number of other channels that can similarly provide such private information. In this subsection I show another related fact: after controlling flexibly for all public information available about a borrower, credit card pricing is strongly increasing in ex-post default probabilities. These price differences likely
reflect private rather than public information because pricing in the credit card market is typically not observable to a lender’s competitors, and because this relationship persists after controlling for the information that is observable to competitors.

Specifically, I control for credit report information using fixed effects for consumer credit scores, as credit scores are expressly designed to be a (scaled) odds of default that is predicted using all available credit report information. I also interact these fixed effects with bank fixed effects, to absorb differences due to possible consumer sorting across banks that may not be reflective of private information per se. Given these controls, I then examine the relationship between ex-post default and pricing,

\[
\text{Default}_{i,t:t+24} = \alpha_{j(i),x(i)} + \sum_{n=2}^{5} \beta_n 1_{q(n)}(p_{i,t}) + \epsilon_{it} \tag{4.2}
\]

Here the dependent variable is an indicator for any instance of default by borrower \(i\) in the subsequent 24 months after period \(t\), and the regressors of interest \(1_{q(n)}(p_{i,t})\) are indicators for whether pricing for borrower \(i\) in period \(t\) lies in the \(n\)th quintile of the within-bank and within-FICO price distribution. The prices used here are the fee-inclusive cost of credit card borrowing analyzed earlier in Table 1, and fixed effects \(\alpha\) implement the controls for non-private information discussed above.

Table 3 reports estimates of the coefficients \(\beta_n\). Ex-post default increases smoothly across the price distribution (all reported coefficients are differences relative to the first quintile), suggestive of lender private information about borrower default risk. This relationship appears whether using a pooled sample as in column 1, a subprime-only sample as in column 2, or a prime-only sample as in column 3. The monotonicity between pricing and default also suggests a procedure by which this private information may be estimated using lenders’ observed pricing schedules, as I detail more in the model exposition.

### 4.2 Model Exposition

This section presents my model of the credit card market.

On the demand side, the backbone of the model is a finite mixture of consumer types, each of whom has logit demand over credit card lenders and over credit card usage. Specifically, for bank \(j\) a consumer can choose to either borrow on that bank’s credit card or hold a credit card from that bank without borrowing, or a consumer can instead choose an outside good (no credit card at all); thus in a market with \(J\) banks there are \(2J + 1\) choices. Consumers choose at most one bank each period and choose whether or not to borrow – that is, I model only the extensive margin of borrowing, not the choice of how much to borrow.\(^{27}\)

\(^{27}\)These two modeling decisions – that consumers single-home over banks and choose extensive rather than intensive-margin borrowing – are primarily made for sake of tractability; similar modeling choices appear in
I denote types by $\theta$. I specify several taste parameters to be estimated for each type, which I summarize in Table 4. First, each type enjoys a flow utility $d_{\theta_j}$ from borrowing with bank $j$ and a flow utility $n_{\theta_j}$ from “transactional” use of a card (i.e., using the card without borrowing) from bank $j$; meanwhile the utility of the outside good (holding no credit card at all) is normalized to zero. Additionally, in order to capture the adjustment costs documented earlier in this section, each type pays a setup cost $s_{\theta_j}$ for opening a new account with bank $j$ and a liquidity cost $l_{\theta_j}$ or paying off a balance and transitioning to transacting (non-borrowing) status after borrowing with bank $j$ in the past period. Additionally, types have heterogeneous marginal utilities of income $\gamma_\theta$ (i.e., the price coefficient in logit demand). The parameters $\{d_{\theta_j}, n_{\theta_j}, s_{\theta_j}, l_{\theta_j}, \gamma_\theta\}_{(\theta,j)\in\Theta\times J}$ are the key demand parameters to be estimated in the model, along with a probability distribution $\mu_\theta$ over types and transition probabilities across types.

Table 4 summarizes how these taste parameters affect consumers’ per-period flow utilities from each possible choice. The three rows of the table correspond to the consumer’s circumstances at the end of the preceding period: a consumer either (i) has an open credit card from some bank $j$ that he used for borrowing, (ii) has a credit card from $j$ that he did not use for borrowing, or (iii) holds no credit card at all. The five columns of the table then correspond to the consumer’s choice in the current period: a consumer either keeps his credit card from the same bank $j$ (columns 1 and 2), or opens a new card with some other bank $j' \neq j$ (columns 3 and 4), or chooses the outside good of no credit card at all (column 5). When holding a credit card, a consumer chooses either to use it for borrowing (columns 1 and 3) or not (columns 2 and 4). In reading the table, note that these banks $j$ and $j'$ can be any bank in the set of banks $J$, so there are $|J|$ distinct values of each parameter subscripted by $j$ or $j'$. An important pattern to note in the table is that consumers only pay setup costs $s$ when transitioning from some bank $j$ to a new bank $j' \neq j$, and only pay liquidity costs $l$ when transitioning from borrowing to transacting (non-borrowing).

As also shown in the table, prices differ for consumers who are newly opening a credit card

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Crawford et al. (2018) about how much firms borrow, in Einav et al. (2010b) about how much annuitants annuitize, and in Einav et al. (2010a) about extensive-margin insurance contract choice. However, these modeling decisions also do not depart much from realism in the credit card market. First, using CCP data, I find that a large majority of consumers hold only one “primary” credit card, where primary is defined as carrying the majority of a consumer’s credit card balances. Depending on FICO score, this share ranges from at least 80% to over 90%. Hence a single-homing model can in many respects be thought of as a model of a consumer’s choice of primary card. Additionally, a majority of deep subprime consumers and a large minority of prime consumers indeed hold only one credit card in CCP data. Second, there is a variety of evidence that firms compete more on the extensive margin using price, and then use credit limits as their preferred instrument on the intensive margin (Trench et al. (2003), Agarwal et al. (2018)). In fact, many credit limits are not disclosed until after a borrower has made the extensive margin choice of whether to open a credit card or not, whereas prices are advertised heavily to consumers considering a new card. Incorporating the intensive margin in the model would therefore require including both prices and credit limits, which would obscure the focus of the model and expand the firms’ strategy space to the point of intractability. Finally, the estimates in Agarwal et al. (2015b) suggest that the effect of the CARD Act on credit limits and account balances is nearly zero, which provides further support for abstracting from the intensive margin in this setting.
with a bank and consumers who held a credit card with that bank in the past period, reflecting the prevalence of new-account discounts ("teaser" rates) in the credit card market. These two prices are denoted $p_j^0(\theta)$ and $p_j^1(\theta)$ respectively. Note also that these prices are one-dimensional, so in practice I use the fee-inclusive borrowing cost introduced in Section 2.2.3 when I estimate these prices in the data; these are also the appropriate marginal prices to use when modeling the extensive margin of borrowing.

The presence of adjustment costs makes the consumer’s problem dynamic. The total expected payoff for a given choice is the sum of the relevant flow utility from Table 4 and a discounted expectation of continuation values, and also, given logit demand, the realization of an extreme value type-1 i.i.d. taste shock. To describe these continuation values, let $k \in \{\text{borrow, transact}\} \equiv \{\text{b,n}\}$ denote a consumer’s choice of how to use his credit card and $j \in J$ again denote a consumer’s choice of card. In this notation I also represent the outside good as $(j,k) = (0,0)$. I then write these continuation values as $V(\theta', j, k)$. Note that $\theta'$ is a consumer’s type in the next period while $j$ and $k$ correspond to the current period. For example, a consumer $i$’s total expected payoff for choosing to borrow ("b") with bank $j$ in the current period after having also borrowed with bank $j$ in the past period is,}

$$
\begin{array}{c}
\text{flow utility} \\
\begin{aligned}
&d_{bj} - \gamma_0 p_j^1(\theta) + \beta \mathbb{E}_\theta [V(\theta', j, b)] + \epsilon_{ijb} \\
\equiv v(j,b|j,b,\theta)
\end{aligned}
\end{array}
$$

(4.3)

Similar expressions are obtained by substituting in the appropriate flow utilities from Table 4.

Integrating over taste shocks $\epsilon$ yields a Bellman equation for continuation values $V$,

$$
V(\theta, j, k) = \log \left( \sum_{j',k'} \exp \left( v(j', k'|j, k, \theta) \right) \right)
$$

(4.4)

where the lower-case $v$ term is as above in expression 4.3; note that $v$ contains $\beta$ as is otherwise familiar in a Bellman equation. The value of $v$ depends on consumers’ past-period and current-period choices as described previously in Table 4.

Besides determining flow utilities as above, consumer types $\theta$ additionally govern heterogeneity in default rates. Specifically, each type defaults at rate $\delta(\theta)$ in periods when he chooses to borrow. Default occurs after all flow utilities are realized in that period. I later discuss how these default rates determine firms’ costs, but here I emphasize how default rates also matter for consumer payoffs.\footnote{These modeling choices draw on Mahoney and Weyl (2014), who suggest a general framework in adversely selected markets where one set of parameters affects both firm and consumer payoffs – that role is played by $\delta$ here – and another set of parameters affects consumer payoffs but not firm payoffs.} In particular, a consumer who defaults has his credit card account “closed” and is reassigned to the outside good (holding no credit card at all) for purposes of computing
adjustment costs in the next period. Hence default rates affect expected payoffs only through the expectation over future continuation values; the effect of default on expected payoffs is formally included through the expectation $E_\theta$.

To tractably model the expectation $E_\theta$ over continuation values, I follow the standard approach in the dynamic discrete choice literature and suppose types evolve according to a Markov process,\textsuperscript{29} with a transition matrix that I denote $T_{\theta\theta'}$. Transitions occur independently of default, consumer choices, and taste shocks. Hence, for consumers who use their credit card for borrowing, the expectation $E_\theta$ can be decomposed as,

$$E_\theta [V(\theta', j, b)] = (1 - \delta(\theta)) T_{\theta\theta'}(\theta) V(\theta', j, b) + \delta(\theta) T_{\theta\theta'}(\theta) V(\theta', 0, 0)$$

(4.5)

where the $\theta$ argument in $T_{\theta\theta'}(\theta)$ selects the relevant row of the matrix $T_{\theta\theta'}$. In the second term on the right-hand-side, recall that I use $(j, k) = (0, 0)$ to denote the outside good.

In contrast, for consumers who do not choose to borrow (i.e., who choose $k = n$ or $k = 0$), the expectation $E_\theta$ does not depend directly on default rates and takes the form,

$$E_\theta [V(\theta', j, n)] = T_{\theta\theta'}(\theta) V(\theta', j, n)$$

(4.6)

The above exposition makes clear how the demand side of the model captures two of the three stylized facts I highlighted – price sensitivity and adjustment frictions. To capture the third stylized fact – the importance of private information – I now describe how the model parameterizes consumer types. Specifically I allow types $\theta$ to have two dimensions, one private component $\psi \in \Psi$ and one “public” component $x \in X$. The latter is public in the sense that it is observable to all firms in the market. Note that the public type $x$ is best thought of as a credit score, as credit scores are expressly designed to be a composite of public information about a consumer, and are indeed observable to all firms in the market. The joint of these two components is then a consumer’s overall type, $\theta \equiv (x, \psi)$.

Two assumptions on borrower types will prove useful in recovering these private information types $\psi$ from the data. One assumption, which is arguably the stronger of the two, is that borrower default rates depend only on types, and in particular do not depend on prices $p^j_0$ and $p^j_1$ or on bank $j$. This can be thought of as a “price-invariance of default” assumption and I will refer to it as Assumption 1:

$$\delta = \delta(\theta) \forall j, p^j_0, p^j_1$$

(4.7)

Several pieces of evidence support this being a reasonable assumption in the credit card
\textsuperscript{29}See Rust (1994) for a review of this literature and a taxonomy of assumptions typically used to help make such models tractable.
market. First, there is direct evidence that price changes have little to no effect on default rates;\(^{30}\) second, the effect of a change in credit card pricing on a typical consumer’s overall budget constraint is arguably negligible;\(^{31}\) third, related research in consumer finance suggests the channel through which credit card price changes could affect default rates is limited (Bhutta et al. (2017), Guiso et al. (2013), Ganong and Noel (2018)). This assumption also follows on other research that has used structural models of selection markets without moral hazard, for example Cohen and Einav (2007) and Einav et al. (2010b). Additionally, I highlight in section 4.3 where the estimation could be adapted should this assumption fail; see footnote 34.

Given this assumption, it is without loss of generality to order private types \(\psi\) by the default rates they induce. Essentially, private types become an index of residual default risk. I order private types \(\psi\) at each public type \(x\) such that default is increasing in \(\psi\),

\[
\psi' > \psi \implies \delta(x, \psi') > \delta(x, \psi) \quad \forall \ x
\]

A second assumption, which I view as the weaker of the two, is a “non-advantageous selection” assumption. This assumption is supported by randomized controlled trial (RCT) evidence showing the credit card market is not merely non-advantageously selected, but is indeed adversely selected (Ausubel (1999), Agarwal et al. (2010)). Formally the assumption is that higher-risk private types also face higher pricing in equilibrium; I term this non-advantageous selection as it is consistent with higher-risk types not having weaker demand to an extent that they would face lower prices despite their higher risk. I refer to this as Assumption 2:

\[
\psi' > \psi \implies p_j^*(x, \psi') > p_j^*(x, \psi) \quad \forall \ x, j
\]

Here \(p_j^*(x, \psi)\) is bank \(j\)’s equilibrium mature-account price for FICO score \(x\) and private type \(\psi\).

Note that this assumption embeds some restrictions on the competitive environment, namely that one lender’s relative quality advantage (as expressed in differences across \(j\) in demand parameters such as the flow utility from borrowing, \(d_{\theta j}\)) does not change so drastically with \(\psi\) such that lenders in fact face lower demand as private risk rises. That is, residual demand curves are non-advantageously selected in the pre-CARD-Act equilibrium. This assumption on residual demand curves is appealing because these are the demand curves which existing RCT evidence confirms are adversely selected.

\(^{30}\)Using the same price variation highlighted above in section 4.1.1, I find that the effect of a 100 basis point increase in interest rates on default rates is statistically indistinguishable from zero, and I can reject resultant increases in default rates of more than 0.5% (not percentage points). This precise null result is supported by similar findings of little default response to price changes in the randomized controlled trial of Castellanos et al. (2018).

\(^{31}\)CCP data show that the median consumer incurs less than a $2 change in their monthly minimum payment summed across all credit card accounts in response to a 100 basis point change in their credit card interest rate. Likewise, for the median consumer the minimum monthly payments due on a credit card are only 17% of total minimum payments due across all other loans including mortgages, auto loans, student loans and other liabilities.
The precise timing of the demand side of the model is as follows. At the start of the period, borrower types $\theta$ are realized and banks post prices $p_0$ and $p_1$ for each type. Consumers choose a bank and a borrowing status after observing these prices, and they enjoy flow utility from their choice. Default then arrives exogenously. Borrowers who default are forced into the outside good (no account with any bank) for purposes of determining their adjustment costs in the following period. Borrowers who do not default continue on to the next period with their chosen bank.

On the supply side of the model, a credit card lender’s price-setting problem has two parts: what price of borrowing to offer on existing accounts, and what promotional or “teaser” price to offer for new customers. As in the consumer’s choice problem, these two sets of prices are denoted $p^j_1(\theta)$ and $p^j_0(\theta)$ respectively, where subscripts denote bank $j$ and consumer type $\theta$.

The key assumption on the supply side of the model is informational: I suppose lenders observe only a consumer’s public type $x$ at the time of account origination. Private types $\theta$, on the other hand, are learned through a relationship with a consumer, and I suppose types $\theta$ are fully observed after one period.\(^{32}\) Consistent with this information structure, I impose the natural restriction that lender pricing strategies on new accounts must be the same for all types $\theta$ that have the same public type $x$,

$$p^j_0(\theta) = p^j_0(x(\theta)) \forall \theta$$

where $x(\theta)$ selects the public component of types $\theta = (x, \psi)$.

Corresponding to these two types of prices, credit card lenders’ costs can also readily be grouped into two types: acquisition costs related to originating a new account, which include underwriting costs, account set-up costs, and marketing expenses; and account maintenance and charge-off costs on existing accounts, which include day-to-day account management plus costs of default net of recoveries. I denote these costs $c^j_0(x)$ and $c^j_1(\theta)$ respectively.

My model focuses on the extensive margin of borrowing, so lender flow profits for consumers who choose to borrow are the difference between the relevant price and cost: that is, flow profits for lender $j$ are $p^j_1(\theta) - c^j_1(\theta)$ for existing borrowers and $p^j_0(x) - c^j_0(x)$ for borrowers opening a new account. I suppose acquisition costs must also be paid for new accounts even if consumers choose not to borrow, given that new-account costs are primarily driven by set-up and marketing expenses rather than default cost. This cost structure implies that expected discounted lifetime

\(^{32}\)It would be interesting to relax the assumption that private types are fully learned after one period, and to study how lenders learn about borrower private types over time. Indeed, Han et al. (2017) provide evidence that credit card issuers may acquire some private information through consumers’ contract choice at take-up. However such learning dynamics are beyond the scope of this paper, as they would introduce a number of issues – consumers’ strategic signaling behavior, and an expanded state space to keep track of the relevant history of signals a consumer has sent – that would obscure the focus of the model here. Note however that this assumption does allow for a signal-jamming behavior in which all consumers try to appear safer or more price sensitive than they truly are, so that lenders nonetheless infer their type.
profits for a new consumer, $\Pi^j_0$, take the form,

$$\Pi^j_0(p^i, p^{-j}, \theta, k) = \Pr^j_0(b|\theta, p, k)p^j_0(\theta) - c^j_0(\theta) +$$

flow profit

$$\begin{align*}
\Pr^j_0(b|\theta, p, k)\beta(1 - \delta(\theta))T_{\theta^p}(\theta)\Pi^j_1(p^i, p^{-j}, \theta', b) + \\
\Pr^j_0(n|\theta, p, k)\beta T_{\theta^p}(\theta)\Pi^j_1(p^i, p^{-j}, \theta', n)
\end{align*}$$

exp. cont. profit | borrow

exp. cont. profit | not borrow

(4.10)

Here the notation $\Pr^j_0(b|\theta, p, k)$ denotes the probability of consumer type $\theta$ choosing to borrow conditional on having opened a new account with lender $j$ in the current period, and conditional on having chosen $k \in \{\text{borrow, transact, out}\} \equiv \{b, n, 0\}$ in the preceding period. Similarly $Pr^j_0(b|\theta, p, k)$ denotes the probability of choosing to transact (i.e., hold a credit card without borrowing). The dependence on $k$ is a result of consumers facing different adjustment costs depending on whether they borrowed in the previous period, and hence exhibiting different choice probabilities in the current period. As in the demand side of the model, $\delta(\theta)$ denotes borrower default probabilities, and the notation $T_{\theta^p}(\theta)$ selects the appropriate $\theta$-specific row of the consumer type transition matrix. Also note that $p = (p^i, p^{-j})$ denotes the market price vector (including both existing-account prices and teaser prices). The final piece of new notation to introduce is $\Pi^j_1(p^i, p^{-j}, \theta', k)$, which is a lender’s continuation profits on existing accounts, as a function of the consumer’s choice $k \in \{\text{borrow, transact}\} \equiv \{b, n\}$ in the current period. These profits on existing accounts are defined further below.

Profits on existing accounts take a similar form to profits on new accounts,

$$\Pi^j_1(p^i, p^{-j}, \theta, k) = \Pr^j_1(b|\theta, p, k)(p^j_1(\theta) - c^j_1(\theta)) +$$

flow profit

$$\begin{align*}
\Pr^j_1(b|\theta, p, k)\beta(1 - \delta(\theta))T_{\theta^p}(\theta)\Pi^j_1(p^i, p^{-j}, \theta', b) + \\
\Pr^j_1(n|\theta, p, k)\beta T_{\theta^p}(\theta)\Pi^j_1(p^i, p^{-j}, \theta', n)
\end{align*}$$

exp. cont. profit | borrow

exp. cont. profit | not borrow

(4.11)

Here firms earn existing-account prices $p^j_1(\theta)$ and incur existing-account costs $c^j_1(\theta)$ rather than the new-account terms $p^j_0(\theta)$ and $c^j_0(\theta)$.

Notwithstanding the apparent similarity in these two profit functions, lenders’ pricing problem on new accounts is starkly different from the pricing problem on existing accounts, because of the different types of information available to lenders on new and existing accounts. As discussed earlier, lenders’ must make new account pricing decisions on the basis of “public” information available in credit reports, whereas pricing on existing accounts can depend on private information
that a lender learns through a lending relationship.

In choosing prices \( p^j_0(x) \) a lender therefore takes into consideration its expectation of which private types \( \psi \) it acquires as new customers at any given price level, expressed below as a sum over types \( \theta \) that share a given FICO score \( x \), competing lenders \( j' \), and borrowers’ past-period choices \( k \),

\[
\tilde{\Pi}^j_0(p^j, p^{-j}, x) = \sum_{j' \neq j} \sum_{\theta: x(\theta) = x} \sum \mu_{j', \theta, k}(p) \Pr(j|p, j', k, \theta) \Pi^j_0(p^j, p^{-j}, \theta, k) \tag{4.12}
\]

Here the weights \( \mu_{j', \theta, k} \) are the share of consumers who are of type \( \theta \), who held a credit card from lender \( j' \) in the prior period (or held no card in the case of \( j' = 0 \)), and who used that card for \( k \in \{\text{borrow, transact, out}\} \equiv \{b,n,0\} \), as a function of the market price vector. In equilibrium, lenders’ expectations over these shares are correct, so lenders accurately take account of how their mix of newly acquired consumer types will change as they change origination prices \( p^j_0(x) \).

Given the above expressions for \( \Pi^j_0(p^j, p^{-j}, x) \) and \( \Pi^j_1(p^j, p^{-j}, \theta, k) \), the lender’s pricing problem can now be written as,

\[
\max_{p^j} \sum_x \tilde{\Pi}^j_0(p^j, p^{-j}, x) + \sum_{\theta} \left[ \mu_{j, \theta, b}(p) \Pi^j_1(p^j, p^{-j}, \theta, b) + \mu_{j, \theta, n}(p) \Pi^j_1(p^j, p^{-j}, \theta, n) \right] \tag{4.13}
\]

In the following subsection I describe how I estimate the supply side of the model using the first-order conditions of this optimization problem. I also describe three distinct steps in estimating the demand side of the model: recovering borrower types \( \theta \) and the probability distribution over types \( \mu_\theta \); estimating the parameters \( \gamma_\theta \) that govern consumers’ price elasticities, conditional on types; and estimating all remaining demand parameters, conditional on both types and estimated elasticities.

4.3 Model Estimation

4.3.1 Demand Estimation: Borrower Private Types

The first step in demand estimation is recovering a type \( \theta \) for each borrower in each time period. To emphasize, rather than estimating a parametric mixture model of types, I instead recover a distinct type for each consumer, each period, and I allow the distribution over types to remain flexible.

\( ^{33} \)In equilibrium it is also necessary to specify lenders’ off-path beliefs in the zero-probability event where these expectations turn out to be wrong, i.e., in case another lender plays an off-path strategy that changes the value of the borrower type weights \( \mu_{j', \theta, k} \). I suppose that lenders continue to expect on-path values of \( \mu_{j', \theta, k} \) in such a case, so that deviations by a lender in one period that change the value of \( \mu_{j', \theta, k} \) in future periods do not induce subsequent strategy changes by other lenders in response. This assumption shares some features with the equilibrium concept in Weintraub et al. (2008), whereby the optimality of a firm’s strategy is evaluated relative to the long-run average of industry state variables rather than transitory changes in state variables.
Recall types $\theta$ are the joint of public and private types, $\theta = (x, \psi)$. Finding borrowers’ public types $x$ is straightforward: I allow each borrower’s public type to be a binned version of his FICO score. I make this choice because FICO scores are expressly designed to be a one-dimensional composite of all publicly available information predicting default, and because FICO scores are readily observable in the data. I use 20-point FICO score bins, which are a standard set of bins, or “breaks,” the credit card industry uses to group borrowers for account management purposes. Additionally I pool all FICO scores of 599 or below into a single bin and all FICO scores of 780 or above into a single bin. This yields a total of 11 distinct public types $x$.

The key step in this exercise is then to recover private types $\psi$. Empirically, my approach here builds on other literatures that seek to identify unobservable ex-ante types from ex-post outcomes, for example the public economics literature on annuities markets that estimates ex-ante frailty using ex-post mortality (Finkelstein and Poterba (2004), Einav et al. (2010b)). Here I use a similar outcome, loan default, to recover ex-ante borrower types. Because borrower types change over time, and also because default is only observed at most once for each account, this exercise is more complex than simply estimating individual-level residual default risk after controlling for FICO. Rather, I develop an empirical strategy that recovers these private types from the observed pricing that each borrower faces in each period.

Here I make use of Assumptions 1 and 2 developed in the previous section. These assumptions together with the fact that default rates $\delta$ are, by construction, increasing in private types $\psi$, imply that default rates and equilibrium prices $p^1_1$ are increasing with respect to each other,

$$\hat{\delta}_{jx}(p^1_1(x, \psi); p^{-j}) \nearrow p^1_1(x, \psi)$$

(4.14)

where $\hat{\delta}_{jx}$ is the default rate as an indirect function of prices charged to each type in equilibrium, among borrowers with FICO score $x$ for lender $j$. Finally, using the inverse of $\delta$ implied by equation 4.8, private types can be recovered by inverting default rates observed at each price level,

$$(x, \psi) = \delta^{-1}_x (\hat{\delta}_{jx} ((p^1_1(x, \psi)))) \forall x$$

(4.15)

Note that equilibrium price schedules $p^1_1$ are lender-specific, as are the indirect functions $\delta_{jx}$ relating these prices to realized default rates. However the inverse $\delta^{-1}_x$ maps default rates, which are common for all borrowers of a given type, back to types. So in estimation, $\hat{\delta}_{jx}$ is estimated separately by lender and by FICO score $x$, while $\delta^{-1}_x$ is estimated across all lenders – i.e., for the market as a whole – within each FICO group.

To do this inversion in practice, I first use isotonic regression to estimate $\hat{\delta}_{jx}$ for each lender $j$ and FICO score group $x$. The default measure I use is delinquencies of 90+ days within the following two years, as this is the outcome FICO scores themselves are specified to predict. In a
few cases where the fitted isotonic functions for a particular lender map onto a strict subset of the population distribution of default rates at a given FICO score, I use linear interpolation or extrapolation to extend the estimated function. This procedure results in \( \hat{\delta}_{jx} \) being a consistent estimate of actual default rates at each price level, as I prove in the appendix.\(^{34}\)

To define the inverse \( \delta^{-1}_x(\cdot) \), I use the fact that private types \( \psi \) are an index of default risk (see equation 4.8), and I therefore specify \( \delta^{-1}_x(\cdot) \) to return quantiles of the population distribution of estimated default rates, for a desired number of quantiles. In my baseline estimation I take 5 such quantiles (i.e., quintiles). This yields 5 private types for each of the 11 public types, for a total of 55 consumer types \( \theta \). I then also bin each lender’s pricing functions \( p_j^1(x, \psi) \) to that lender’s average price at each bin.

This process is illustrated for two actual lenders in the data in Figure 3. As can be seen, a borrower of a given type shares a common default rate regardless of her current bank, while the price faced by each borrower is different depending on the bank she chooses. The raw data also show that the fit of the isotonic regressions is quite good – that is, true pricing functions do appear to be (nearly) monotone in default rates. Across all banks and credit scores, the R-squared of these isotonic fits in explaining the actually observed default rates is 97.9%. This also reflects the strong monotonicity of the relationship between ex-post default risk and loan pricing seen previously in Table 3.

The consumer types estimated in this process make it straightforward to study the dynamics of how types change over time. In particular, the transition matrix \( T_{\theta\theta'} \) can be estimated non-parametrically off of type-to-type transition rates for borrowers who are observed in two successive periods. This takes advantage of the independence of type transitions from borrower choices: type transitions do not depend on borrower choices and borrowers do not choose entry or exit from the market in anticipation of type transitions, as these transitions are not yet realized at the time choices are made.

The estimated transition matrix is illustrated as a contour plot in Figure 4. Here, the integer-labeled type indices correspond to the 11 different 20-point FICO score groups described earlier, while the sub-ticks within each integer index correspond to the 5 discrete private types \( \psi \) within each FICO group. As can be seen, types are strongly but not perfectly persistent, in both public and private dimensions. The rippling pattern evident in the plot shows how private types are predictive of future changes in public times, as borrowers of highly risky private types are more likely to be downgraded to a lower FICO score next period than other borrowers are.

Finally, after verifying that the estimated transition matrix \( T_{\theta\theta'} \) is ergodic, this matrix can be used to recover the probability distribution over types \( \mu_{\theta} \). Ergodicity implies a unique steady

\(^{34}\)On the other hand, if Assumption 1 were to fail then the relationship \( \hat{\delta}_{jx} \) would need to be rotated clockwise to account for the effect of higher prices inducing higher default, by the appropriate amount given the elasticity of default with respect to price. As noted in footnote 30, I precisely estimate this effect of pricing on default to be near zero, implying no such rotation is necessary.
state \mu_\theta that satisfies the equation \mu_\theta = T_{\theta \theta} \mu_\theta.

4.3.2 Demand Estimation: Demand Elasticities

The next demand parameters to estimate are price elasticities of borrowing demand \eta_{ij}, across consumers \iota and credit card banks \jmath. I use the quasi-experimental pricing variation introduced above in Section 4.1.1, as illustrated in the previous Figure 5.

I start from the relationship between demand elasticities and marginal utilities of income in logit demand,

\eta_{ij} = -\gamma_i p_{ij} (1 - Q_{ij})
(4.16)

The key primitive to be estimated is \gamma_i, consumer \iota’s marginal utility of income. Meanwhile \eta_{ij} is consumer \iota’s fee-inclusive price of borrowing from lender \jmath, and \gamma_i is consumer \iota’s probability of choosing to borrow from lender \jmath. In particular I use \eta_{ij} to denote the elasticity of continued borrowing among current borrowers, so that the price on the right-hand side denotes lender \jmath’s pricing on mature credit card accounts, and \gamma_i denotes a retention probability for current borrowers. Intuitively in this expression higher marginal utilities of income make borrowers more price elastic.

To derive an estimating equation for \gamma_i that uses the aforementioned price variation from Figure 5, I first substitute for \eta_{ij} using the definition of an elasticity,

\frac{d \log(Q_{ij})}{d \log(p_{ij})} = -\gamma_i p_{ij} (1 - Q_{ij})
(4.17)

I then draw on the form of borrower heterogeneity specified in section 4.2, and I take this equation from the level of individual consumers \iota to the level of consumer types \theta. This simply changes \iota subscripts to \theta subscripts in the above, and substitutes observed type-level retention rates \theta_{ij} in lieu of of individual retention probabilities \eta_{ij}.

Finally I use difference-in-differences in logs as empirical analogs of infinitesimal changes in logs,

\log(Q_{\theta jt}) = \alpha_{\theta j} + \alpha_t + \beta_j t - \gamma_\theta \log(P_{\theta jt}) + \epsilon_{\theta jt}
(4.18)

Here the fixed effects denoted by \alpha implement difference-in-differences, and the term \beta_j is a price term scaled as in equation 4.17 above, with scalars taken from the period immediately prior to the repricing event denoted here by \tau = 0,

\log(P_{\theta jt}) = (1 - Q_{\theta j0}) p_{\theta j0} \log(p_{\theta jt})
(4.19)

These base-period values are chosen because they correspond to demand elasticities at the time of the repricing, as in equation (4.16). Meanwhile the \beta term is included to account for different trends among the included banks; I explore robustness to excluding this term below. This
equation differs from the earlier event-study version shown in equation 4.1 only through the regressor \( P_{\theta jt} \), which, following the above derivation, makes it possible to recover the primitives \( \gamma_{\theta} \) rather than just a local elasticity.

I estimate \( \gamma_{\theta} \) using both limited-information maximum likelihood (LIML) and two-stage least squares (2SLS), with instruments that isolate the repricing variation highlighted in Figure 5. Specifically, I instrument for the endogenous price term \( P_{\theta jt} \) with a dummy instrument \( Z_{jt} \) equal to unity in all periods \( t \) following a repricing campaign by lender \( j \). As is standard in a model that is fully interacted with consumer types \( \theta \), these instruments are also interacted with indicators for borrower types \( \theta \), so that there are \( |\Theta| \) instruments corresponding to the \( |\Theta| \) endogenous regressors \( P_{\theta jt} \). Note that these instrumental variables address two econometric issues, both the endogeneity of prices \( p_{\theta j} \) with borrowers’ marginal utilities \( \gamma_{\theta} \), and, in time period 0, the appearance of \( Q_{\theta j0} \) on both the right- and left-hand sides. In summary, the first and second stage equations are then,

\[
\log P_{\theta jt} = a_{\theta j} + a_t + b_j \times t + \pi_\theta Z_{jt} \times 1_{\theta} + \epsilon_{\theta jt} \tag{4.20}
\]

\[
\log Q_{\theta jt} = \alpha_{\theta j} + \alpha_t + \beta_j \times t - \gamma_{\theta} \log P_{\theta jt} + \epsilon_{\theta jt} \tag{4.21}
\]

Given that \( P_{\theta jt} \) contains the estimated quantity \( Q_{\theta j0} \), I follow Cameron and Miller (2015) in bootstrapping over both individuals and clusters to calculate standard errors.

Table 5 presents estimates of the price coefficient \( \gamma \) in equation 4.21 where, for sake of illustration, this coefficient is restricted to take on a single value for all types \( \theta \). The first column shows OLS estimates of equation 4.21, while the second column then shows corresponding 2SLS estimates that use variation from the first-stage equation 4.20. Comparing these two estimates lends credence to the instrumental variables strategy: the OLS estimate of \( \gamma \) is substantially closer to 0 than is the 2SLS estimate, as would be expected if the instruments overcome the standard endogeneity problem whereby higher prices are charged to less price-sensitive borrowers in equilibrium. The 2SLS estimate also implies a long-run elasticity larger than 1 (equal to \(-1.8\)), consistent with profit maximization.

The next column of the table then examines how estimates change with the exclusion of bank-specific time trends \( \beta_j \). As can be seen, the inclusion of bank-specific trends changes the resulting estimates of \( \gamma \) only slightly, with estimates falling from .089 to .067 when these trends are excluded. The final column repeats the specification from column (2) while using LIML in place of 2SLS. The high number of instruments that result from the instrument \( Z_{jt} \) being fully interacted with consumer types \( \theta \) motivates using limited-information maximum likelihood estimates as a robustness check, to help overcome 2SLS bias in a setting with many instruments. The LIML estimate is larger in magnitude than the 2SLS estimate but not statistically distinguishable from it, so I use 2SLS estimates as my baseline in estimating the model.

The estimates of \( \gamma \) I ultimately use are presented in Table 6, where I also present a number
of parameters that are estimated later in this section. The estimates of $\gamma$ in Table 6 give further validation of the instrumental variables strategy, showing that the 2SLS estimates successfully recover higher marginal utilities of income for lower-credit score borrowers, as would be expected given these borrowers’ lower average incomes.

It should also be emphasized that these heterogeneous estimates of $\gamma$ determine how consumers place insurance value on credit card pricing in the model: these estimates capture how marginal utilities of income vary across states, and hence they determine how consumers value low pricing more in some states than in other states. I discuss the role of such insurance value further in Section 5.3.

4.3.3 Demand Estimation: Taste Parameters

I calibrate firms’ discount factor to .98 quarterly and consumers’ discount factor to .90 quarterly. Given the above estimates of each consumer’s type $\theta$ and borrowers’ price sensitivities $\gamma$, the remaining model parameters to be estimated are then the flow utilities $d_{\theta j}$, $n_{\theta j}$, $s_{\theta j}$, and $l_{\theta j}$. Recall these terms are, respectively, flow utilities from borrowing, flow utilities from transacting (rather than borrowing), setup costs for opening an account with a new lender, and liquidity costs for paying off a balance in order to transition from borrowing to transacting. These are estimated by matching key moments of the data corresponding to the three key facts outlined in section 4.1, each moment being an observed probability that is matched to a corresponding likelihood predicted by the model. In particular, these moments are: borrowers’ persistence in borrowing behavior; non-borrowing consumers’ persistence in non-borrowing behavior; account closure rates for borrowers; and account opening rates for consumers not holding credit cards.

Not all moments are available for all borrower types or lenders – for example, account opening rates calculated in the CCP cannot be estimated at the lender level, given that the dataset is anonymous as to lender identities. I therefore use as many such moments as are available and restrict parameter heterogeneity as needed. This yields just-identified parameters of the form $d_{\theta j}$, $n_{xj}$, $s_x$, and $l_{\theta j}$, where subscripts indicate how heterogeneity is restricted.

4.3.4 Supply Estimation

The lender’s maximization problem in equation 4.13 has tractable first-order conditions because many pricing decisions are made independently. This independence follows from lenders’ lack of commitment power in the pre-CARD-Act regulatory regime, which implies a deviation in $p^1_1(\theta)$ only affects profits earned on existing accounts for consumers of type $\theta$, and does not affect take-up of new accounts; likewise a deviation in $p^0_0(x)$ only affects profits earned on new accounts among consumers of public type $x$. Furthermore, continuation profits are unaffected by these one-period deviations. The first-order condition for $p^1_1(\theta)$ at the equilibrium price vector $p^*$ is
Thus, for a given $\theta$,

$$
\sum_{k \in \{b,n\}} \mu_{b,\theta,k}(p^*) \Pr_i^j(b|\theta, p^*, k) = \sum_{k \in \{b,n\}} \gamma_{\theta \mu_{b,\theta,k}}(p^*) \Pr_i^j(b|\theta, p^*, k) \left(1 - \Pr_i^j(b|\theta, p^*, k)\right) \times 
$$

\[\quad \left[p_i^j(\theta) - c_i^j(\theta) + \beta(1 - \delta(\theta)) T_{\theta \theta'}(\theta) \Pi_{i}^j(p^*, \theta', b)\right] \quad \text{(own-price effect)}
\]

\[\quad - \gamma_{\theta \mu_{n,\theta,k}}(p^*) \Pr_i^j(b|\theta, p^*, k) \left(\Pr_i^j(n|\theta, p^*, k)\right) \times \left[\beta(1 - \delta(\theta)) T_{\theta \theta'}(\theta) \Pi_{i}^j(p^*, \theta', n)\right] \quad \text{(cross-price effect)}
\]

(4.22)

First-order conditions for newly originated account prices $p_{0,0}(x)$ are similarly, for a given $x$,

$$
\sum_{j' \neq j} \sum_{\theta : x(\theta) = x} \sum_{k \in \{b,n,0\}} \mu_{j',\theta,k}(p) \Pr_{0,0}^j(b|p^*, j', k, \theta) = 
$$

\[\quad \sum_{j' \neq j} \sum_{\theta : x(\theta) = x} \sum_{k \in \{b,n,0\}} \gamma_{\theta \mu_{j',\theta,k}}(p^*) \Pr_{0,0}^j(b|p^*, j', k, \theta) \left(1 - \Pr_{0,0}^j(b|p^*, j', k, \theta)\right) \times 
\]

\[\quad \left[p_{0,0}^j(\theta) - c_{0,0}^j(\theta) + \beta(1 - \delta(\theta)) T_{\theta \theta'}(\theta) \Pi_{1}^j(p^*, \theta', b)\right] \quad \text{(own-price effect)}
\]

\[\quad - \gamma_{\theta \mu_{n,j',\theta,k}}(p^*) \Pr_{0,0}^j(b|p^*, j', k, \theta) \Pr_{0,0}^j(n|p^*, j', k, \theta) \times \left[\beta T_{\theta \theta'}(\theta) \Pi_{1}^j(p^*, \theta', n)\right] \quad \text{(cross-price effect)}
\]

(4.23)

To incorporate information on how default rates vary across consumer types, I parameterize the $c_i^j(\theta)$ terms as $c_i^j(\theta) = a_j x(\theta) + b_j \delta(\theta)$. I then estimate the parameters $(a_j, b_j, c_{0,0}^j(x))$ by minimizing squared violations of the above FOCs.

### 4.4 Model Parameter Estimates

Table 6 presents my estimates of model parameters. Rows correspond to consumers’ public types (FICO score groups), and each column presents a different set of model parameters, taking averages over private types and over banks within a row as needed.

The first column of the table shows estimates of the flow utility from borrowing $d_{\theta_j}$. For brevity these are averaged over private types $\psi$ within $\theta = (x, \psi)$ and over banks $j$ to give an average at the level of public type $x$. These flow utilities are decreasing in FICO score such that higher risk consumers enjoy more flow utility from borrowing; this correlation is consistent with the adverse-selectedness of the credit card market. In results not shown in the table, I find
this adverse-selectedness also appears within public types: the correlation across private types between default rates $\delta_\theta$ and the flow utility from borrowing $d_{\theta j}$ ranges from .44 to as high as .88, depending on the bank $j$ and the FICO score group.

The next column of the table shows estimates of price coefficients $\gamma_x$ across FICO scores. Recall from section 4.2 that these price coefficients are marginal utilities of income, so that the negative correlation between FICO scores and price coefficients is further confirmation that the instrumental variables strategy in section 4.3 successfully recovers realistic parameter values: consumers with lower FICO scores, who on average have lower incomes, indeed have higher marginal utilities of income.

The third column of the table shows estimates of the flow utility from transactional use of a credit card $n_{xj}$, i.e., the utility from holding a credit card without using it for borrowing. These estimates are near-zero for all consumers except those with the highest FICO scores, where the estimates become similar in magnitude as, though still smaller than, flow utilities from borrowing. Interestingly, these positive flow utilities for high-credit-score consumers are consistent with these consumers earning rewards, such as airline miles, from transactional use of a credit card. In contrast, for subprime cards where such rewards are less common, the estimates of $n_{xj}$ imply transactional use of a credit card is approximately no better or worse than the outside good, for example the use of cash or a debit card for purchases.

The fourth and fifth columns of the table show estimates of the two adjustment costs present in the model: the setup cost $s$ incurred to open a credit card account with a new bank, and the liquidity cost $l$ incurred to pay off one’s balance and transition to non-borrowing status. Setup costs are highest for consumers with the lowest credit scores, consistent both with these consumers receiving fewer direct mail offers to open new credit card accounts (CFPB (2017)), or being less optimistic about their chance of approval when applying. Liquidity costs are also highest for consumers with the lowest credit scores, consistent with generally high credit constraints in this population (Bhutta et al. (2015)). Setup costs are the more substantial of the two, and, consistent with other research examining similar adjustment costs in consumer demand for financial products (see Handel (2013) on health insurance choice and Illanes (2016) on annuity choice), these setup costs are economically significant. For example, for FICO 680 consumers, the dollarized setup cost is equal to the average pecuniary benefit from from switching to a new credit card amortized over 3.3 years.\footnote{This back-of-the-envelope calculation uses the average price difference for FICO 680 consumers between new and mature accounts, as documented in Appendix Tables 1 and 2, as well as the value of $\gamma_x$ for these consumers in Table 6.}

The final columns of the table show average estimates of lenders’ cost parameters $c^1_\theta(\theta)$ (column 6) and $c^0_x(x)$ (column 7), together with average default rates at each FICO score (column 8). Estimates of costs for existing accounts, $c^1_\theta(\theta)$, are strongly positively correlated with actual default rates, helping confirm the validity of marginal cost estimates recovered from the first or-
der conditions in section 4.3.4. New-account acquisition costs $c^j_0(x)$ are increasing in credit score, consistent with lenders needing both greater marketing expenses – for example, more direct mail offers per account opened, as in Grodzicki (2014) – and greater expense on account-opening bonuses – such as the payout of a lump sum of airline miles within the first few months of using a new credit card.\footnote{Note that, while these costs are on average all positive, in four cases the estimated acquisition costs are negative for particular combinations of lender and FICO score, consistent with fee revenue at the time of origination such as application fees, which otherwise is not accounted for in the price data used to estimate the model. All of these cases appear for subprime credit scores. When I later simulate the effects of the CARD Act price restrictions, I address these few instances of negative acquisition costs by imposing that these costs be no more than 25% of average credit limits at a given FICO score, consistent with the CARD Act’s “fee harvester” restrictions on initial fees being no more than 25% of initial credit limits.}

5 Equilibrium Effects of CARD Act Price Restrictions

I use the model from the previous section to study the CARD Act’s pricing restrictions. I impose these restrictions in the model and I analyze these restrictions’ effects on pricing, borrowing choices, and total welfare after the model converges to a new equilibrium under the new regime. This exercise deliberately holds constant other features of the pre-CARD-Act environment in order to focus on a precise sense of these restrictions effects: \textit{ceteris paribus} effects that emerge separately from, rather than in conjunction with, other contemporaneous economic shocks and regulatory changes.

5.1 Modeling CARD Act Price Restrictions

I model the CARD Act price restrictions as a mandate that firms commit to a single long-run price on each credit card contract at the time of origination. Contracts also include a promotional or “teaser” rate for one period before the long-run price takes effect, as such teasers were an important carve-out still permitted under the Act.

A credit card contract under the new restrictions therefore takes the form of a duple $(p^j_0, p^j_1)$ for lender $j$, containing an initial teaser rate and a subsequent long-run rate. This duple depends only on a consumer’s public type (FICO score) at origination, $x_0$. In particular, a contract’s long run price can no longer depend on private information $\psi_t$ revealed to a lender over the course of an account-holding relationship, as these private types are unobservable at origination. A contract’s long run price also can no longer depend on updated FICO scores $x_t$ over time. So,

\begin{align*}
\text{Pre-CARD-Act: } & p^j_1 = p^j_1(x_t, \psi_t) \\
\text{Post-CARD-Act: } & p^j_1 = p^j_1(x_0)
\end{align*}

(5.1)
However teaser rates continue to depend only on public types at origination, as they did in the pre-CARD-Act regime.

The choice to include teaser rates in my implementation of the CARD Act price restrictions leads to considerably greater computational difficulty, as it doubles the size of lenders’ strategy space and state space. Including teaser rates is important, however, as banks’ ability to effectively set different prices for consumers who are and are not willing to switch accounts frequently has the potential to undo some of the price-pooling effects of the Act that I aim to study.

Granted, the restrictions modeled in expression 5.1 also abstract from some details of the Act, in particular, minor exemptions that would still permit discretionary price changes in some circumstances. As discussed in Section 2.1, these exceptions have been rarely used in practice, so abstracting from these provides considerable additional tractability without substantial departure from the content of the Act.

I study an equilibrium where each firm can offer only one contract to each public type at origination. I make this restriction in part for sake of realism and in part for tractability, as this restriction avoids the difficulty of solving for an entire menu of contracts for each lender and each public type in an imperfectly competitive environment (Stole (2007)). As my model results later confirm, this “one contract per firm per origination credit score” specification still allows substantial price dispersion at each public type, as differentiated lenders post different price duples \((p_0, p_1)\) to each public type.

### 5.2 Solving for the post-CARD-Act Equilibrium

Specifying the firm’s problem in the presence of the CARD Act repricing restrictions requires keeping track of the share of consumers of each type \(\theta\) who hold a contract that they originated when they were of type \(x_0\), where \(x_0\) is potentially different from the current public type \(x(\theta)\). Previously I used \(\mu_{j,\theta,k}(p)\) to denote the share of consumers of each type \(\theta\) who hold a credit card with bank \(j\), who use that card the purpose \(k \in \{\text{borrow, transact}\} \equiv \{b,n\}\), in a market with price vector \(p\). I now use \(\mu_{j,\theta,x_0,k}(p)\) where the subscript \(x_0\) denotes types at origination. As before, this vector denotes the long-run distribution of consumers across contracts and choices for a given price vector \(p\).

Bank \(j\)’s expected discounted lifetime profits on a mature account can then be written in a

\[33\]
form similar to equation 4.11,

\[
\Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta, x_0, k) = \underbrace{\text{flow profit for type } \theta, \text{ contract } x_0}_{\text{newly acquired accounts}} + \\
\underbrace{\Pr_j^1(b|\theta, p, x_0, k)\left(p_j^1(x_0) - c_j^1(\theta)\right)}_{\text{flow profit for type } \theta, \text{ contract } x_0} + \\
\underbrace{\Pr_j^1(b|\theta, p, x_0, k)\beta(1 - \delta(\theta))T_{\theta \theta'}(\theta)\Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta, x_0, b)}_{\text{exp. cont. profit | borrow}} + \\
\underbrace{\Pr_j^1(n|\theta, p, x_0, k)\beta T_{\theta \theta'}(\theta)\Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta', x_0, n)}_{\text{exp. cont. profit | not borrow}}
\]  

(5.2)

Expected discounted lifetime profits on new accounts are defined analogously, by making slight revisions to equation 4.10 to depend on a consumer’s origination type \(x_0(\theta)\),

\[
\Pi_{0,\text{post}}^j(p^j, p^{-j}, \theta, k) = \underbrace{\text{flow profit}}_{\text{newly acquired accounts}} + \\
\underbrace{\Pr_0^j(b|\theta, p, k)p_0^j(x_0(\theta)) - c_0^j(x_0(\theta))}_{\text{newly acquired accounts}} + \\
\underbrace{\Pr_0^j(b|\theta, p, k)\beta(1 - \delta(\theta))T_{\theta \theta'}(\theta)\Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta, x_0(\theta), b)}_{\text{exp. cont. profit | borrow}} + \\
\underbrace{\Pr_0^j(n|\theta, p, k)\beta T_{\theta \theta'}(\theta)\Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta', x_0(\theta), n)}_{\text{exp. cont. profit | not borrow}}
\]  

(5.3)

and likewise by revising equation 4.12 to reflect a sum over inflows from competitors’ contracts originated at types \(x_0\),

\[
\tilde{\Pi}_{0,\text{post}}^j(p^j, p^{-j}, x) = \sum_{j' \neq j} \sum_{\theta : x(\theta) = x} \sum_{x_0} \sum_{k \in \{b, n, 0\}} \mu_{j', \theta, x_0, k}(p)\Pr(j|p, j', \theta, x_0, k)\Pi_{0,\text{post}}^j(p^j, p^{-j}, \theta, k) 
\]  

(5.4)

With this notation in hand, a lender’s total expected discounted profits across both new and mature accounts under the restricted equilibrium can be written as,

\[
\Pi_j(p^j, p^{-j}) = \sum_x \tilde{\Pi}_{0,\text{post}}^j(p^j, p^{-j}, x) + \\
\sum_{\theta} \sum_{x_0} \sum_{k \in \{b, n, 0\}} \mu_{j, \theta, x_0, k}(p)\times \Pi_{1,\text{post}}^j(p^j, p^{-j}, \theta, x_0, k)
\]  

(5.5)

I use successive lender best-replies that maximize this profit function to compute the new equilibrium, beginning this process at the pre-CARD-Act equilibrium price vector. At each iteration, each lender computes its best reply to the prior iteration’s market price vector, given consumer behavior determined by the demand side of the model; all of these best replies then
together form the market price vector for the next iteration. \textsuperscript{38} Equilibrium convergence is then defined in terms of stability in the overall market price vector from one iteration to the next. In practice, I find that pricing on the most thickly traded contracts stabilizes relatively early in this iterative process, while subsequent iterations are mostly needed to pin down prices on thinly traded contracts that few consumers choose in equilibrium.

5.3 Equilibrium Effects of CARD Act Price Restrictions

The new equilibrium shows how prices, quantities, and welfare – both for lenders and for different consumer types – change under the CARD Act price restrictions.

5.3.1 Prices and Quantities

I find that the Act’s pricing restrictions induce moderately severe market unraveling for consumers with the lowest credit scores: pooling increases, and contract prices newly exceed willingness to pay for roughly 30\% of the safest private types within subprime scores. At higher credit scores, nearly all consumer types face lower prices. Meanwhile, because selection changes the composition of consumers who stay in the market and of contracts that get retained over time, average \textit{transacted} prices – that is, prices actually paid by consumers who choose to borrow – decrease at all credit score levels.

I present my estimates of the Act’s effects on prices and borrowing behavior in a series of figures. In Figure 6, panels (a), (b), and (c) show these effects in three FICO score groups across the range of the score distribution: deep subprime consumers with scores of 580-599; consumers at the cusp between subprime and prime, with scores of 680-699; and superprime consumers with scores of 780 and above. The left figure in each panel shows equilibrium effects on contract prices across consumer private-information types on the x-axis, and the right figure in each panel shows equilibrium effects on borrowing behavior, or the share of all consumers who choose to borrow on a credit card, for the same groups. In each plot, the two lines correspond to the observed pre-CARD-Act equilibrium and the estimated post-CARD-Act equilibrium.

Turning first to deep subprime consumers in Panel (a), the left figure shows a shift from heterogeneous pricing (a separating equilibrium) across private-information types in pre-CARD-Act data, to nearly complete pooling in the estimated post-CARD-Act equilibrium. Under this pooled pricing, all private types with FICO scores of 580 are now estimated to pay a fee-inclusive

\textsuperscript{38}These best replies serve both as a computational tool to iteratively find the new equilibrium, and as an equilibrium selection device. Similar to some other empirical work that has simulated a new market equilibrium under a new regulatory regime (e.g., Ryan (2012)), it is difficult to rule out the presence of multiple equilibria in my setting. This process of successive best-replies from the pre-CARD-Act equilibrium seems most plausible as a device to select the post-CARD-Act equilibrium (as opposed to, for example, a starting price vector where all firms charge prices of zero). For evidence that firms indeed may converge on a new equilibrium gradually after a regulatory change by playing best replies to other firms’ most recently observed pricing strategies, see Doraszelski et al. (2018).
cost of credit in excess of 50% annualized. Only for the very riskiest and most inelastic of private types is this a lower rate than the average paid in pre-CARD-Act data, and all other types face higher prices than they faced before.

These high prices are an equilibrium outcome driven in part by market unraveling: that is, the safest private-information types exit from borrowing as they are pooled with riskier peers; the cost of lending to the remaining, riskier private-information types then drives prices higher still; these higher prices then induce further exit by relatively safe private-information types; and so on. The right-side figure of Panel (a) illustrates this unraveling by showing changes in borrowing behavior for the same FICO 580 group from Panel (a). In the pre-CARD-Act data, at least 30% of each private-information type used credit cards for borrowing; among all but the highest (riskiest) quintile, the shares who borrowed were roughly equal. In contrast, in the estimated post-CARD-Act equilibrium, the right-side figure in Panel (a) shows that the safest private-information types exit almost entirely from borrowing, and even the median private-information type has its borrowing share fall by over two-thirds. Meanwhile, the riskiest private-information types increase their borrowing share in response to the lower prices they face.

Turning to the remaining panels of the figure, other credit score segments do not experience the same degree of unraveling as was seen among deep subprime consumers in Panel (a). In Panel (b), within the FICO 680 group nearly all private information types experience lower prices as a result of lower markups in the estimated post-CARD-Act equilibrium; only the safest quintile of private-information types face higher prices while being pooled with their riskier peers. The right-side figure of Panel (b) then shows how these relative price changes affect borrowing shares across types. The very safest private types exit somewhat from borrowing in response to the higher prices they face in the estimated post-CARD-Act equilibrium, though they do not exit to the same degree as was seen in Panel (a). Meanwhile a greater share of all other private types borrow, reflecting these types’ price decreases in the estimated post-CARD-Act equilibrium.

Panel (c) shows even broader price decreases at higher credit scores: among FICO 780 consumers, all private-information types in fact face either reduced or nearly unchanged loan pricing. Correspondingly, all private-information types in the FICO 780 group have greater borrowing shares in the estimated post-CARD-Act equilibrium.

To emphasize, the prices shown in Figure 6 are averages across the contract prices offered to a consumer given the consumer’s current type. Average transacted prices may differ from these prices for two reasons. First, Figure 6 shows that consumers who face price increases tend to exit the market, which changes the composition of which prices are transacted. Second, consumer types also change over time – for example, a prime consumer may later become subprime – and, as modeled in Equation 5.1, the CARD Act restrictions can allow a consumer to retain her earlier contract and its pricing as her type changes.

These borrowing rates in fact track closely to some APRs seen among deep subprime credit cards in recent years, for example a 79.9% APR subprime credit card marketed in 2010 (Prater, 2010).
To summarize the effects of these two compositional changes, Figure 7 shows averages of the actual prices paid at each FICO score among all consumers with that FICO score who choose to borrow. These transacted prices fall more after the CARD Act than the contract prices shown in the prior figure did, reflecting both some consumers’ exit from the market and other consumers’ retention of relatively favorable prices over time. Among subprime consumers in particular, this difference between contract and transacted prices reflects how relatively few subprime consumers transact at the (increased) contract prices available to them in the new equilibrium.

It is instructive to compare the changes in average transacted prices from Figure 7 with comparable estimates from prior work. Qualitatively, there are strong similarities with the results in Agarwal et al. (2015b): transacted prices fall throughout the score distribution, and these price decreases are greatest among subprime consumers. Quantitatively, the percentage changes I estimate are greater than those in Agarwal et al. (2015b).40 Two differences between the papers’ approaches seem likely to account for these differences. First, I estimate the effect of only the CARD Act pricing restrictions, whereas Agarwal et al. (2015b) estimate the effect of the Act as a whole, including its non-price provisions; inspection of these other provisions suggests that they may likely have shifted credit card borrowing demand outward, which would contribute to the differences in estimates.41 Second, my empirical strategy holds constant other features from the pre-CARD-Act period such as consumer demand and risk characteristics, in order to provide the precise ceteris paribus estimates of the CARD Act restrictions’ effects I have emphasized above; Agarwal et al. (2015b)’s estimates correspond to the Act’s effects in a different, post-crisis context as compared to the pre-CARD-Act context I study.

5.3.2 Welfare: Consumer and Total Surplus

The estimates discussed above suggest that the Act’s implications for consumer as well as total surplus could be ambiguous: on the one hand, I find the Act causes prices to rise for some consumer types, who partly exit the market in response; on the other hand, I find the Act causes transacted prices to fall among the set of consumers who remain in (or newly enter) the market. To quantify the effects of these changes for consumer welfare, I calculate lifetime expected consumer surplus for each consumer type under both the pre-CARD-Act equilibrium and the estimated post-CARD-Act equilibrium, and I use each consumer type’s marginal utility of income (i.e. the price coefficients estimated with quasi-experimental variation in Section

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40 Focusing on percentage changes is valuable because the price levels in the two papers are not directly comparable: whereas Agarwal et al. (2015b) estimate price effects weighted by outstanding balances, I estimate price effects with equal weights for each consumer. Higher pricing correlates with lower balances, both due to credit card fees not scaling with balances and due to consumers potentially choosing to borrow less when interest rates are higher. The balance-weighting approach scales down pricing by a factor of 2.4 on average relative to equal weighting across consumers, generating much of the gap between the two papers in level terms.

41 In particular, these changes made credit card borrowing more predictable and transparent for consumers; see footnote 13.
4.3.2) to dollarize these surplus differences. Because utility is quasi-linear in income when holding consumer types fixed, this yields both the compensating and equivalent variation from the CARD Act for each consumer type. Then to quantify overall welfare, I add per-account lender profits to these estimates of per-account consumer surplus, yielding an estimate of total surplus under both the pre- and post-CARD-Act equilibria.

I find that consumer surplus conditional on credit score in fact rises across all FICO groups as a result of the CARD Act price restrictions, with gains of $40 per person among subprime consumers and $95 per person among superprime consumers. These gains are plotted in Figure 8 Panel (a). I further discuss sources for these gains below.

In contrast with these consumer surplus results, the CARD Act price restrictions’ effects on total surplus (i.e., the sum of lender profits and consumer surplus) differ markedly by credit score. To illustrate these effects, Figure 8 Panel (b) shows estimated total surplus per consumer before and after the Act and across different credit score segments. In the subprime segment of the market, I find that the gains in consumer surplus under the Act are mostly offset by a fall in lender profits: that is, total surplus is mostly unchanged in the subprime segment of the market, where gains in consumer surplus largely reflect a transfer away from firms via reduced markups. In contrast, I estimate that total surplus rises in the prime and superprime segments of the market as a result of the Act.

I return to the model as a tool to explore the sources for these surplus gains. I perform a set of exercises where I counterfactually remove features of the market that potentially contribute to the Act’s effects, and I examine how the Act’s effects on consumer surplus differ in these alternative environments. For example, one source of surplus gains could be reducing the incidence of account setup costs (the parameter $s_x$): when lenders cannot raise prices on existing accounts, borrowers have less need to transfer balances serially to new credit card accounts and incur repeated account setup costs. To explore the particular channel for surplus gains in that example, I counterfactually set account setup costs to zero, and I study how the Act changes consumer surplus in such an environment. I conduct several such counterfactual exercises to study different sources of surplus gains.

Specifically, for each counterfactual environment that I consider, I recompute each consumer type’s lifetime expected surplus at the observed pre-CARD-Act price vector, and I likewise recompute consumer surplus at the estimated post-CARD Act price vector. I leave the two price vectors unchanged from the baseline (not counterfactual) case, in order to focus on mechanisms for surplus gain within the pre- and post-CARD-Act equilibria already discussed. Hence these counterfactual consumer surplus estimates provide a partial-equilibrium decomposition of the sources of surplus gain under the CARD Act. For each counterfactual environment, I analyze consumer surplus gains across consumer types in percent terms, so as to make these changes comparable across different environments.
Table 7 presents estimates from two counterfactual environments in particular: (1) an environment in which consumers have no demand for insurance against price changes because consumer types are perfectly persistent (i.e., the transition matrix $T_{\theta \theta}'$ is the identity matrix); and (2) an environment in which consumers face no account setup costs when opening a new account (i.e., setup costs $s_x$ are set to zero). The first row of the table shows consumer surplus gains from the CARD Act in the baseline (no counterfactual) case, equal to the consumer surplus gains already presented in Figure 8 Panel (a). The next two rows of the table show consumer surplus gains in the two counterfactual cases.

In the counterfactual case with no insurance demand, consumer surplus gains under the CARD Act are substantially reduced for consumers with higher credit scores. Superprime consumers, for example, experience more than a doubling of consumer surplus from pre- to post-CARD-Act in the baseline case, but this increase falls to just 17% in the case with no insurance demand. Prime consumers similarly see their surplus gains under the CARD Act more than halved by removing the Act’s insurance value. In contrast, subprime consumers see little change to their surplus gains under the CARD Act in the counterfactual with no insurance demand, as this group’s gains are nearly indistinguishable between the first two rows of the table. These differences underscore how consumers with higher credit scores benefit primarily from the CARD Act’s effects in future, uncertain states, which prime consumers do not reach if their types are perfectly persistent; meanwhile subprime consumers benefit directly from the Act in their current state, as their surplus gain remains similar even with perfectly persistent types.

The insurance value of the CARD Act also reflects the heterogeneity in marginal utilities of income (the model parameters $\gamma_x$) that I estimated using quasi-experimental variation in Section 4.3.2. As shown earlier in Table 6, my estimates of marginal utilities roughly double as credit scores fall from superprime to subprime, and as in classic insurance applications, heterogeneity in marginal utilities across different states generates demand for insurance. The CARD Act price effects shown above in Figure 7 illustrate how the Act in part provides such insurance, as the greatest decreases in transacted prices under the Act are realized for credit scores with the highest marginal utilities of income.

Meanwhile in the counterfactual case with no account setup costs, surplus gains are lower for all consumer types. The first and third rows of Table 7 show that subprime and prime consumers’ surplus gains under the CARD Act are both nearly halved by eliminating account setup costs, whereas superprime consumers’ surplus gains are lowered by about a quarter. These reduced surplus gains illustrate how the CARD Act’s benefits for consumers in part emerge from the presence of setup costs or switching costs in the credit card market. As switching credit cards

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42To emphasize, these differences in marginal utilities are across consumer types, and, as described in Section 4.2, these types change probabilistically from one period to the next. Hence there is demand for insurance over time even as utility is quasi-linear in prices conditional on type. This quasi-linearity is appealing given how credit card price changes are unlikely to be large enough to induce large within-period wealth changes; see the back-of-the-envelope calculations in footnote 31.
becomes easier, the CARD Act’s protections against price increases on existing accounts become less valuable for consumers and the Act’s consumer surplus benefits diminish.

These counterfactual results also underscore how the estimated consumer surplus gain in the subprime part of the market is an important result: consumer surplus rises despite there not being a particularly important role among subprime consumers for either insurance value or reduced “churn.” This surplus gain therefore points to the importance of the demand-relevant private information that, in the absence of the Act’s pricing restrictions, allows lenders to charge high markups to the most inelastic of subprime borrowers. Even though the Act’s pricing restrictions prevent prices from adjusting for risk, these markups are important enough that the subprime market still does not fully unravel, making consumer surplus gains possible.

6 Conclusion

I study the consequences of restricting lenders from adjusting borrowers’ loan pricing in response to information acquired over the course of lending relationships. I focus on such restrictions in the 2009 CARD Act. I find reduced-form evidence that the Act limited the pricing of risk- and demand-relevant information, compressed the price distribution, and changed the selection of consumers in and out of borrowing. Building on this evidence, I develop and estimate a structural model that assesses the distributional and efficiency effects of the Act’s price restrictions in equilibrium. Model estimates also uncover new facts about the credit card market, including the degree of borrowers’ price sensitivity, the importance of consumers’ adjustment frictions across credit cards, and the correlation of demand characteristics with risk.

When I impose the CARD Act price restrictions in the model, I find that the post-CARD-Act equilibrium involves a nontrivial degree of unraveling, especially on subprime accounts; nevertheless, average prices fall among consumers who still choose to borrow on their credit cards, and average consumer surplus rises at all credit scores. For subprime consumers, surplus gains are mostly transfers from lenders, whereas at higher credit scores, total surplus inclusive of firm profits rises as well.

One mechanism contributing to these results is that the CARD Act price restrictions effectively provide price insurance for borrowers with deteriorating risk over time. Therefore, even though credit cards are not insurance products per se, they involve a tradeoff between reclassification risk and adverse selection similar to insurance contracts. Interestingly, I find some similar results to what the recent work of Handel et al. (2015) finds in the context of health insurance, here in a credit market setting: the welfare gains from restricting the pricing of certain types of information can be greater than the resulting welfare costs due to unpriced risk. Promising areas for future work may be to explore which other credit markets offer similar conclusions and how public policy or alternative credit products can be optimally designed in response.
References


——— (1999): “Adverse selection in the credit card market,” Working paper, University of Maryland. 4.2


Bhutta, N., P. M. Skiba, and J. Tobacman (2015): “Payday loan choices and consequences,” Journal of Money, Credit and Banking, 47, 223-260. 4.4


FEDERAL RESERVE BOARD (2007): *Report to the Congress on Credit Scoring and its Effects on the Availability and Affordability of Credit*, Board of Governors of the Federal Reserve System. 3.2


FULFORD, S. L. (2015): “How important is variability in consumer credit limits?” *Journal of Monetary Economics*, 72, 42–63. 1


7 Figures

Figure 1: Repricing Probabilities and Price Dispersion

(a) Interest Rate Repricing

(b) Interquartile Ranges in Credit Card Interest Rates by Vintage

Notes: Panel (a) shows the incidence of interest rate increases on current borrowers over 1-month, 6-month, and 12-month horizons, excluding interest rate increases permitted by the CARD Act (i.e., increases coinciding with the expiration of a promotional rate, with changes in an index rate, or with delinquencies of 60 days or more). Dotted lines extrapolate from the most recent available datapoint when these horizons overlap with the implementation of the CARD Act’s interest rate repricing restrictions in February 2010. Panel (b) shows the interquartile range (IQR) of annual percentage rates on borrowing accounts by origination cohort, after partialling out origination credit score and origination month. The date shown for each cohort is at its age of maturity (18 months), by which point introductory promotional rates have typically expired. Credit score controls are 20-point bins, and the sample is restricted to include only accounts in the same credit score bin at the date observed as at origination. The vertical black lines in each panel show the date of implementation for the CARD Act’s restrictions on interest rate increases, in February 2010.
Figure 2: Pricing of Origination Risk and Emergent Risk

(a) Pre-CARD-Act

(b) Post-CARD-Act

(c) Adverse Retention and Risk Pricing

Notes: Panel (a) shows two different gradients of risk in the pre-CARD-Act era (2008Q3 to 2009Q2) on two pairs of axes. On the left and bottom axes, the figure plots the average annual percentage rate (APR) on newly originated accounts across quantiles of the credit score distribution, together with a line of best fit. On the right and top axes, the figure plots the average current APR on mature accounts across quantiles of those accounts' change in credit score since origination, after partialling out origination credit score, together with a line of best fit. See equations 3.1 and 3.2 in the text. Panel (b) presents the same price-risk gradients as in Panel (a) but in post-CARD-Act data (2011Q3 to 2014Q2). The two y-axes have the same axis scale, but the axis ranges are shifted to facilitate comparison of the two gradients. Panel (c) presents quarterly attrition rates from borrowing (including both attrition through account closure and also attrition through paying off a credit card’s balance) across quantiles of borrowing accounts’ changes in FICO score since origination, separately in pre-CARD-Act data and post-CARD-Act data (2008Q3 to 2009Q2 and 2011Q3 to 2014Q2, respectively); these are the same changes in FICO score as are plotted in the top axes of Panels (a) and (b). See equation 3.3 in the text.
Figure 3: Recovering Private-Information Types from Equilibrium Pricing

(a) Step 1: Inverse Pricing Functions for Ex-Post Default

(b) Step 2: Isotonic Inverse Pricing Functions

(c) Step 3: Discretizing Private Types $\psi$ from Pricing Functions

Notes: The figure illustrates the process of recovering private-information types from observed equilibrium pricing in pre-CARD-Act data, as described in equations 4.14 and 4.15 in the text. This example is taken from the market segment defined by the credit score range 760-779. Panel (a) shows raw data on observed default rates at quantiles of price levels on two different banks, labeled Bank A and Bank B. Default is defined as delinquencies of 90+ days at any time over the subsequent 2 years. Panel (b) shows isotonic regression estimates of the relationship between default and equilibrium pricing, together with the raw data from panel (a) for sake of comparison. Panel (c) then shows how borrowers at different quantiles of the population distribution of default rates within this credit score range are grouped into discrete private-information types $\psi$ that share a common default rate, but face different prices depending on their choice of lender.
Notes: The figure displays a contour plot of period-to-period transition probabilities among consumer types. These probabilities are estimated quarterly among borrowers observed for two subsequent quarters, using the joint of public and private types recovered through the process illustrated in Figure 3. The integer values of the index correspond to the public dimension of types, in order of increasing credit score; for example the range [0,1) corresponds to the 580-599 FICO score group, the range [1,2) corresponds to the 600-619 FICO score group, and so-on. Within integers, the sub-ticks correspond to the five private-information types recovered at each FICO score level, in order of increasing risk.

Figure 4: Transition Rates Among Public and Private Types

Notes: The figure plots an example of a repricing quasi-experiment (left panel) and subsequent attrition from borrowing (right panel) in pre-CARD-Act data. In the left panel, the solid red lines plot deciles of the distribution of annual percentage rates (APRs) on mature, borrowing accounts for one lender in the data, denoted Bank A. All deciles of this distribution rise by 100 basis points in the month labeled event time 0, emphasizing how this repricing campaign affects (nearly) all accounts in the portfolio. The dotted blue line shows the average APR for all other lenders’ mature, borrowing accounts. In the right panel, log monthly attrition rates from borrowing are shown relative to their value in event time 0 for Bank A and for all other banks. Here attrition includes attrition through paying off a balance, through refinancing with another lender, or through closing a card. See equation 4.1 in the text.

Figure 5: Example of Repricing Quasi-Experiment and Borrowing Response

Notes: The figure plots an example of a repricing quasi-experiment (left panel) and subsequent attrition from borrowing (right panel) in pre-CARD-Act data. In the left panel, the solid red lines plot deciles of the distribution of annual percentage rates (APRs) on mature, borrowing accounts for one lender in the data, denoted Bank A. All deciles of this distribution rise by 100 basis points in the month labeled event time 0, emphasizing how this repricing campaign affects (nearly) all accounts in the portfolio. The dotted blue line shows the average APR for all other lenders’ mature, borrowing accounts. In the right panel, log monthly attrition rates from borrowing are shown relative to their value in event time 0 for Bank A and for all other banks. Here attrition includes attrition through paying off a balance, through refinancing with another lender, or through closing a card. See equation 4.1 in the text.
Figure 6: Equilibrium Changes in Contract Pricing and Borrowing Behavior

(a) FICO 580-599 Consumers

(b) FICO 680-699 Consumers

(c) FICO 780+ Consumers

Notes: The left-side figure in each panel shows observed average contract prices for each consumer type in three selected credit score groups in the pre-CARD-Act equilibrium, together with model results for these types’ equilibrium contract prices after imposing the CARD Act price restrictions. The prices shown are annualized, account-level averages at a quarterly frequency inclusive of both interest charges and fees, normalized by the amount borrowed. This price measure is described in Section 2.2.3 of the text. The right-side figure in each panel shows the share of consumers who use a credit card for borrowing among various consumer types. Shares for the new equilibrium with price restrictions reflect the effect of CARD Act price restrictions when implemented in the model, holding constant other parameter estimates from the pre-CARD-Act equilibrium. Private-information types are shown across the x-axis of each figure. The three panels show three selected public information (credit-score) groups across the range of the credit score distribution.
**Figure 7:** Changes in Transacted Prices

*Notes:* The figure shows average transacted contract prices in the observed pre-CARD-Act equilibrium and in the estimated equilibrium with CARD Act price restrictions. Transacted prices are averages of the actual prices paid at each FICO score among all consumers with that FICO score who choose to borrow. FICO scores across the x-axis refer to consumer’s contemporaneous scores rather than scores at the time of contract origination, so transacted prices at each credit score include prices retained from some contracts originated at other scores in earlier periods. Prices shown are individual-weighted averages across private types and across lenders; see Section 5.3 for a discussion of individual-weighted versus balance-weighted prices.
Figure 8: Consumer and Total Surplus

(a) Consumer Surplus

Notes: Panel (a) shows estimated per-person lifetime consumer surplus (including both borrowers and non-borrowers) in the pre-CARD-Act equilibrium and also in the new equilibrium found in the model after imposing the CARD Act price restrictions. Surplus is dollarized using each type’s marginal utility of income (the price coefficient $\gamma_\theta$) and using average borrowed balances for a type’s credit score group. Per-person surplus numbers are averaged to coarser credit-score groups using the type probability distribution $\mu_\theta$. Panel (b) shows estimated per-person total surplus (including both borrowers and non-borrowers’ lifetime consumer surplus as well as the present value of firm profits) in the pre-CARD-Act equilibrium and also in the new equilibrium found in the model after imposing the CARD Act price restrictions. Subprime refers to accounts with FICO scores below 660; prime refers to accounts with FICO scores of 660 or above but below 720; superprime refers to accounts with FICO scores of 720 and above.
<table>
<thead>
<tr>
<th>FICO</th>
<th>Panel A: Changes in Interest Charges (% Ann.)</th>
<th>Panel B: Changes in Fee-Inclusive Charges (% Ann.)</th>
<th>Panel C: Changes in Borrowing and Credit Card Holding</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P10</td>
<td>P25</td>
<td>Mean</td>
</tr>
<tr>
<td>580 - 599</td>
<td>2.46</td>
<td>-0.03</td>
<td>-2.52</td>
</tr>
<tr>
<td>600 - 619</td>
<td>2.16</td>
<td>0.89</td>
<td>-1.54</td>
</tr>
<tr>
<td>620 - 639</td>
<td>2.66</td>
<td>1.70</td>
<td>-0.75</td>
</tr>
<tr>
<td>640 - 659</td>
<td>3.03</td>
<td>2.49</td>
<td>0.12</td>
</tr>
<tr>
<td>660 - 679</td>
<td>3.01</td>
<td>2.95</td>
<td>0.88</td>
</tr>
<tr>
<td>680 - 699</td>
<td>2.67</td>
<td>3.15</td>
<td>1.38</td>
</tr>
<tr>
<td>700 - 719</td>
<td>1.44</td>
<td>3.22</td>
<td>1.59</td>
</tr>
<tr>
<td>720 - 739</td>
<td>0.44</td>
<td>3.18</td>
<td>1.56</td>
</tr>
<tr>
<td>740 - 759</td>
<td>-0.99</td>
<td>2.68</td>
<td>1.45</td>
</tr>
<tr>
<td>760 - 779</td>
<td>-2.54</td>
<td>1.91</td>
<td>1.07</td>
</tr>
</tbody>
</table>

Notes: Panels (a) and (b) show percentage point changes in two price measures across the FICO score distribution from before the CARD Act to after (2008Q3 to 2009Q2 and 2011Q3 to 2014Q2 respectively). The first price measure, shown in Panel (a), is an account’s annualized percentage interest charges, defined as annualized monthly interest charges divided by borrowed balances. The second price measure, shown in Panel (b), adds fee charges to the numerator of the first price measure. Panel (c) shows the share of credit card accounts that are used for borrowing in the same pre- and post-CARD-Act periods (“borrowing share”), and the share of consumers who hold a credit card at all in the same pre- and post-CARD-Act periods (“credit card holding share”). The final column of panel (c) reports percent changes in the credit card holding share from pre- to post-CARD-Act data.
Table 2: Returns after Price Elasticity Signals and Risk Signals

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No Signal:</td>
<td>Over-Limit but not Delinquent:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Late by &lt; 30 Days</td>
<td>Over-Limit and Delinquent:</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Late by 30 - 59 Days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Late by 60+ Days</td>
</tr>
<tr>
<td>780 - 799</td>
<td>9.24</td>
<td>2.66*</td>
<td>-0.72</td>
</tr>
<tr>
<td>760 - 779</td>
<td>8.82</td>
<td>2.44*</td>
<td>-0.45</td>
</tr>
<tr>
<td>740 - 759</td>
<td>7.92</td>
<td>1.70*</td>
<td>-0.32</td>
</tr>
<tr>
<td>720 - 739</td>
<td>6.99</td>
<td>1.02*</td>
<td>-0.10</td>
</tr>
<tr>
<td>700 - 719</td>
<td>6.02</td>
<td>0.02*</td>
<td>-0.09</td>
</tr>
<tr>
<td>680 - 699</td>
<td>5.09</td>
<td>-0.93</td>
<td>0.09*</td>
</tr>
<tr>
<td>660 - 679</td>
<td>4.35</td>
<td>-1.53</td>
<td>0.61*</td>
</tr>
<tr>
<td>640 - 659</td>
<td>3.69</td>
<td>-2.31</td>
<td>0.76*</td>
</tr>
<tr>
<td>620 - 639</td>
<td>3.30</td>
<td>-3.33</td>
<td>0.52*</td>
</tr>
<tr>
<td>600 - 619</td>
<td>2.99</td>
<td>-5.24</td>
<td>0.05*</td>
</tr>
<tr>
<td>580 - 599</td>
<td>0.89</td>
<td>-10.10</td>
<td>-1.28</td>
</tr>
</tbody>
</table>

Notes: The table shows baseline annualized percent lender returns on accounts in each FICO score group (column 1) in the pre-CARD-Act period (2008Q3 to 2009Q2), and differences from these baseline returns that are predicted in the pre-CARD-Act period by the signals in each column. For ease of presentation, signals that predict higher returns in a given FICO score group are denoted with a “+”. Returns are calculated by dividing finance charge and fee revenue less default cost by borrowed balances; see equation 3.4 in the text.

Table 3: Default Rates by Pricing Quintile

<table>
<thead>
<tr>
<th>Pricing Quintile (relative to Lowest Quintile):</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample: All Accounts</td>
<td>Dependent Variable: Two-Year Default Rate</td>
<td>OLS</td>
<td>Subprime OLS</td>
</tr>
<tr>
<td>2nd Quintile</td>
<td>0.00791***</td>
<td>0.0157***</td>
<td>0.00423***</td>
</tr>
<tr>
<td>(0.0000837)</td>
<td>(0.000174)</td>
<td>(0.0000813)</td>
<td></td>
</tr>
<tr>
<td>3rd Quintile</td>
<td>0.0417***</td>
<td>0.106***</td>
<td>0.00537***</td>
</tr>
<tr>
<td>(0.0000862)</td>
<td>(0.000178)</td>
<td>(0.0000839)</td>
<td></td>
</tr>
<tr>
<td>4th Quintile</td>
<td>0.0679***</td>
<td>0.167***</td>
<td>0.0118***</td>
</tr>
<tr>
<td>(0.0000883)</td>
<td>(0.000180)</td>
<td>(0.0000866)</td>
<td></td>
</tr>
<tr>
<td>5th Quintile</td>
<td>0.0970***</td>
<td>0.202***</td>
<td>0.0379***</td>
</tr>
<tr>
<td>(0.0000943)</td>
<td>(0.000188)</td>
<td>(0.0000941)</td>
<td></td>
</tr>
<tr>
<td>Uncond. Mean in Lowest Pricing Quintile</td>
<td>0.168</td>
<td>0.320</td>
<td>0.083</td>
</tr>
<tr>
<td>Bank x FICO FEs</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Number of observations</td>
<td>324024678</td>
<td>117288343</td>
<td>206736335</td>
</tr>
<tr>
<td>Number of clusters</td>
<td>61703574</td>
<td>34694908</td>
<td>50892205</td>
</tr>
</tbody>
</table>

Notes: The table shows estimates of average default rates by pricing quintile. Reported coefficients are differences relative to the first (lowest) pricing quintile, the unconditional mean of which is reported in the final row of the table. The prices used are annualized, account-level averages at a quarterly frequency inclusive of both interest charges and fees, normalized by the amount borrowed. This price measure is described in Section 2.2.3 of the text. Default is defined as any delinquency of 90+ days at any time over the subsequent 2 years. FICO fixed effects are 20-point bins of FICO score. Column (1) includes all borrowing accounts; column (2) includes only subprime accounts (FICO scores of 660 or less); column (3) includes only prime accounts (FICO scores over 660). See equation 4.2 in the text.
### Table 4: Demand Model: Consumers’ One-Period Payoffs by State

<table>
<thead>
<tr>
<th>Prior Period</th>
<th>Current Period: Same Bank $j$</th>
<th>New Bank $j'$</th>
<th>No Credit Card with Any Bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Borrower, on Credit Card with Bank $j$</td>
<td>$d_{j} - y_{0} p_{1j}$</td>
<td>$n_{j} - l_{j}$</td>
<td>$d_{j} - s_{j} - y_{0} p_{0j}$</td>
</tr>
<tr>
<td>Non-Borrower, on Credit Card with Bank $j$</td>
<td>$d_{j} - y_{0} p_{1j}$</td>
<td>$n_{j}$</td>
<td>$d_{j} - s_{j} - y_{0} p_{0j}$</td>
</tr>
<tr>
<td>No Credit Card with Any Bank</td>
<td>(choice not available)</td>
<td>(choice not available)</td>
<td>$d_{j} - s_{j} - y_{0} p_{0j}$</td>
</tr>
</tbody>
</table>

Notes: The table shows a consumer’s one-period flow payoffs depending on the consumer’s circumstances at the end of the previous period (by row) and the consumer’s choice in the current period (by column). The parameters shown include the flow utility from borrowing, $d_{j}$, and the flow utility from holding a credit card without borrowing, $n_{j}$, as well as disutility from price (marginal utilities of income), $y_{0}$, and two adjustment costs, including setup costs for opening new accounts, $s_{j}$, and liquidity costs for paying off existing balances, $l_{j}$. The subscripts $j$ and $j'$ can refer to any bank in the set of banks $J$, while subscripts $\theta$ refer to consumer types.
Table 5: Borrower Price Sensitivity

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimator:</td>
<td>OLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Price Coefficient (γ)</td>
<td>0.00001**</td>
<td>0.08933***</td>
<td>0.0673**</td>
</tr>
<tr>
<td>(0.00001)</td>
<td>(0.01333)</td>
<td>(0.01369)</td>
<td>(0.06731)</td>
</tr>
<tr>
<td>Bank-Specific Trends</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Number of observations</td>
<td>60638012</td>
<td>60638012</td>
<td>60638012</td>
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<tr>
<td>Number of clusters</td>
<td>550</td>
<td>550</td>
<td>550</td>
</tr>
<tr>
<td>1st-Stage F-Statistic</td>
<td>98.172</td>
<td>98.172</td>
<td>146.45</td>
</tr>
<tr>
<td>Dependent variable: Log(Retention Rate)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table shows estimates of price coefficients (marginal utilities of income) estimated via OLS, 2SLS, and LIML using quasi-experimental lender repricing. 2SLS and LIML estimators use a total of 55 instruments from repricing event dummies interacted with consumer types; this variation is presented visually in Figure 5 and Appendix Figure 3. Parentheses show bootstrapped clustered standard errors at the level of bank × consumer type, following the procedure in Cameron and Miller (2015). Controls for bank-specific trends are the terms βjt × t; see equation 4.20 and 4.21 in the text.

Table 6: Demand Model Parameter Estimates by FICO Group

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FICO</td>
<td>d</td>
<td>γ</td>
<td>n</td>
<td>s</td>
<td>l</td>
<td>c</td>
<td>k</td>
</tr>
<tr>
<td>580 - 599</td>
<td>12.3</td>
<td>0.266</td>
<td>-0.08</td>
<td>40.4</td>
<td>4.65</td>
<td>39.2</td>
<td>32.0</td>
</tr>
<tr>
<td>600 - 619</td>
<td>8.74</td>
<td>0.229</td>
<td>-0.37</td>
<td>35.2</td>
<td>4.07</td>
<td>19.1</td>
<td>43.0</td>
</tr>
<tr>
<td>620 - 639</td>
<td>7.92</td>
<td>0.206</td>
<td>-0.06</td>
<td>26.8</td>
<td>3.63</td>
<td>16.0</td>
<td>65.9</td>
</tr>
<tr>
<td>640 - 659</td>
<td>4.38</td>
<td>0.132</td>
<td>-0.24</td>
<td>16.0</td>
<td>3.75</td>
<td>13.4</td>
<td>72.8</td>
</tr>
<tr>
<td>660 - 679</td>
<td>3.54</td>
<td>0.135</td>
<td>-0.02</td>
<td>14.6</td>
<td>4.25</td>
<td>11.2</td>
<td>89.8</td>
</tr>
<tr>
<td>680 - 699</td>
<td>3.95</td>
<td>0.171</td>
<td>0.07</td>
<td>14.8</td>
<td>4.09</td>
<td>9.26</td>
<td>103.8</td>
</tr>
<tr>
<td>700 - 719</td>
<td>3.67</td>
<td>0.166</td>
<td>0.38</td>
<td>15.5</td>
<td>3.86</td>
<td>7.35</td>
<td>116.5</td>
</tr>
<tr>
<td>720 - 739</td>
<td>2.94</td>
<td>0.122</td>
<td>0.75</td>
<td>18.2</td>
<td>3.88</td>
<td>5.64</td>
<td>126.7</td>
</tr>
<tr>
<td>740 - 759</td>
<td>4.74</td>
<td>0.166</td>
<td>1.88</td>
<td>21.2</td>
<td>3.79</td>
<td>4.23</td>
<td>146.9</td>
</tr>
<tr>
<td>760 - 779</td>
<td>3.64</td>
<td>0.114</td>
<td>1.69</td>
<td>21.4</td>
<td>3.66</td>
<td>3.23</td>
<td>149.4</td>
</tr>
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<td>780 - 799</td>
<td>2.84</td>
<td>0.087</td>
<td>1.54</td>
<td>23.4</td>
<td>3.47</td>
<td>2.36</td>
<td>151.2</td>
</tr>
</tbody>
</table>

Notes: The table shows average model parameter estimates for the FICO score group in each row, where averages are taken across banks and across private-information types (using the type probability distribution μθ) as necessary. The parameters shown in each column respectively are: flow utilities from borrowing, d; disutility from price (marginal utilities of income), γ; flow utility from holding a credit card without borrowing, n; setup costs for opening a new account, s; liquidity costs for paying off existing balances, l; lender marginal costs on mature accounts used for borrowing, c; lender acquisition costs for new accounts, k; and default probabilities, δ. These default probabilities are estimated through the process illustrated in Figure 3 and are then transformed from two-year default rates to equivalent quarterly default probabilities. See the model exposition in Section 4.2, and the demand-side payoff summary in Table 4.

Table 7: Counterfactual Decomposition of Consumer Surplus Gains

<table>
<thead>
<tr>
<th>Percent Change in Consumer Surplus due to CARD Act:</th>
<th>Subprime</th>
<th>Prime</th>
<th>Superprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>130.5%</td>
<td>165.3%</td>
<td>143.0%</td>
</tr>
<tr>
<td>No Insurance Value</td>
<td>126.8%</td>
<td>48.9%</td>
<td>16.6%</td>
</tr>
<tr>
<td>No Account Setup Costs</td>
<td>73.0%</td>
<td>84.0%</td>
<td>111.8%</td>
</tr>
</tbody>
</table>

Notes: The table shows results from counterfactual exercises to decompose various sources of surplus gains under the CARD Act. The first row shows consumer surplus gains from the CARD Act in the baseline (no counterfactual) case, equal to the consumer surplus gains presented in Figure 8 Panel A. The second row shows consumer surplus gains under the CARD Act in an environment where consumers have no demand for insurance against price changes because consumer types are perfectly persistent (i.e., the transition matrix Tθθ′ is the identity matrix). The third row shows consumer surplus gains under the CARD Act in an environment where consumers face no account setup costs when opening a new account (i.e., setup costs sθ are set to zero). For each counterfactual environment, I recompute each consumer type’s lifetime expected surplus at the observed pre-CARD Act price vector, and I likewise recompute consumer surplus at the estimated post-CARD Act price vector. See Section 5.3 of the text. Per-person surplus numbers are averaged to coarser credit-score groups using the type probability distribution μθ. Subprime refers to accounts with FICO scores below 660; prime refers to accounts with FICO scores of 660 or above but below 720; superprime refers to accounts with FICO scores of 720 and above.
A Appendix

This supplementary appendix contains three sections. The first section proves the consistency of the estimator used to recover consumers’ private types. The second section provides supplementary figures discussed in the text, and the third section provides supplementary tables.

A.1 Estimation of Consumer Private Types

A.1.1 Primitives and Definitions

By Assumption 1, an individual $i$ of type $\theta_i$ defaults with probability $\delta(\theta_i)$. Types $\theta$ are duples of a public type $x$ and a private type $\psi$, i.e., $\theta_i \equiv (x_i, \psi_i)$. Without loss of generality, private types $\psi$ are ordered such that, as in equation 4.8,

$$\psi' > \psi \implies \delta(x, \psi') > \delta(x, \psi) \quad \forall \ x$$  \hspace{1cm} (A.1)

Fix $x$ and for ease of notation suppress conditioning on $x$; the following definitions and proof are conditioned on $x$ except where noted. Let $\psi$ be continuously distributed with full support on a bounded interval $[\underline{\psi}, \overline{\psi}]$. Then $\delta(\psi)$ is continuously distributed with full support on $[\underline{\psi}, \overline{\psi}]$, and, by Assumption 2, for any lender $j$, mature-account pricing\(^{43}\) $p^t(\psi)$ is continuously distributed with full support on $[\underline{p}^t, \overline{p}^t]$. Denote the probability mass function of $\psi$ on $[\underline{\psi}, \overline{\psi}]$ as $\mu(\psi)$, and let $q^\tau_\psi$ denote the $\tau$th quantile of this distribution. Denote type $\psi$’s equilibrium probability of borrowing from lender $\omega$ as $\sigma_{\psi, \omega}$. Assume the demand parameters of Section 4.2 are continuous with respect to $\psi$ so that $\sigma_{\psi, \omega}$ is also continuous with respect to $\psi$. For notational convenience define $\mu_j \equiv \int \mu(\psi) \psi_j d\psi$ and $\mu \equiv \sum_j \mu_j$.

Let $\delta_{\text{iso}}^j(p) \in [0, 1]$ be fitted values from the isotonic regression of binary default on observed prices $p$ for lender $j$. For some positive integer $K$ that does not depend on $x$, partition the range $[\underline{\psi}, \overline{\psi}]$ with the finite sequence $\{\delta_1, \delta_2, \ldots, \delta_{K-1}\}$ such that, for $k = 1 \ldots K$, each interval $[\delta_{k-1}, \delta_k]$ contains equal mass $\mu/K$ of types $\psi$ for which $\delta_{\text{iso}}^j(p^t(\psi)) \in [\delta_{k-1}, \delta_k]$,

$$\int_{\underline{\psi}}^{\overline{\psi}} \mu(\psi) \sum_j \psi_j \mathbb{1}_{\delta_{\text{iso}}^j(p^t(\psi)) \in [\delta_{k-1}, \delta_k]} d\psi = \frac{\mu}{K} \quad \forall \ k$$  \hspace{1cm} (A.2)

Note the extreme endpoints are defined by the support of $\delta(\psi)$, so that $\delta_0 \equiv \underline{\psi}$ and $\delta_K \equiv \overline{\psi}$. Define $k(i)$ by the interval containing the individual’s true default probability, $\delta(\psi_i) \in [\delta_{k(i) - 1}, \delta_{k(i)}]$.

Similarly, for $k = 0 \ldots K$ define,

$$p^t_k \equiv \sup \{p : \delta_{\text{iso}}^j(p) = \delta_k\}$$  \hspace{1cm} (A.3)

$$\psi^t_k \equiv \sup \{\psi : \delta_{\text{iso}}^j(p^t(\psi)) = \delta_k\}$$  \hspace{1cm} (A.4)

For each interval $k = 1 \ldots K$ of the partition, take the average isotonic fitted default rate $\hat{\delta}(k)$ as

$$\hat{\delta}(k) \equiv \frac{1}{\mu_j} \int_{\psi^t_{k-1}}^{\psi^t_k} \mu(\psi) \psi_j \delta_{\text{iso}}^j(p^t(\psi)) d\psi$$  \hspace{1cm} (A.5)

\(^{43}\)In the main text, mature-account pricing is denoted $p^t_1$, with a subscript to differentiate from teaser pricing; in this proof I suppress the subscript for ease of notation and to avoid confusion with the partition $p^t_k$ below.
where the term in the denominator provides the appropriate normalization of the weights,

\[ \mu_{jk} \equiv \int_{\psi_{k-1}^j}^{\psi_k^j} \mu(\psi) \sigma_{\psi j} d\psi \]  

(A.6)

Similarly define the average price paid in each interval \( k \), \( \hat{p}^j(k) \),

\[ \hat{p}^j(k) \equiv \int_{\psi_{k-1}^j}^{\psi_k^j} \frac{\mu(\psi) \sigma_{\psi j}}{\mu_{jk}} p^j(\psi) d\psi \]  

(A.7)

Examples of these average isotonic fitted default rates \( \hat{\delta}^j(k) \) and average prices \( \hat{p}^j(k) \) in the case where \( K = 5 \) are, respectively, the y-axis and the x-axis values in Figure 3 of the main text.

For an individual \( i \) observed to pay mature-account price \( p^j(i) \) to lender \( j \), the individual’s estimated private type is then the index \( k(p^j(i)) = \{ k : p^j(i) \in [p^j_{k-1}, p^j_k] \} \). Let \( \delta(p^j(i)) = \hat{\delta}(k(p^j(i))) \) denote individual \( i \)'s estimated default rate.

A.1.2 Claim

The claim to be proved is that \( \delta(p^j(i)) \) provides a consistent estimate of \( \delta(\psi_i) \). Formally, with \( N = MK \) denoting sample size and \( M \) being the number of observations in each interval of the partition defined in equation A.2, for any \( \epsilon > 0 \),

\[ \lim_{K \to \infty} \lim_{M \to \infty} P \left( |\delta(p^j(i)) - \delta(\psi_i)| > \epsilon \right) = 0 \]  

(A.8)

A.1.3 Proof

For fixed \( K \), define \( D_K(i) \) as an indicator for whether \( k(p^j(i)) = k(i) \), that is, whether individual \( i \)’s true default probability \( \delta(\psi_i) \) lies in the interval corresponding to \( i \)’s assigned private type \( k(p^j(i)) \),

\[ D_K(i) = 1\{ \delta(\psi_i) \in [\delta_{k(p^j(i))-1}, \delta_{k(p^j(i))}] \} \]  

(A.9)

Then,

\[ P \left( |\delta(p^j(i)) - \delta(\psi_i)| > \epsilon \right) \leq P(D_K(i) = 1) P \left( |\delta(p^j(i)) - \delta(\psi_i)| > \epsilon |D_K(i) = 1 \right) + P(D_K(i) = 0) \]  

(A.10)

First take the limit as \( M \to \infty \). For any lender \( j \), by the consistency of isotonic regression and by the monotonicity of \( p^j(\psi) \), isotonic fitted values converge (in probability) to true default probabilities,

\[ \delta_{iso}^j(p^j(\psi)) \overset{P}{\to} \delta(\psi) \]  

(A.11)

Two applications of this convergence will be useful. First, note that \( \delta_{iso}^j(p^j(\psi)) \in [\delta_{k(p^j(i))-1}, \delta_{k(p^j(i))}] \) by monotonicity \( \delta_{iso}^j(\cdot) \) and by construction of the interval endpoints. Refer to this interval as \( I_k(i) \). It then follows from expression A.11 that, for any \( \bar{\epsilon} > 0 \),

\[ \lim_{M \to \infty} P \left( \min_{d \in I_k(i)} |\delta(\psi_i) - d| > \bar{\epsilon} \right) = 0 \]  

(A.12)
which is to say, the distance between $\delta(\psi_i)$ and the nearest point of the interval $I_k(i)$ converges in probability to zero. Thus by definition of $D_K(i)$, we have $\lim_{M \to \infty} P(D_K(i) = 0) = 0$, and, taking the complement, $\lim_{M \to \infty} P(D_K(i) = 1) = 1$.

Having taken the limit as $M \to \infty$ for two of the terms in expression A.10, it then remains to show,

$$\lim_{K \to \infty} \lim_{M \to \infty} P\left( |\delta(p^j(i)) - \delta(\psi_i)| > \epsilon |D_K(i) = 1 \right) = 0 \quad \text{(A.13)}$$

Applying expression A.11 again, note that the endpoints of the interval corresponding to $i$'s assigned private type, $[\delta_k(p^j(i)) - 1, \delta_k(p^j(i)) + 1]$, converge in probability to default probabilities at the $(k-1)$th and $k$th quantiles of the type distribution $\mu(\psi)$,

$$\{\delta_k(p^j(i)) - 1, \delta_k(p^j(i)) + 1 \} \xrightarrow{p} \{\delta(q^{(k-1)/K}), \delta(q^{k/K})\} \quad \text{(A.14)}$$

It is then useful to note that the difference in expression A.13 satisfies the following inequalities when $D_K(i) = 1$,

$$|\delta(p^j(i)) - \delta(\psi_i)| \leq |\delta_k(p^j(i)) - \delta_k(p^j(i)) - 1|$$

$$= |\delta_k(p^j(i)) + \delta(q^{(k-1)/K}) - \delta(q^{(k-1)/K}) + \delta(q^{k/K}) - \delta(q^{k/K}) - \delta_k(p^j(i)) - 1|$$

$$\leq |\delta_k(p^j(i)) - \delta(q^{k/K})| + |\delta(q^{(k-1)/K}) - \delta_k(p^j(i)) - 1| + |\delta(q^{k/K}) - \delta(q^{(k-1)/K})|$$

where the first inequality results from both $\delta(p^j(i))$ and $\delta(\psi_i)$ being contained in the interval $[\delta_k(p^j(i)) - 1, \delta_k(p^j(i)) + 1]$ when $D_K(i) = 1$, and the final line follows from the triangle inequality. Hence,

$$P\left( |\delta(p^j(i)) - \delta(\psi_i)| > \epsilon |D_K(i) = 1 \right) \leq P\left( |\delta_k(p^j(i)) - \delta(q^{k/K})| > \epsilon/3 \right)$$

$$+ P\left( |\delta(q^{(k-1)/K}) - \delta_k(p^j(i)) - 1| > \epsilon/3 \right) + P\left( |\delta(q^{k/K}) - \delta(q^{(k-1)/K})| > \epsilon/3 \right) \quad \text{(A.16)}$$

Take the limit as $M \to \infty$ of the three probabilities on the right-hand side of the previous expression. Note that the third probability does not depend on $M$, and expression A.14 shows the first and second probabilities converge to zero. Hence it remains to show only,

$$\lim_{K \to \infty} P\left( |\delta(q^{k/K}) - \delta(q^{(k-1)/K})| > \epsilon/3 \right) = 0 \quad \text{(A.17)}$$

Yet this result is straightforward: because $\psi$ is continuously distributed with full support on the bounded interval $[\underline{\psi}, \overline{\psi}]$ and default probabilities are likewise continuously distributed with full support on an interval necessarily contained by $[0, 1]$, the distance between adjacent quantiles in A.17 can be made arbitrarily small by taking $K$ sufficiently large.
A.2 Appendix Figures and Tables

Appendix Figure 1: CARD Act Effects on Penalty Fees

(a) Over-Limit Fees

Notes: Panel (a) shows the monthly incidence of over-limit fees on current borrowers, excluding any fees subsequently reversed. The implementation date of the CARD Act’s over-limit fee restrictions in February 2010 is marked by the vertical black line. Panel (b) shows annualized lender returns from late fees relative to total outstanding balances on borrowing accounts (left axis) and the average incidence of late fees across accounts (right axis). The vertical black lines show the CARD Act’s implementation dates for restrictions on interest-rate increases and over-limit fees in February 2010 and for restrictions on late fee amounts in August 2010.

Notes: Panel (a) shows the monthly incidence of over-limit fees on current borrowers, excluding any fees subsequently reversed. The implementation date of the CARD Act’s over-limit fee restrictions in February 2010 is marked by the vertical black line. Panel (b) shows annualized lender returns from late fees relative to total outstanding balances on borrowing accounts (left axis) and the average incidence of late fees across accounts (right axis). The vertical black lines show the CARD Act’s implementation dates for restrictions on interest-rate increases and over-limit fees in February 2010 and for restrictions on late fee amounts in August 2010.

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Appendix Figure 2: Prevalence of Balance Transfer Activity by FICO Score

Notes: The figure shows the rate of balance transfers by credit score in the pre-CARD-Act period, calculated as the ratio of incoming balance transfers at promotional rates or on newly originated accounts, to the number of mature borrowing accounts without promotional rates in effect. Borrowing is defined as not paying a balance in full for two subsequent billing cycles.

Appendix Figure 3: Example of Repricing Quasi-Experiment and Borrowing Response (Appendix Version)

Notes: This figure reproduces Figure 5 while excluding bank-specific trends when estimating the retention probabilities reported in the right panel; that is, the right panel is estimated using a version of equation 4.1 that excludes the term $\beta_t$. 
Appendix Table 1: Pre-CARD Act Price Distribution on Mature Accounts

<table>
<thead>
<tr>
<th>FICO Group</th>
<th>Cum. Months of Borrowing</th>
<th>Share within Group of Borrowing</th>
<th>Interest Charges (% Ann.)</th>
<th>Fee-Inclusive Charges (% Ann.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>FICO Group</td>
<td>P25</td>
<td>Mean</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>1.81%</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>1-2</td>
<td></td>
<td>2.13%</td>
<td>10.23</td>
<td>17.90</td>
</tr>
<tr>
<td>3-5</td>
<td></td>
<td>4.10%</td>
<td>8.31</td>
<td>16.14</td>
</tr>
<tr>
<td>6-11</td>
<td></td>
<td>20.79%</td>
<td>9.50</td>
<td>16.73</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>71.16%</td>
<td>11.62</td>
<td>18.29</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>5.33%</td>
<td>4.78</td>
<td>12.89</td>
</tr>
<tr>
<td>1-2</td>
<td></td>
<td>4.23%</td>
<td>2.11</td>
<td>9.56</td>
</tr>
<tr>
<td>3-5</td>
<td></td>
<td>6.33%</td>
<td>1.23</td>
<td>8.56</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>60.77%</td>
<td>6.13</td>
<td>11.07</td>
</tr>
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<td>15.86%</td>
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<td></td>
<td>8.01%</td>
<td>2.11</td>
<td>9.56</td>
</tr>
<tr>
<td>3-5</td>
<td></td>
<td>9.27%</td>
<td>1.23</td>
<td>8.56</td>
</tr>
<tr>
<td>6-11</td>
<td></td>
<td>24.03%</td>
<td>3.10</td>
<td>9.32</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>42.83%</td>
<td>6.13</td>
<td>11.07</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>44.68%</td>
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<td>.</td>
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<tr>
<td>1-2</td>
<td></td>
<td>14.22%</td>
<td>0.00</td>
<td>7.59</td>
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<td>3-5</td>
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<td>10.97%</td>
<td>0.27</td>
<td>8.26</td>
</tr>
<tr>
<td>6-11</td>
<td></td>
<td>16.24%</td>
<td>3.79</td>
<td>8.82</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>13.89%</td>
<td>5.46</td>
<td>9.71</td>
</tr>
</tbody>
</table>

Notes: The table shows price quartiles and means at selected FICO score groups and across accounts with different cumulative months of borrowing over the course of the year in the pre-CARD-Act period (2008Q3 to 2009Q2). This sample includes only mature accounts (observed at 18 or more months since origination). The two price measures shown are, first, an account’s annualized percentage interest charges, defined as annualized monthly interest charges divided by borrowed balances, and second, a price measure that adds fees charged to the numerator of the first price. Borrowing is defined as not repaying a balance in full at the end of a given month.

Appendix Table 2: Pre-CARD Act Price Distribution on New Accounts

<table>
<thead>
<tr>
<th>FICO Group</th>
<th>Cum. Months of Borrowing</th>
<th>Share within Group of Borrowing</th>
<th>Interest Charges (% Ann.)</th>
<th>Fee-Inclusive Charges (% Ann.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>FICO Group</td>
<td>P25</td>
<td>Mean</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>2.03%</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>1-2</td>
<td></td>
<td>2.49%</td>
<td>0.00</td>
<td>6.90</td>
</tr>
<tr>
<td>3-5</td>
<td></td>
<td>4.90%</td>
<td>0.00</td>
<td>10.99</td>
</tr>
<tr>
<td>6-11</td>
<td></td>
<td>38.15%</td>
<td>0.84</td>
<td>11.78</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>52.43%</td>
<td>4.77</td>
<td>12.41</td>
</tr>
<tr>
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<td>6.47%</td>
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<td>.</td>
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<tr>
<td>1-2</td>
<td></td>
<td>5.44%</td>
<td>0.00</td>
<td>6.90</td>
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<td>8.27%</td>
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<td>6.58</td>
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<td>6-11</td>
<td></td>
<td>38.84%</td>
<td>0.00</td>
<td>6.81</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>40.98%</td>
<td>0.00</td>
<td>8.16</td>
</tr>
<tr>
<td>0</td>
<td></td>
<td>15.00%</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>1-2</td>
<td></td>
<td>8.83%</td>
<td>0.00</td>
<td>3.94</td>
</tr>
<tr>
<td>3-5</td>
<td></td>
<td>11.36%</td>
<td>0.00</td>
<td>3.49</td>
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<tr>
<td>6-11</td>
<td></td>
<td>36.24%</td>
<td>0.00</td>
<td>3.46</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>28.58%</td>
<td>0.00</td>
<td>5.36</td>
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<tr>
<td>0</td>
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<td>28.17%</td>
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<tr>
<td>1-2</td>
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<td>14.11%</td>
<td>0.00</td>
<td>3.37</td>
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<td></td>
<td>14.66%</td>
<td>0.00</td>
<td>2.74</td>
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<tr>
<td>6-11</td>
<td></td>
<td>25.25%</td>
<td>0.00</td>
<td>2.38</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td>13.81%</td>
<td>0.00</td>
<td>3.62</td>
</tr>
</tbody>
</table>

Notes: The table shows price quartiles and means at selected FICO score groups and across accounts with different cumulative months of borrowing over the course of the year in the pre-CARD-Act period (2008Q3 to 2009Q2). This sample includes only young accounts (observed at 12 or fewer months since origination). The two price measures shown are, first, an account’s annualized percentage interest charges, defined as annualized monthly interest charges divided by borrowed balances, and second, a price measure that adds fees charged to the numerator of the first price. Borrowing is defined as not repaying a balance in full at the end of a given month.
### Appendix Table 3: Persistence in Consumer Revolving Behavior

<table>
<thead>
<tr>
<th>FICO Group</th>
<th>Recent Borrowers</th>
<th>All Accounts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Transactor</td>
<td>Borrower</td>
</tr>
<tr>
<td>580</td>
<td>0.16</td>
<td>0.85</td>
</tr>
<tr>
<td>600</td>
<td>0.14</td>
<td>0.89</td>
</tr>
<tr>
<td>620</td>
<td>0.13</td>
<td>0.89</td>
</tr>
<tr>
<td>640</td>
<td>0.12</td>
<td>0.89</td>
</tr>
<tr>
<td>660</td>
<td>0.12</td>
<td>0.89</td>
</tr>
<tr>
<td>680</td>
<td>0.11</td>
<td>0.88</td>
</tr>
<tr>
<td>700</td>
<td>0.10</td>
<td>0.88</td>
</tr>
<tr>
<td>720</td>
<td>0.09</td>
<td>0.87</td>
</tr>
<tr>
<td>740</td>
<td>0.08</td>
<td>0.87</td>
</tr>
<tr>
<td>760</td>
<td>0.08</td>
<td>0.86</td>
</tr>
<tr>
<td>780</td>
<td>0.08</td>
<td>0.82</td>
</tr>
</tbody>
</table>

**Notes:** The table shows probabilities of next-quarter borrowing in the pre-CARD-Act period (2008Q3-2009Q2) for consumers who are either transactors (non-borrowers) or borrowers in the current period. The first two columns restrict the sample to consumers who have borrowed at least once in the past 6 months (recent borrowers), and the latter two columns extend these results to the full sample of active credit-card holders.