Unraveling Information Sharing in Consumer Credit Markets

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Abstract

We study the breakdown of information sharing in US consumer credit markets; showing that sharing is sensitive to innovations enabling targeting profitable customers. Between 2013 and 2022, the sharing of credit card actual payments information with credit reporting agencies decreased by 53 percentage points, without any decrease for other credit products. Credit card lenders are responding to an innovation that uses this information to reveal heterogeneous credit card behaviors: spending that drives interchange revenue, and revolving debt that drives interest revenue. By not sharing this information, lenders limit their competitors' ability to target high spenders. Mandating information sharing increases competition.

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1 Introduction

Information is central to the functioning of financial markets. Historically, voluntary information sharing among firms has developed through the establishment of intermediaries such as trade associations and exchanges. In consumer credit markets, consumer credit reporting agencies (e.g., Equifax, Experian, and TransUnion) act as intermediaries to facilitate information sharing between lenders. Despite the central role of these intermediaries in markets with information asymmetry, little is empirically known about the limits of such information sharing arrangements.

This paper documents and explains the reasons for the breakdown of voluntary information sharing in US consumer credit markets. We study the sharing of information about how much credit card account holders actually paid ("actual payments"). Figure 1 shows that between 2013 and 2022, we find that the fraction of credit card accounts that shared actual payments information with credit reporting agencies *decreased* by 53 percentage points. None of the six largest credit card lenders share actual payments information, and none plan to voluntarily do so (Consumer Financial Protection Bureau, 2023). Also, between 2013 and 2022, sharing actual payments information *increased* for auto loans, mortgages, and unsecured loans. We call this breakdown of co-operative information sharing between credit card lenders an "unraveling" in the spirit of classical information economics (e.g., Akerlof, 1970; Rothschild and Stiglitz, 1976; Roth and Xing, 1994).[1]

The timing of this information sharing breakdown follows an innovation created by credit reporting agencies. Before 2013, lenders observing two credit cardholders with the same statement balance could not distinguish one cardholder who pays the minimum due and whose statement balance is mostly "revolving debt" generating interest

[1]We call this paper "unraveling" both due to being inspired by the information economics literature, with a breakdown in the co-operative market for firms voluntarily sharing information, and because this paper unravels the economic reasons for this breakdown in information sharing occurring. The information economics literature uses the term "unraveling" to characterize several different economic ideas associated with asymmetric information. Akerlof (1970) shows how private information can mean that a market with exogenous contracts unravels such that only the lowest quality of good is traded in equilibrium. Rothschild and Stiglitz (1976) show private information can mean companies have incentives to modify their contracts to cream skim lower-risk consumers from their competitors, and no pure strategy equilibrium exists. Although unraveling is the term used to describe both Akerlof (1970) and Rothschild and Stiglitz (1976), they are mutually exclusive events (Hendren, 2014). Private information can remove all gains from trade under endogenous contracts, and the residual dispersion can explain which markets unravel (Hendren, 2013). The term "unraveling" is used in matching markets (e.g., Roth and Xing, 1994; Li and Rosen, 1998). In matching markets, there can be large efficiency gains from centralized clearing connecting many buyers and sellers, however, coordination failures can mean market participants move early in an uncoordinated fashion resulting in matches based on incomplete information. Doing so reduces the volume in the centralized process or, in the extreme, means that no centralized process occurs.

revenue, from another cardholder who pays their full statement balance and has a high flow of new spending generating interchange revenue. This changed in 2013 when credit reporting agencies launched a new product: "Trended Data". A key component of this product uses histories of credit card statement balances and actual payments information to create measures of revolving debt and spending. This product reduces the amount of asymmetric information and enables lenders to distinguish heterogeneous credit card behaviors.

Why would credit card lenders respond to this innovation by stopping sharing actual payments information? In this paper, we provide evidence that this is because the innovation is a competitive threat to incumbent credit card lenders. Credit cards, and other consumer credit markets, are selection markets (e.g., Einav et al., 2021) where profitability is determined by consumers' uncertain behaviors after origination. It is therefore important for lenders to accurately predict consumers' profitability. Lenders need to know a credit cardholder's behavior to decide which marketing offer they are likely to accept, which credit card product (if any) is profit maximizing to offer, and which contract terms to offer (e.g., interest rate, credit limit). Lenders can use the innovation's measures of revolving debt and spending to locate profitable consumers and send targeted marketing of pre-selected credit card offers to attempt to acquire them. However, if lenders do not share the actual payments information that the innovation relies on, it potentially limits the ability of competitors to target and acquire such profitable consumers. We show three pieces of evidence that are consistent with this explanation.

We first show the value of observing actual payments information for predicting consumer credit profits and its components. We estimate lifetime credit card profits and find that actual payments information increases the ability to predict, measured by R^2, account-level profits over a ten-year horizon. This is driven by the increased ability to predict interchange revenue (the transaction fees credit card lenders receive from merchants when a consumer spends on their card) net of rewards by 31%, and to predict financing charges (the sum of interest and fees) net of charge-offs by 4%. This information increases the ability to predict overall profits. Hence, observing actual payments information increases the accurate targeting of profitable cardholders, especially high-spending ones, by credit card lenders. In contrast, in auto loans and unsecured loans, we show that observing actual payments information does little to predict profits. This result makes sense given that these other products do not have a direct revenue stream tied to actual payments, which explains why these lenders are willing to continue sharing such information.

The second piece of evidence is that the selection of credit card lenders by their actual payments information sharing decisions is consistent with the innovation being a particular competitive threat to incumbent lenders. Lenders that stop sharing information have higher profitability portfolios with 36% higher financing charges net of charge-offs and higher spending, generating interchange revenue, with 31% higher mean and 41% higher standard deviation compared to lenders who keep sharing information. The higher standard deviation shows that these lenders had a potentially larger incentive to hide these behaviors to make it more difficult for competitors to successfully target their profitable customers. Lenders that do not share information before the innovation also appear to have higher spending portfolios than the rest of the market. The credit card lenders that stop sharing information have portfolios with lower credit risk and better characteristics on non-credit risk dimensions (e.g., longer tenure, higher balance) after controlling for credit risk. The credit card lenders who continue to share information have portfolios with the lowest types on multiple dimensions (the "lemons" in Akerlof, 1970).

The third piece of evidence is showing that the innovation is a competitive threat as its introduction immediately increases switching. We use a difference-in-differences design with varying treatment intensity where our source of variation is the fraction of a consumer's credit card balances held with lenders that share actual payments information before the innovation. More information would be revealed for consumers with a higher fraction. We find that more exposed consumers open relatively more new credit cards after the innovation. We interpret such switching prompts incumbent lenders to stop voluntarily sharing information.

If lenders do not voluntarily share information, how would mandating information sharing affect markets? The sharing of actual payments information is not mandatory, and therefore in the last part of our paper we instead learn from studying the effects of a prior historical event: the Federal Trade Commission mandating sharing of credit card limit information. We use a difference-in-differences design with varying treatment intensity by how much information a cardholder's credit card limit reveals. Cardholders who this information reveals to be lower-risk take out new credit cards from other "outside" lenders (Petersen and Rajan, 1995) to which cardholders' information is revealed. We interpret these results as showing mandating information sharing can increase switching in line with increasing competition. The US Consumer Financial Protection Bureau (2023) is investigating the lack of actual payments information sharing and our research findings support a policy to mandate information sharing.

We make two contributions. Our first contribution is empirically documenting the fragility of information sharing, which is sensitive to innovations enabling the targeting of profitable customers. We show how, in a large and highly developed market, an innovation enabling targeting of profitable customers pushes incumbent firms beyond their limit to voluntarily share information. Theoretical literature shows, under information asymmetry, that it can be beneficial for firms to voluntarily share information with their competitors through intermediaries (e.g., Ramakrishnan and Thakor, 1984), but it is ambiguous whether they do (e.g., Pagano and Jappelli, 1993; Raith, 1996; Bouckaert and Degryse, 2006), and it is also ambiguous whether innovations lead to more or less information sharing (e.g., Hauswald and Marquez, 2003). With increased data generated over time, it becomes increasingly important and challenging for policymakers to consider which information should be shared and used for lending decisions (e.g., Fuster et al., 2022; Blattner et al., 2023; Gibbs et al., 2024; Jansen et al., 2024). Our paper's contribution to empirically document the limits of voluntary information sharing also connects with an emerging literature studying the sharing of consumer finance data through open banking (e.g., He et al., 2023; Babina et al., 2024; Nam, 2024) by showing how incumbent lenders respond to innovations. While our paper studies consumer credit markets, it more generally contributes to the literature on information economics and the economics of data (e.g., Bergemann and Bonatti, 2019; Jones and Tonetti, 2020) with the idea that incumbent firms can preserve their market position by stopping sharing information, as doing so undermines technological innovations that pose a competitive threat.

Our second contribution is revealing two new insights for understanding the credit card market: the importance of spending and card tenure. Default risk is a well-documented source of information asymmetry in lending markets (e.g., Jaffee and Russell, 1976; Adams et al., 2009). We show credit card lenders face a second source of uncertainty: how much a cardholder will spend and so generate in interchange revenue. We document a new fact: credit card tenure varies across and within the credit risk distribution. This fact indicates a need to evaluate credit card profitability over a card's lifetime rather than on a fixed-period basis. A card lifetime perspective helps to understand why credit card lenders lend to and heavily concentrate their marketing towards high-credit-score consumers (e.g., Consumer Financial Protection Bureau, 2021) despite these generating little-to-no revenue from financing charges. But it makes sense given that acquiring new consumers incurs an up-front fixed cost, so consumers with longer tenures can be profitable on interchange alone over their card's lifetime. These insights advance research on the supply of credit cards (e.g., Ausubel, 1991; Agarwal et al., 2015, 2018; Han et al., 2018; Nelson, 2025), credit card rewards (e.g., Agarwal et al., 2023), and payment systems (e.g., Evans and Schmalensee, 2004; Mukharlyamov and Sarin, 2024; Wang, 2024).

The paper proceeds as follows. Section 2 explains the institutional background on credit reporting and our data. Section 3 describes the breakdown of information sharing. We understand this breakdown by studying and predicting profitability in consumer credit markets in Section 4 and then examining the selection of credit card lenders by their information sharing decisions in Section 5. Section 6 shows the effects of mandating sharing of information on credit card limits. Finally, Section 7 concludes.

2 Institutional Background and Data

2.1 Institutional Background on Consumer Credit Reporting

Consumer credit reporting agencies are intermediaries created as a coordination mechanism for lenders to share information about their borrowers. Credit reporting data record information on consumers' borrowing histories. Credit information sharing reduces information asymmetries about credit applicants (e.g., Pagano and Jappelli, 1993; Liberti et al., 2022), helping to limit credit rationing (e.g., Jaffee and Russell, 1976; Stiglitz and Weiss, 1981), and expand credit supply (e.g., Djankov et al., 2007). Information sharing games may have multiple equilibria, and which equilibrium outcome occurs is theoretically ambiguous (e.g., Raith, 1996; Bouckaert and Degryse, 2006). The credit agencies' technology is to ingest, collate, and store data from many lenders and then produce variables on consumers that are value-added for lenders (and non-lenders). See Gibbs et al. (2024) for a review of the economics of credit reporting.

Lenders demand credit information as it helps to reduce adverse selection (e.g., Bouckaert and Degryse, 2006) and moral hazard (e.g., Padilla and Pagano, 1997, 2000), with network effects as more information is shared (e.g., Pagano and Jappelli, 1993). US consumer credit reports – and credit scores derived from them – are used for managing credit risk, marketing, and screening. Their primary purpose is for credit risk assessments: underwriting new credit applications, managing existing portfolios, and pricing credit based on repayment risk. Lenders can attempt to acquire new customers by purchasing consumer lists from credit reporting agencies to use for pre-selected credit card offers. In these offers, lenders will screen consumers by specifying the targeting criteria for credit reporting agencies to use to create these lists, and lenders will tailor their product offers to these consumers (e.g., Stango and Zinman, 2016; Han et al., 2018; Grodzicki, 2023).

In the US, sharing credit information is voluntary, and access to information is non-reciprocal. There is no law that requires lenders to share information with credit reporting agencies. There is also no requirement that sharing be reciprocal: lenders who want to access information shared by other lenders do not need to share their own information. Although sharing is voluntary, the Fair Credit Reporting Act (FCRA) amended with the

"Furnisher Rule" of the Fair and Accurate Credit Transactions Act (FACTA) regulates *how* information should be shared, see Internet Appendix A for the relevant legal exerts. This requires that information shared with credit reporting agencies is done both "accurately" and "with integrity", and provides guidelines for reporting. Information is reported "accurately" if it reflects the terms, liability, and performance of the account. Information is reported "with integrity" if it includes data such that "absence would likely be materially misleading in evaluating a consumer's creditworthiness, credit standing, credit capacity". The specific categories of information that lenders should share with credit reporting agencies, if they decide to share, are not specified, except for a requirement to share credit card limit information. In addition to these laws, the industry body – the "Consumer Data Industry Association" (CDIA) – governs the terms and format of sharing information. In practice, to satisfy regulation (and the industry body's terms) if lenders share information with credit reporting agencies, they must include information on an account's outstanding balance, delinquency status, closing date, origination terms, scheduled payment amount, and credit limit.

Economic theory can rationalize why lenders are willing to voluntarily share information on a non-reciprocal basis. Lenders have strong economic incentives to share information to reduce adverse selection (e.g., Pagano and Jappelli, 1993) and moral hazard (e.g., Padilla and Pagano, 2000). Sharing information can increase the likelihood that a consumer repays their debt and avoids the lender incurring costly charge-offs from unpaid debt. In addition, consumers have non-exclusive contracts with different lenders over time (e.g., Bizer and DeMarzo, 1992; De Giorgi et al., 2023). Such "sequential banking" means that the lending decision of one lender can affect the repayment of another lender's loan. This interdependence can mean that lenders are privately incentivized to reduce how adversely selected their competitors are by sharing information even if other lenders do not reciprocate. However, lenders will trade off these benefits against the risks of increased competition. More specifically, by sharing their private information with competitors, lenders can risk giving away a competitive advantage that exists due to the private information they hold and enabling competitors to target their profitable customers. This may explain why some credit market segments do not voluntarily share information. For example, most "buy now, pay later" (BNPL) loans, most payday loans, and some subprime auto loans do not share information with credit reporting agencies.

Another theoretical explanation for sharing information can be found in Bouckaert and Degryse (2006). Their paper provides a framework for the conditions under which lenders voluntarily and non-reciprocally share all, partial, or no information with their competitors. An incumbent's decision whether to share information depends upon the extent of adverse selection and market power from consumer switching costs, with lenders sometimes willing to non-reciprocally share information to limit the scope of competition from potential entrants. Separate to this theory, another possible explanation is that voluntary information sharing is the strategic response within a repeated game of lenders with regulators. Regulatory guidance "encourages voluntary furnishing of information" by lenders (Internet Appendix A). Once a lender grows large enough, regulatory pressure to voluntarily share information can accumulate – as most recently seen with the Consumer Financial Protection Bureau (CFPB) pressuring BNPL lenders to do so.[2] A final potential reason is that the industry body helps to create a social norm of sharing data and a firm deviating from this harms its reputation in the market. In this paper, we take the initial voluntary information sharing as given and try to understand the breakdown of information sharing.

2.2 Data

Consumer Credit Reporting Data

We use data from the University of Chicago Booth TransUnion Consumer Credit Panel, "BTCCP" (TransUnion, 2023). The BTCCP is anonymized consumer credit reporting data from a US consumer credit reporting agency: TransUnion. The BTCCP is a 10% random sample of consumers with US consumer credit reports, with new entrants added each month to keep the panel representative of the population of credit reports. We use monthly data from 2009 to 2022. Each month of data is a historical archive recreating how a credit report appeared. See Gibbs et al. (2024) for more details on such consumer credit reporting data, including practical guidance for researchers using such data.

The BTCCP contains information at the consumer level (e.g., credit scores) and at the tradeline level, i.e., monthly observations for each of the consumer's credit accounts (such as auto loans, credit cards, mortgages, unsecured loans). Importantly for our paper, the BTCCP tradeline data includes the actual payments variable for each credit account. Each row of tradeline data contains variables for account opening details (e.g., origination date, origination amount, scheduled term) and subsequent performance (e.g., delinquency status, outstanding balance, credit limit, scheduled payment due amount).

Individual consumers and individual lenders are not identified in the BTCCP. The BTCCP has anonymized consumer and tradeline identifiers. It also contains anonymized identifiers for the firm reporting tradeline-level information. This enables us to observe

[2] www.consumerfinance.gov/about-us/newsroom/cfpb-study-details-the-rapid-growth-of-buy-now-pay-later-lending/

what information each firm ("furnisher") shares over time. One lender's data may be reported by multiple furnishers, which may correspond to different regional branches, different portfolios, or be due to internal operational reasons. For credit cards and most credit markets, furnishers are typically the lenders themselves. In the mortgage market, the furnisher of data may be the firm that services the loan as opposed to the firm that originated the loan. Furnishers enter and exit these data over time.

We drop consumers with missing birth dates and who do not appear in tradeline data. We drop tradeline months not updated in the last twelve months. In addition, when we study portfolios as of December 2012, we drop inactive accounts: we drop those that are closed, are 180+ days past due, and, for credit cards, have no balance on the account in the last twelve months. For account-level analysis, we de-duplicate accounts attached to multiple consumers (i.e., joint accounts, accounts with authorized users) by assigning them to the card's primary cardholder. We deal with outliers by top coding variables at their 99.99 percentiles, and, for variables that can have negative values, also at their 0.01 percentiles. We study three consumer credit markets, credit cards, auto loans, and unsecured loans, that have $3.4 trillion in outstanding balances in December 2022.

Classifying Credit Card Lenders

The BTCCP includes anonymized furnisher identifiers in the data. This is the relevant unit of analysis, since the data furnisher is the firm that makes the decision on what information to share. To predict credit card profitability and to understand the selection of lenders in their sharing decisions, we keep the credit card furnishers where we observe at least 10,000 active credit cards (i.e., their portfolio is representative of at least 100,000 cards) in December 2012 and in December 2015. This leaves us with 84 credit card furnishers whose joint market share is 92%. The six largest furnishers jointly account for 66% of the market. For our 84 furnishers, we follow outcomes on these accounts over time, including if the furnisher identifier changes.

We examine these 84 credit card furnishers' sharing of actual payments information and classify them into four groups: the *Always*, the *Stoppers*, the *Nevers*, and the *Others*. The *Always* group is 18% of accounts and contains the furnishers that share actual payments information for more than 75% of their credit cards in both December 2012 and December 2015. The *Stoppers* group is 47% of accounts and are the furnishers that share actual payments information for more than 75% of their credit cards in December 2012 and for less than 10% in December 2015. The *Nevers* group is 32% of accounts and consists of the furnishers that share actual payments information for less than 10% of their credit cards in both December 2012 and December 2015. Finally, the *Others* group contains the remaining furnishers, just 3% of accounts, and we exclude these. Internet Appendix

Figure C1 shows that the precise threshold values chosen would not substantially affect our classification. We use a dataset of 33.3 million open credit card accounts in December 2012, which is representative of the population of 333 million credit card accounts. For these credit card accounts, the mean average credit score is 728, card tenure is 106 months, credit limit is $9,614, statement balance is $2,336, and utilization rate is 35%. For these accounts, we examine monthly data from January 2009 to December 2022 (inclusive).

Other Data

We refer to public data released by the US Consumer Financial Protection Bureau (2023) summarizing its findings from interviews with credit card lenders about their sharing of actual payments information. We also use aggregated summary data on the credit card industry from R.K.Hammer to show the profitability of this market and the costs of acquisitions, see Internet Appendix B.

3 The Breakdown of Information Sharing

3.1 Describing The Breakdown

In consumer credit reports, the "actual payments" variable records information on the total amount of actual payments made on an account in the last month, and if a consumer makes multiple payments in a month, then this is the sum of these. Actual payments information is *not* required to be shared under FCRA or other laws. If a lender voluntarily shares this information, then other lenders can non-reciprocally access this information and measures derived from it.

For credit cards, but not other consumer credit products, *actual* payments frequently substantially differ from *scheduled* payments. Figure 2 shows the CDF of actual payments in excess of scheduled payments, by credit product. Actual payments on credit card accounts are highly dispersed: 26% are at or within one percentage point of the scheduled payment amount (the minimum payment due), a third are paying the full statement amount (or more), and the rest are spread in-between, and this finding is consistent with previous research (Keys and Wang, 2019). In contrast, for other consumer credit products, the majority of actual payments are at or within one percentage point of the scheduled payment amount: 91% of mortgages, 89% of auto loans, and 85% of unsecured loans. These results provide early evidence that actual payments information is potentially much more informative in distinguishing heterogeneous credit card behaviors than it is for auto or unsecured loans.

Figure 1 Panel A shows the fraction of accounts in consumer credit reports where actual payments information is observed. We define actual payments information as observed if it is non-zero and non-missing. This coverage measure is calculated for each consumer credit product: auto loans, credit cards, mortgages, and unsecured loans. The numerator and denominator of this measure are restricted to accounts with positive statement balances and where the date of the last payment is in the last month.

We find a 53.3 percentage point (59.8%) decline in credit card accounts sharing actual payments information from a peak of 89.1% in November 2013 to 35.8% in December 2022. Between 2010 and 2012, the coverage of actual payments information in credit reports is stable, with the majority of credit cards, auto loans, mortgages, and unsecured loans accounts sharing this information. There is a short-lived increase in credit cards sharing actual payments information during 2013 due to one furnisher starting to share this information. This furnisher later reverses its decision and stops sharing this information. The decline in coverage occurs sharply between 2013 and 2015, resulting in 75 million *fewer* US consumers having such information on their credit reports, and persists after 2015. Credit card lenders are still reporting their credit card accounts to credit reporting agencies, and other information on these accounts (e.g., credit limits, scheduled payment amounts) in our data, consistent with the Consumer Financial Protection Bureau (2020) concluding that "the coverage of other data variables in a consumer's consumer report, such as balance amount and credit limit, are consistently furnished across loan types". Internet Appendix Table C1 provides an illustrative example of how a credit card account appears in credit reports before and after lender stops reporting this information. Our results are robust to not conditioning on the date of the last payment, weighting accounts by balances or credit limits, and including retail or private label credit cards, shown in Internet Appendix C. Our results are not specific to TransUnion credit reports. Consumer Financial Protection Bureau (2020) displays a consistent pattern in their consumer credit reporting data, showing a decline in actual payments information reporting on credit cards from a peak of 88% in Q3 2013 to 40% from 2015 onwards, while Lee and Maxted (2023) report that only 30% of their Experian data has non-missing credit card actual payments information.

165 million credit card borrowers are missing actual payments information on at least one of their open credit cards with a positive balance in December 2022, and only 24% of credit cardholders have actual payments information on all their open credit cards with positive balances. Credit cards are of central importance for consumers' credit reports: 46% of open accounts with positive balances on credit reports are credit cards and 83% of consumers with a positive balance on any credit product in their credit report have at least one active credit card with a positive balance in December 2022.

Consumer Financial Protection Bureau (2023) names the six large credit card lenders who do not share actual payments information as American Express, JP Morgan Chase, Citibank, Bank of America, Capital One, and Discover. Since 2005, these six lenders have had a market share of over two thirds of credit card balances with a market share of 69% in 2021.[3] Two of these large credit card lenders have not shared actual payments information since 2012 or earlier. One of these large credit card lenders used to share information but stopped doing so in 2014. Following this, one of these large credit card lenders stopped sharing information in 2014 and the remaining two of these large credit card lenders also stopped in 2015. The remaining set of credit card lenders sharing actual payments information as of 2022 contains none of these six large credit card lenders. None of these lenders intends to voluntarily start sharing information and there are no material barriers that prevent them from doing so (Consumer Financial Protection Bureau, 2023). Other smaller lenders beyond these six large lenders may have also stopped sharing information during this time, but this was not reported by the CFPB.

There is no decline in sharing actual payments information for installment loans: auto loans, mortgages, and unsecured loans. Figure 1 Panel A shows that coverage trends up over time for all types of installment loans and is effectively 100% by December 2022. Actual payments information is shared for 98.4% of auto loans in 2022 (79.4% in 2013), 99.6% of mortgages (84.1% in 2013), and 97.9% of unsecured personal loans (74.4% in 2013).

3.2 Innovation

"*Trended Data is the most important tool developed by the credit reporting agencies since the advent of the credit score*" – Director of Credit Card Risk at a Large Regional Bank, 2014.[4]

What changed to prompt large credit card lenders to stop sharing actual payments information? We explain that this followed the launch of a technological data innovation. From 2013, TransUnion launched a new product: "Trended Data", with similar Trended Data products also launched by the other credit reporting agencies, Equifax and Experian, between 2013 and 2015. This innovative new product offers a new bundle of variables extracting more insights from information – most notably actual payments – that lenders already shared with credit reporting agencies. Trended Data combines information from the latest available point in time with information in historical archives. Before Trended

[3] www.consumerfinance.gov/about-us/blog/examining-the-factors-driving-high-credit-card-interest-rates/; www.wallethub.com/edu/cc/market-share-by-credit-card-issuer/25530

[4] www.ratezip.com/trended-credit-data-tcd-put-revolver/

Data, consumer credit reports created variables using data from the latest available point in time. For example, they may show a consumer's total outstanding credit balances as of last month. By linking data across multiple archives, Trended Data enables the creation of variables to examine trends. For example, a consumer's total outstanding credit balances in each of the last 24 months can reveal whether a consumer's balances have been increasing or decreasing.

In the context of our study, the relevant part of Trended Data is how it uses histories of credit card statement balances and actual payments to create new measures that reveal heterogeneous credit card behaviors. Trended Data products include measures of credit card spending and credit card revolving debt. Before Trended Data, these measures were not observed. These Trended Data measures are available to purchase for highly targeted marketing; screening consumers based on their revolving and spending behaviors, of a given credit risk and statement balance. Use of Trended Data for marketing and other purposes (e.g., credit risk) is on a non-reciprocal basis. Lenders can purchase Trended Data without sharing the input data they require – most notably credit card actual payments.

Why are lenders still willing to keep sharing such information on installment loans, but not for credit cards after this innovation? Trended Data is a more disruptive innovation for competition for credit cards than for installment loans because it enables targeted marketing based on credit card behaviors. This information increases the ability to target a competitor's profitable credit cardholders. For example, Experian states that its spending measure helps clients to *"calculate profit by providing an estimate of consumer spend"*, including to *"prioritize marketing investments and target higher spending consumers"*, and to *"optimize enhanced value propositions to the right spending segments"*.[5] Similarly, Equifax describes how *"a national bank wanted to build more market share and also proactively target consumers who are more likely to be high-spenders in the next 12 months. They needed a solution to more accurately predict propensity to spend while creating profitable returns on marketing investments"*.[6]

For installment loans, Trended Data's value is in improving credit risk assessments. In the mortgage market, Fannie Mae found *"including Trended Data materially improved modeling of loan performance"*, and from 2016 requires its use for underwriting.[7] This finding is consistent with statements by Equifax, Experian, TransUnion, and also with both

[5] www.experian.com/consumer-information/consumer-spending-behavior

[6] www.equifax.com/resource/-/asset/case-study/trended-credit-data-helps-target-high-value-customers-increase-revenue-improve-marketing-success/

[7] www.fanniemae.com/research-and-insights/perspectives/trended-credit-data-improves-du-risk-assessment-and-supports-access-mortgage-credit

FICO and VantageScore who both incorporate Trended Data into the latest versions of their credit scoring models (VantageScore 4.0 available from 2017, and FICO 10T available from 2020), and both of these scores are approved for use by the Federal Housing Finance Agency in 2022.[8] This indicates that a lack of sharing of credit card actual payments information may have a negative externality worsening credit risk evaluations, and therefore misallocating or mispricing capital in auto loan, mortgage, and unsecured loan markets. The lack of credit card actual payments information for 165 million credit cardholders also means that if these cardholders repay their credit card debt in full, this behavior is unobserved in their credit report. This means that such positive behavior does not necessarily improve their credit score, despite these cardholders expected to be lower credit risk since they are not revolving credit card debt, and may potentially even be a disincentive for highly informed consumers from doing so.

Why was Trended Data launched in 2013? From 2010, the CARD Act limited credit card financing charges: fees (e.g., Agarwal et al., 2015) and interest (e.g., Nelson, 2025). Pressures on these credit card revenue streams increased the relative importance of interchange revenue.[9] Substantial charge-offs incurred due to the 2008 financial crisis meant lenders increasingly shifted their focus away from short-term risky profits, and so, as a lower risk source of revenue, interchange revenue became increasingly attractive. The 2010 Durbin Amendment also restricted interchange fees on debit cards but not on credit cards (e.g., Mukharlyamov and Sarin, 2024).

Technically, lenders could construct spending and revolving debt measures before Trended Data by purchasing historical account-level credit reporting data archives that contain balances and actual payments. However, discussions with industry participants have confirmed that lenders did not do so in practice. This is for a combination of three reasons. First, in 2012, and earlier, there were technological constraints with storing and processing the volume of data. Even Equifax reports on its 2013 earnings call: *"It took us time just to build the infrastructure to house the data"*.[10] Similarly, Barclays Research said, *"Intuitively Trended Data sounds like a no-brainer (with value seen across the credit chain of acquisitions, origination and account management) but the limitations of the technology have his-*

[8] https://assets.equifax.com/assets/usis/trended_data_solutions.pdf; www.experian.com/blogs/ask-experian/fico-10-score-changes-what-it-means-to-your-credit/; https://newsroom.transunion.com/fannie-mae/; https://fico.gcs-web.com/news-releases/news-release-details/fico-introduces-new-fico-score-10-suite; www.vantagescore.com/releasing-the-power-of-trended-credit-data; www.fhfa.gov/Media/PublicAffairs/Pages/FHFA-Announces-Validation-of-FICO10T-and-Vantage-Score4-for-FNM-FRE.aspx

[9] www.experian.com/consumer-information/consumer-spending-behavior

[10] https://seekingalpha.com/article/1571712-equifax-inc-efx-management-discusses-q2-2013-results-earnings-call-transcript

torically prevented its widespread use". Second, before Trended Data, constructing measures from account-level data would require purchasing at least twelve historical archives. This can be prohibitively costly – especially for marketing purposes of prospective customers – as such data is charged on a per-archive basis. Third, industry participants told us that the use of historical archives could potentially expose them to costly legal FCRA compliance issues. The credit reporting agencies' Trended Data products are FCRA compliant.

Trended Data was also later launched in Canada (e.g., TransUnion in 2015) and the UK (e.g., TransUnion in 2019). In Canada and the UK, unlike in the US, it did not prompt a breakdown of sharing actual payments information for credit cards (or other loans). This is explained by different institutional arrangements. The UK's industry agreements require reciprocity in sharing information, and data cannot be used for marketing.[11] The UK caps interchange revenue meaning high-spending consumers generate less revenue than they do in the US where there is no cap. This means that by UK lenders sharing information on credit card actual payments they were not, unlike the US, at greater risk of their profitable cardholders being targeted by competitors. Like the US and unlike the UK, Canada's credit reporting arrangements do not have reciprocity in data sharing. However, unlike the US, Canada does not allow individual marketing of credit cards, but only allows aggregated data on geographic areas to be used for targeting. Without the channel of targeted offers, there may be less of the potential longer-term competitive gains from Trended Data in Canada and the UK than there would be in the US.

3.3 Effect of Innovation on Information Sharing

3.3.1 Difference-in-Differences Methodology

We now extend our earlier descriptive evidence to apply a difference-in-differences methodology to estimate the causal effect of Trended Data on credit card actual payments information sharing. Consumer Financial Protection Bureau (2023)'s interviews with lenders provide further corroborating evidence for taking such an approach: *"One company mentioned that, as an impetus to start suppressing data in 2013, some nationwide consumer reporting companies were starting to market new data solutions to lenders that leveraged the actual payment variable without requiring data buyers to furnish it"*.

We estimate the effects of Trended Data using the OLS regression specified in Equation 1, with one observation per furnisher's credit product portfolio (p), per year-month (t), and including fixed effects for each furnisher's credit portfolio (γ_p) and each year-month (γ_t). We weight observations by the number of accounts in each furnisher's credit

[11] www.scoronline.co.uk/wp-content/uploads/2021/07/PoR-version-41-final-June-2021.pdf

product portfolio. Our parameters of interest, δ_τ, show the interaction between calendar year-month indicators (D_τ) and an indicator for a furnisher's credit card portfolio ($CRED_p$). These are τ months after the 2013 launch of Trended Data, with the omitted time period being December 2012. We cluster standard errors by furnisher. We restrict the sample to furnishers with credit portfolios in both 2010 and 2022. We conduct regressions changing the sample to include either auto loans or unsecured loans as the control group (where $CRED_p = 0$), restricting to furnishers' portfolios observed throughout this period to produce a balanced panel of monthly data from 2010 to 2022. Auto loans and unsecured loans are used as control groups based on the rationale that these credit markets are less disrupted by Trended Data than credit cards.

$$Y_{p,t} = \sum_{\tau \neq \text{Dec 2012}} \delta_\tau \Big(D_\tau \times CRED_p \Big) + \gamma_p + \gamma_t + \varepsilon_{p,t} \tag{1}$$

3.3.2 Empirical Results

Our difference-in-differences results in Figure 1 Panel B and Table 1 show a 50.9 (s.e. 15.0) percentage point decline in December 2015, relative to December 2012, in the fraction of accounts sharing actual payments information on credit cards compared to auto loans, and a 54.8 (s.e. 15.0) percentage point decline compared to unsecured loans. While sharing of credit card actual payments information changes little between 2015 and 2022, sharing of actual payments information for auto loans and unsecured loans grows over time and therefore, by December 2022, our difference-in-differences estimates show 65.1 (s.e. 16.1) and 68.5 (s.e. 16.0) percentage point declines relative to auto loans and unsecured loans, respectively. Our results are significant at the one percent significance level, but we note that the standard errors after 2013 are wide, 15 to 16 percentage points, due to clustering at the furnisher level, where a small number of large credit card furnishers drive the overall results. Our results are robust to not conditioning on the date of the last payment and weighting accounts by balances, see Internet Appendix Figure C7 and Table C2. We interpret our estimates as showing the reduction in information sharing is an unintended response of credit card lenders to consumer credit reporting agencies' innovation designed to reduce information asymmetry and increase information sharing.

4 Consumer Credit Profitability

We understand the breakdown of information sharing by showing, in Section 4.1, how actual payments information reveals heterogeneous credit card behaviors. Such behaviors are informative to lenders if they predict profitability, as evaluated in Section 4.2.

4.1 Measuring Credit Card Behaviors

Two credit cards with identical product features can yield substantially different realized profits. This is because credit card profits have multiple, uncertain sources of revenues and costs which are determined by cardholder behaviors after origination. Because cardholder behaviors are heterogeneous, the ability to observe and predict cardholder behaviors is crucial to determining whether they are profitable to lend to and, if so, which credit card type to market to a consumer (e.g., a low interest rate card or a high rewards card).

Observing actual payments information, $p_{i,t}$, enables the measurement of two credit card behaviors: "revolving debt", $d_{i,t}$, and "spending", $s_{i,t}$. A credit card's statement balance, $b_{i,t}$, is the amount on a credit card at the time the statement is issued. This includes new spending, revolving debt, and financing charges. Credit card revolving debt is a stock measure defined in Equation 2 as the credit card statement balance, $b_{i,t-1}$, less actual payments, $p_{i,t}$, made against that statement (i.e., it is the amount revolved from one statement to the next statement), and where negative values are coded as zeros. This differentiates accounts into (1) "revolvers" where some debt is revolved from one statement to the next ($d_{i,t} > 0$) who generate interest revenue, and (2) "transactors" who do not ($d_{i,t} = 0$). The term $b_{i,t-1}$ rather than $b_{i,t}$ is used in this equation because credit cards have a grace period where payments are due by a specified date at least 21 days after the date a statement is issued, and therefore the actual payments observed in this month's credit archive correspond to the statement balance in the previous month's archive. This is why multiple credit archives need to be observed, as enabled by Trended Data, to accurately measure revolving debt. Revolving debt is important for lenders because interest revenue is generated proportionally from revolving debt. For a given interest rate, higher interest revenue is generated from higher revolving balances and from revolving balances for longer durations.

$$d_{i,t} \equiv \begin{cases} b_{i,t-1} - p_{i,t} & \text{if } b_{i,t} - p_{i,t} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Credit card spending, $s_{i,t}$, is the flow value of new transactions from one statement to the next statement, defined in Equation 3, which is a measure of consumption previously used in Ganong and Noel (2020). Multiple credit archives need to be observed, as enabled by Trended Data, to accurately measure spending. This measure is inclusive of financing charges and negative values are coded as zeros. Even if we measure revolving debt perfectly, this is insufficient for measuring spending because some consumers can and do pay more than the statement balance (e.g., paying before their statement is issued, or paying their outstanding balance); this occurs for approximately 8% accounts in our data. For example, consider a consumer with \$0 statement balance at both time $t = -1$ and $t = 0$, their revolving debt is zero ($d_t = 0$), however, their spending could be zero or a positive number. Spending behavior is important for lenders as credit card interchange revenue is a function of spending. If a consumer's historical revolving and spending behaviors are observed and are persistent over time, lenders may be better able to predict interest and spending revenues, and ultimately profitability.

$$s_{i,t} \equiv \begin{cases} b_{i,t} - b_{i,t-1} + p_{i,t} & \text{if } b_{i,t} - b_{i,t-1} + p_{i,t} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

We evaluate how much error is added to the measurement of credit card behaviors when actual payments are not observed. If we observe both statement balances and actual payments, then we can construct these measures and so mechanically there is no unexplained variation (i.e., $R^2 = 1$). We evaluate R^2 relative to this benchmark by estimating OLS regressions shown in Equation 4 where outcomes $Y_{i,t}$ are revolving debt and spending and where predictive inputs are the current statement balance ($b_{i,t}$), previous statement balance ($b_{i,t-1}$), the difference between these conditional on being non-negative ($\tilde{\Delta} b_{i,t}$), and indicators for non-zero current and previous statement balances. We run this regression for all credit scores and then separately for each credit score segment: subprime (the lowest credit score group containing the highest credit risks), near prime, prime, prime plus, and superprime (the highest credit score group containing the lowest credit risks). We use data in December 2013 as the period of highest coverage of actual payments information and dropped data from the furnishers not sharing payments information. There is one observation per credit card account (i).

$$Y_{i,t} = \alpha + \beta_1\, b_{i,t} + \beta_2 b_{i,t-1} + \beta_3 \tilde{\Delta} b_{i,t} + \beta_4 \mathbf{1}\{b_{i,t} > 0\} + \beta_5 \mathbf{1}\{b_{i,t-1} > 0\} + \varepsilon_{i,t} \tag{4}$$

Figure 3 summarizes our results for measuring revolving debt, the black bars, and spending, the orange bars, without actual payments information. Across all credit scores, revolving debt is measured with an R^2 of 0.94; this shows that not observing actual payments increases measurement error relative to a benchmark of $R^2 = 1$. The R^2 is decreasing in credit score and is substantially lower for the superprime group where $R^2 = 0.60$, showing that it is more challenging to determine heterogeneous consumer behaviors within this group.[12] Our results show that the actual payments variable is even more important for measuring spending. Across all credit scores, spending is measured with significant noise when actual payments information is unobserved, with an R^2 of 0.51, relative to a benchmark of $R^2 = 1$ when observed.[13] Adding other variables—credit score, zipcode income, scheduled payment, and trends in statement balances—does not change our findings, as shown in Internet Appendix Figure D1. This noise in measuring credit card behaviors driving profitability limits the value of Trended Data products to realize their innovative potential for reducing information asymmetry and increasing competition. Such noise is also problematic for academic researchers who want to measure revolving credit card debt or credit card spending as a consumption measure.

4.2 Predicting Consumer Credit Profitability

Lenders' expectations of profitability determine which new accounts to attempt to acquire. For acquired accounts, after their contract terms (e.g., interest rate, credit limit, loan size and duration) are determined the lender remains uncertain about how a consumer will use the account and the profits the account will ultimately generate. If the consumer behaviors driving profitability are more persistent over time, then lenders may be better able to predict profitability. If so, historical data such as actual payments information can potentially be informative for predicting profits. In Section 4.2.1, we explain how we construct measures of realized lifetime profits at the account-level for credit cards, auto loans, and unsecured loans, with more details provided in the Internet Appendix D. Section 4.2.2 provides our methodology to evaluate the marginal value of actual payments information for predicting account-level profits, and its components. Section 4.2.3 shows the results of this predictive exercise.

4.2.1 Measuring Profitability

Credit Cards

Measuring realized profits for credit cards requires calculating financing charges, interchange net of rewards, and charge-offs. We introduce a new methodology to estimate credit card financing charges in credit reporting data despite these data not containing a

[12] R^2 are 0.99 (subprime), 0.98 (near prime), 0.96 (prime), 0.89 (prime plus). R^2 results are similar out-of-sample: 0.94 (all) 0.99 for (subprime), 0.98 (near prime), 0.96 (prime), 0.89 (prime plus), and 0.61 (superprime).

[13] R^2 are 0.54 (subprime), 0.58 (near prime), 0.56 (prime), 0.53 (prime plus), 0.50 (superprime). R^2 are similar out-of-sample: 0.50 (all), 0.42 (subprime), 0.50 (near prime), 0.58 (prime), 0.54 (prime plus), and 0.50 (superprime).

variable for this or key product terms (e.g., interest rates). We do so using an insight from the formula in Equation 5 that credit card lenders use to calculate minimum payments. Its first component is a floor dollar amount $\$\mu$. The second component is the sum of (i) a percentage $\theta\%$ of B_t: the statement balance before financing charges ($B_t \equiv b_t - r_t - f_t$) and (ii) financing charges ($r_t + f_t$).

$$M_t^{CRED} = \max\left\{\$\mu,\ \theta\%\, B_t + r_t + f_t\right\} \tag{5}$$

Because minimum payments are calculated deterministically with Equation 5 formula, observing statement balances and scheduled minimum payments (both inclusive of financing charges) suffices to estimate the parameters $\$\mu$ and $\theta\%$ for each lender. If a cardholder has zero financing charges, this formula simplifies to $M_t^{CRED} = \max\left\{\$\mu,\ \theta\%\, b_t\right\}$ and as we observe both M_t^{CRED} and b_t we can find the lowest combination of $\$\mu$ and $\theta\%$ that matches the data. If we find the correct parameters, this would not be expected to match all data points, as many observations will have financing charges ($r_t + f_t > 0$) and therefore have higher values of M_t^{CRED} for a given b_t. Having inferred $\$\mu$ and $\theta\%$, we can then estimate the minimum payment *before* financing charges for each month of data. Estimated financing charges are then the difference between the observed minimum payment, which includes financing charges, and our predicted minimum payment before financing charges. We deduct charge-offs from this estimate to calculate estimated financing charges net of charge-offs.

Our methodology for estimating financing charges appears reasonable in several ways. The most common combination of parameters we find is $\$\mu = \$25$ and $\theta\% = 1\%$ and the most common $\theta\%$ is 1% which is in line with the CFPB's public database of credit card agreements.[14] Using this methodology, we estimate the mean financing charges of $211 in 2012 which is close to prior research using regulatory datasets. Agarwal et al. (2015) finds mean annualized financing charges of $223 (April 2008 to December 2011) while Agarwal et al. (2023) finds mean financing charges of $17.02 in March 2019, which is $204 annualized, and our estimates would not be expected to exactly match given those studies examine different time periods and use different datasets, which may have different variable definitions and samples. Figure 4 Panel A shows that we find a hump shape in financing charges by credit score as found in prior research (e.g., Nelson, 2025) and also find financing charges being higher for accounts revolving debt than for those transacting debt: these findings are despite our methodology not using this information. If actual payments are observed, researchers can potentially add additional assumptions to

[14] www.consumerfinance.gov/credit-cards/agreements/

this methodology to separate financing charges into fees and interest, and also estimate effective interest rates. More details on this methodology are provided in the Internet Appendix D.

As interchange net of rewards is proportional to spending, we calculate this by measuring spending (exclusive of estimated financing charges) and then applying a 0.5% factor. This 0.5% factor is based on the market average interchange revenue being approximately 2%, and rewards and related expenses are approximately 1.5% (Agarwal et al., 2015, 2018, 2023; Wang, 2024).

Credit cards are opened-ended products, which means it is uncertain at the time of origination how long a consumer will use a card for, with longer tenure expected to increase profits given up-front costs of acquisition. Using industry data from R.K.Hammer, acquisition costs, including marketing and underwriting costs, are approximately \$140 per acquired account, and range from \$50 to \$390 in 2012, reflecting the heterogeneity in credit card profitability. Lenders also have other organizational-level costs, such as costs of funds and operations. R.K.Hammer and Agarwal et al. (2018) estimate the costs of funds of under 2%, and the organization costs of 7% to 8% in 2012. See Internet Appendix B for summary R.K.Hammer data on the profitability of the credit card market, and the costs of acquisition over time.

Installment Loans

Measuring realized profits for auto loans and unsecured loans is fairly straightforward as we observe a loan's origination terms and charge-offs. At origination, installment loans typically have a fixed loan amount (A^{INST}), number of scheduled payments (N^{INST}), and scheduled monthly payment (M^{INST}). These three loan terms are sufficient to calculate the scheduled financing charges: $M^{INST} \times N^{INST} - A^{INST}$. This means that, in contrast to credit cards, interest revenue (r_t) is known at the time of origination. Installment loan profitability is subject to two main sources of uncertainty after origination. First, as with credit cards, charge-offs. Auto loans and unsecured loans also have a second source of uncertainty, prepayment. If a consumer decides to pay down their loan earlier than scheduled ("prepayment"), the lender may receive less interest revenue than originally scheduled. Prepayment is a substantial risk faced by lenders in the auto loan market (e.g., Grunewald et al., 2020; Katcher et al., 2024). We account for loan prepayment by subtracting a proportion of scheduled financing charges in cases where the loan is repaid before its scheduled end date. The other relevant aspect to highlight is that installment loans do not generate an interchange revenue stream, and therefore there is not a direct revenue stream attached to actual payments that lenders can monetize, in contrast to credit cards.

4.2.2 Methodology for Predicting Profitability

Using data up to December 2012, we predict account-level outcomes ($Y_{i,2012+j}$) for profitability and its component parts over different time horizons (j) up to ten years. This exercise replicates the problem of a lender evaluating which accounts (i) to attempt to acquire and how much profit they can expect to generate from their own accounts. For installment loans, the ten-year time horizon usually exceeds the loans' scheduled lifetime, which is typically eight years or less. The ten-year horizon covers the lifetime of most credit cards: Only 15% of active credit cards in December 2012 remain active (open, not severely delinquent, and without persistent zero balances) by December 2022, shown in Internet Appendix Figure E7.

We show credit card results for lenders who $Always$ share actual payments information, as these are the lenders that we observe outcomes data for their card's lifetime. We show that our results are robust to including the $Stoppers$, who stop sharing actual payments information, for whom we need to impute spending (classifications described in Section 2.2), with more details on this in Internet Appendix D. We cannot evaluate the value of actual payments information for the lenders that never share this information, the $Nevers$, and can only compare the baseline predicting of financing charges net of charge-offs in this to other samples, shown in Internet Appendix Figure D3.

Our baseline model in Equation 6 uses the vector $X'_{i,2012}$ of predictors observed in December 2012. The vector $X'_{i,2012}$ does not include actual payments information. The vector $X'_{i,2012}$ includes indicators for 100 credit score quantiles, and credit score interacted with other account-level information: up to three years of balances, delinquency, utilization rates, estimated financing charges, card tenure, and credit limits. For installment loans, we interact credit score with: origination amount, scheduled loan duration, and scheduled payment amount. We examined different specifications of predictors and, for each market, use the specification that best predicts out-of-sample.

$$Y_{i,2012+j} = X'_{i,2012}\beta + \varepsilon_{i,2012+j} \tag{6}$$

The comparison model in Equation 7 takes the baseline model and adds information on up to three years of actual payments information ($Z'_{i,2012}$) to the set of predictors. These predictors include interactions and combinations with other variables such as credit score and balances. In the case of credit cards, these additional predictors include measures of spending and revolving debt, both derived from actual payments information.

$$Y_{i,2012+j} = X'_{i,2012}\beta + Z'_{i,2012}\lambda + \varepsilon_{i,2012+j} \tag{7}$$

We predict profitability using OLS regressions trained on half the data and test its performance on the remaining half. We evaluate the value-add of actual payments information for predicting profitability using the out-of-sample R^2 for the baseline and the comparison model.

4.2.3 Results Predicting Profitability

Table 2 shows the out-of-sample R^2 from models without and with actual payments information to predict lifetime (ten-year) profits on credit cards, auto loans, and unsecured personal loans. We find that actual payments information increases the ability to predict lifetime profits for credit cards R^2 from 0.1919 to 0.2003: a 4.4% increase. Internet Appendix Figure D4 shows that results hold for predicting profitability ranging from one- to ten-year horizons. In contrast, actual payments information does not substantially improve the ability to predict lifetime profits for either auto loans or unsecured personal loans. These results help to explain why installment loans are willing to keep sharing actual payments information after Trended Data is launched because doing so does not pose a competitive threat enabling competitors to target their profitable customers. Actual payments information may have been expected to increase profits by improving the prediction of prepayment on installment loans; however, we find little evidence of this. This is because prepayments are often made through one large bullet payment (Katcher et al., 2024), which means that there is little-to-no information before the loan is prepaid early. While credit cards have a revenue stream directly dependent on spending – interchange – that actual payments information can be used to target, installment loans do not have an analogous revenue stream, and so Trended Data is less of a competitive threat.

Credit card lenders have different business models and risk tolerances and may not all want to lend to the same consumers. This means that lenders are interested not only in predicting overall profitability, but also its component parts. Public annual reports show that the majority of the revenue generated by many large credit card lenders, such as Capital One, comes from financing charges (the sum of interest revenue and consumer fee revenue) as opposed to interchange revenue. At the other extreme, the majority of American Express's revenue comes from interchange revenue. American Express and Discover are both credit card lenders and payment network providers, and so retain more interchange revenue than other credit card lenders who use MasterCard or VISA payment networks, which comes at the cost of splitting the interchange revenue. Capital One's proposed merger with Discover is expected to enable them to earn higher interchange revenue. Predicting a consumer's profitability can help lenders not only work out which consumers to attempt to acquire but also which of the large array of available credit card products to market to them. Marketing the wrong card to a profitable consumer may yield a low conversion rate or make them less or even unprofitable. Marketing costs are a large expense for credit card lenders irrespective of their diverse business models, for example, public annual reports show that marketing spending for American Express and Capital One was \$5.5 billion and \$4.0 billion respectively in 2021.

How does actual payments information increase the ability to predict the components of credit card profitability? Figure 5 summarizes the out-of-sample R^2 results for predicting lifetime profits, and its components. Table 3 shows the out-of-sample R^2 for outcomes over one- and ten-year horizons. We also evaluate performance in Table 4 by comparing the realized portfolio values of the top ranked 100,000 accounts when ranking accounts by the out-of-sample predictions made with and without using actual payments information. This portfolio approach shows that actual payments increases the net present value of lifetime profits by 2.7%. Figure 5 and Tables 3 and 4 are all calculated for the $Always$ sample, and these results are robust to using the $Always + Stoppers$ sample, with results shown in the Internet Appendix Figure D5 and Tables D1 and D2.

Actual payments information substantially improves the prediction of interchange net of rewards. Table 3 shows that actual payments information increases the R^2 for predicting interchange net of rewards over a one-year horizon by 53% from 0.401 to 0.614, and over a ten-year horizon by 31% from 0.129 to 0.169. Table 4 shows that observing actual payments information increases the portfolio value of interchange net of rewards over a one-year horizon by 24%, a \$42 mean increase, and over a ten-year horizon by 13%, a \$63 increase. Internet Appendix Table 4 shows that the results are robust to using the $Always + Stoppers$ sample. Actual payments information increases R^2 by 49% from 0.415 to 0.619 on a one-year horizon, where spending is observed for both the $Always$ and the $Stoppers$ groups, and by 33% from 0.181 to 0.241 on a ten-year horizon, where spending post-2013 is imputed for the $Stoppers$. Internet Appendix Figure D5 shows that this pattern is robust to measuring this outcome over alternative time horizons. We interpret these results as showing how observing actual payments information improves the ability of lenders to target high-spending accounts generating high interchange net of rewards.

Actual payments information also improves the prediction of financing charges net of charge-offs. Table 3 shows that actual payments information increases the R^2 for predicting financing charges net of charge-offs over a one-year horizon by 0.2% from 0.217 to 0.222, and by over a ten-year horizon by 4.2% from 0.192 to 0.200. Table 4 shows that observing actual payments information increases the portfolio value of financing charges net of charge-offs over a one-year horizon by 1%, a \$14 mean increase, and over a ten-year horizon by 3%, a \$140 increase. These results are similar using the $Always+Stoppers$ sample, shown in Internet Appendix Tables D1 and D2, and measuring over alternative time horizons, as shown in Internet Appendix Figure D5. The predictive increases are smaller for financing charges net of charge-offs than for interchange net of rewards; however, as the former is a larger component of profits, even these small percentage uplifts are quantitatively important in levels.

Our results are likely to underestimate the importance of interchange revenue for four reasons. First, we assume a flat 0.5% margin of interchange net of rewards, however, rewards cards—most common for higher credit score consumers where high-spenders are—have higher margins (Agarwal et al., 2023). Second, interchange net of rewards may increase further if lenders are able to convert an account from a standard card to a rewards card, as doing so causes higher spending and so generates more interchange revenue (e.g., Agarwal et al., 2024, 2023; Han, 2024) and also more revenue via annual fees. Third, improved predictability would also be expected to reduce acquisition costs by enabling lenders to send pre-selected credit card offers that more closely align to consumer behaviors and so may yield improved solicitation response rates. Pre-selected credit offers are highly targeted (e.g., Han et al., 2018). Better prediction reduces the degree of adverse selection a lender faces and enables improved screening through pre-selected credit offers. For example, a lender may send a consumer a high rewards card that also has a high annual fee to screen for high-spending consumers and deter applications from high-risk consumers who cannot afford the up-front annual payment. Fourth, our results do not include lenders that do not share actual payments information. In the next section, we show that such lenders appear to have higher spending accounts and so would generate more interchange revenue.

5 Selection in Credit Card Lenders Sharing Information

In this section, we explore the selection of credit card lenders by their sharing decisions to understand lenders' motivations for no longer sharing information. Section 5.1 examines default risk, and Section 5.2 studies non-default behaviors. Section 5.3 provides causal evidence for how the innovation affected account openings. Then Section 5.4 discusses how to interpret the breakdown of information sharing given our results.

5.1 Default Risk

The decision of credit card lenders to share actual payments information is non-random. The *Nevers* group who never share this information, compared to the *Always* group who always share this information, or the *Stoppers* group who stop sharing this information, have portfolios with higher mean credit scores and credit limits, lower mean utilization rates, higher mean and higher standard deviation card tenure and statement balances, see Internet Appendix Table E1 for more details.

Can default risk explain differential information sharing decisions across credit card lenders? Adverse selection due to default risk is well-documented in the prior literature in the credit card market (e.g., Ausubel, 1991; Agarwal et al., 2010). In our data, lenders that never share information, the *Nevers*, have more creditworthy cardholders, with a mean credit score of 744, than the *Always* or the *Stoppers* groups, who both have mean credit scores near 720, see Internet Appendix Table E1 for details. This shows that ex-ante credit risk does not explain why lenders share or stop sharing actual payments information. What about differences in ex-post defaults? We examine this by conditioning cards on their default risk in December 2012 and examine whether these cards are more likely to become delinquent (90+ days past due or 180+ days past due) at any point from January 2013 to December 2022. Default rates convexly decline in credit score. Default rates conditional on credit score are generally similar across lenders with different information sharing decisions, as shown in Internet Appendix Figure E2. Given these results, default risk does *not* appear to be the primary reason for the differential information sharing decisions across credit card lenders.

5.2 Non-Default Behaviors

We next show how non-default credit card behaviors, after accounting for default risk, explain differential information sharing decisions across credit card lenders. We present results in two ways. First, Table 5 shows the residualized means and standard deviations in cardholder behaviors. We residualize using OLS regressions of outcomes on values of credit scores, and add back in the population means to ease interpretation ($Y_i - \widehat{Y}_i + \bar{Y}$). Second, Figure 6, as well as additional Figures in Internet Appendix E, shows the means and the standard deviations in non-default behaviors for 50 quantiles of credit score where the quantile thresholds are defined globally and fixed across classifications of lenders (*Always*, *Stoppers*, *Nevers*). We use this approach to present results because the distribution of credit scores is uneven with a low density mass for a large number of low-credit-score values but a high density for particular high-credit-score values. 60% of cards are prime plus or superprime and 38% of cards are superprime, the full CDFs are in Internet Appendix Figure E1. The means of non-default behaviors are important as they show how important different behaviors that drive different revenue streams are to different lenders' business models. The standard deviations of non-default behaviors are informative because they show how much different lenders potentially gain from hiding variation in such behaviors to make it more difficult for competitors to successfully target their profitable customers.

5.2.1 Revolving Behaviors

Table 5 shows that the portfolios of lenders who stop sharing information, the *Stoppers* group, have 11% higher mean and 12% higher standard deviation residual revolving debt than those who keep sharing information, the *Always* group. Figure 6 Panel A shows the difference in means is only in the middle of the credit score distribution, while Panel B shows this gap in standard deviations is present across the whole distribution. Figure 4 Panel B shows how these differences in revolving behavior translate into the *Stoppers* having more profitable portfolios than the Always group. Financing charges net of charge-offs, across 2013 to 2022, for *Stoppers* have a 27% ($155) higher mean and a 4% ($99) higher standard deviation relative to the *Always*, whose mean is $573 and standard deviation is $2,519. Internet Appendix Figure 6 shows that this result is robust to measuring card financing charges net of charges from 2012 to 2022, and Internet Appendix Figure E6 shows that it is also robust to focusing on 2012 revolvers.

We do not observe revolving debt for the $Nevers$, and instead use the statement balance as an observed proxy for revolving debt. We find monotonicity, *Nevers* > *Stoppers* > *Always*, in means and standard deviations; however, this relationship only holds for below median credit scores, shown in Internet Appendix Figure E3. The other way we infer the *Nevers*'s revolving debt is comparing our *Always+Stoppers* group estimates to public revolving debt estimates produced by the Federal Reserve Bank of Philadelphia using FR Y-14K data.[15] FR Y-14K data for Q4 2012 estimates revolving debt is 77% of balances and 71% of accounts revolve debt. Aggregating the *Always* and the *Stoppers* in our data, we estimate that revolving debt is 73% of balances and 63% of accounts revolve debt. This indicates the *Nevers* group revolves a slightly higher share of balances, and have more accounts revolving debt than the *Stoppers* or the *Always*, however, we caveat that the FR Y-14K data only covers lenders with over $100bn in assets with material credit card portfolios covering three quarters of the population of outstanding balances so it is not an exact like-for-like comparison.

[15] www.philadelphiafed.org/surveys-and-data/large-bank-credit-card-and-mortgage-data

5.2.2 Spending Behaviors

Figure 6 Panel D shows a substantial dispersion in spending conditional on credit score. This shows how spending is a second source of uncertainty that lenders experience beyond default risk. Differences in spending behaviors residual of default risk between lenders appear to most clearly explain differential information sharing decisions: with adverse selection of lenders into sharing information. Higher mean spending is important to lenders' business models as it generates higher interchange revenue. In addition, high-spending cardholders may also be more willing to pay high annual fees associated with rewards cards, as for low spending customers the potential rewards benefits of such cards may not outweigh their annual fee cost.

Table 5 shows the *Stoppers*'s spending, residual of default risk, is 31% ($1,643) higher mean and 41% ($4,275) higher standard deviation than the *Always*, who have a mean of $5,246 and a standard deviation of $10,345. Higher standard deviation in spending is important as that shows that even if a competitor knows the mean value of spending conditional on credit score, there is wide uncertainty in whether they will be targeting a low-spender or a high-spender, who are very different in their profitability. Figure 6 Panel D shows that the differences in standard deviations of spending between the *Stoppers* and the *Always* occur across the credit score distribution, and Figure 6 Panel C shows that the differences for mean spending occur for prime, prime plus, and super-prime segments, which often contain transactors. Some of this variation may arise given that consumers often hold multiple credit cards, and cards are competing to be "top of wallet" – the main card a consumer uses. Discussions with industry participants indicate that a cardholder needs to spend at least $10,000 to $20,000 per year for several years to overcome their acquisition and other costs to become profitable on interchange revenue alone, and airline credit cards, where profits are split between the airline and the credit card provider (whereas with a lender's own-brand products there is no split), need to have longer-duration contracts for it to be a worthwhile venture for the lender. Internet Appendix Figure E6 shows that our results are robust to focusing on the spending of 2012 transactors.

How does the spending of the $Nevers$ compare? The *Nevers* have more cards held by high-credit-score consumers that would be, on average, expected to generate higher spending. We examine a proxy for spending – change in statement balances conditional on being positive ($\tilde{\Delta} b_{i,t}$) – that we observe across the *Always*, *Stoppers*, and *Nevers*. Equation 8 shows how this proxy measure is spending plus a non-random error term $\nu_{i,t}$, which is biased downwards as actual payments increase ($p_{i,t}$ can only be greater than or equal to zero), and the error is only zero if both payments ($p_{i,t}$) and financing charges ($r_{i,t} + f_{i,t}$)

are zero or, by chance, net out at zero. Table 5 presents this measure (residual of default risk) and shows that the *Nevers* have a higher mean and a higher standard deviation than the *Stoppers*, who in turn have a higher mean and a higher standard deviation than the *Always*, see Internet Appendix Figures E4 and E5 for results by credit score. We also compare our estimates to public, population estimates of total market credit card spending being $2.55 trillion in 2012 from the Federal Reserve Payment Study (conducted triennially).[16] If we calculate spending aggregating the *Always* and the *Stoppers* and multiply by their market share, it would imply total spending of $2.43 trillion and so indicates that the *Nevers*'s mean spending is higher than the rest of the market average.

$$\tilde{\Delta} b_{i,t} \equiv \begin{cases} b_{i,t} - b_{i,t-1} \equiv s_{i,t} - \underbrace{p_{i,t} + r_{i,t} + f_{i,t}}_{\nu_{i,t}} & \text{if } b_{i,t} - b_{i,t-1} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

5.2.3 Card Tenure

The longer a credit card is held, the more private information a lender may hold, which they could use to extract information rents from the cardholder (e.g., Nelson, 2025). Holding a card for longer may indicate that a consumer's switching costs have increased – potentially due to preferring that card to alternatives.

We document a new fact that card tenure varies across and within the credit score distribution, as displayed in Figure 6 Panels E (mean card tenure) and F (standard deviation card tenure). There is a clear pattern of adverse selection in information sharing decisions by card tenure. Table 5 shows the *Nevers*'s card tenure, residual of default risk, has the highest means and standard deviations (mean 136 months, standard deviation 106 months) compared to the *Stoppers* (mean 98 months, standard deviation 76 months) and the *Always* (mean 71 months, standard deviation 74 months). Figure 6 Panel E shows that this pattern exists in the means across the distribution of credit scores, and in the differences in standard deviation between the *Nevers* and the *Always+Stoppers* groups. Internet Appendix Figure 6 shows that this result is robust to measuring card tenure by 2022.

Substantial differences in card tenure have important broader implications for how to measure credit card profitability. Traditionally, credit card profits have often been measured in empirical economic research on a per-period basis using data on realized profits covering a few years (e.g., Agarwal et al., 2015) or a single point-in-time (e.g., Agarwal et al., 2023). Given that we find different segments of the credit score distribution, cards

[16] www.federalreserve.gov/paymentsystems/2022-The-Federal-Reserve-Payments-Study-Initial-Data-accessible.htm

within these segments, and different credit card lender portfolios have substantial variation in card tenures, the lifetime profitability of credit cards may differ from the profitability over a short, fixed horizon. For example, consider that credit card A is held for five years and generates $100 per year in profits, whereas credit card B is held for ten years and generates $80 per year in profits. Over a five year (or less) horizon, card A appears more profitable: generating $100 more than card B. However, over these cards' lifetimes, card B is more profitable: generating $300 more than card A.

This lifetime perspective can also help explain an otherwise puzzling fact that credit card lenders lend to and heavily concentrate marketing toward high-credit-score consumers despite these consumers frequently being transactors generating little-to-no revenue from financing charges, as shown in Figure 4 Panel B. 60% of credit card accounts are held by high-credit-score consumers (Internet Appendix Figure E1), the overwhelming majority of marketing offers are sent to very high ("prime plus" or "superprime") credit score consumers (Consumer Financial Protection Bureau, 2021), and such offers are primarily for rewards cards (Consumer Financial Protection Bureau, 2015). High-credit-score transactors' longer tenure can mean their accounts can have a positive net present value on interchange – especially if they can find high-spenders and get these to take out rewards cards with higher profitability margins (e.g., Agarwal et al., 2024, 2023; Han, 2024) – and also avoids future acquisition costs. This explanation is in line with industry statements. For example, Capital One's US Head of External Affairs states "Even those customers who pay in full every month are profitable and desirable customers for Capital One and other issuers across the industry." It also explains why credit card lenders lobby against legislation such as the Credit Card Competition Act that would be expected to restrict credit card interchange revenue.[17] Similar aggressive competition for low-risk consumers is also observed in other markets with adverse selection, such as healthcare where a small number of firms profitably operate with high mark-ups (Kong et al., 2023).

The portfolios of the credit card lenders remaining in the market for sharing actual payments information are the lowest residual types, the "lemons" in Akerlof, 1970, on multiple dimensions: they have lower residual tenure, spending, statement balances, revolving debt, and financing charges net of charge-offs. Thus, the market for sharing information is adversely selected. Our results are consistent with the *Nevers* and *Stoppers* groups holding information rents over other lenders. As incumbent lenders, they are especially exposed to actual payments information in Trended Data being used for mar-

[17] www.youtube.com/watch?v=bkYx9R2k5pk; https://secureamericanopportunity.com/take-action/oppose-credit-card-routing-mandates-radio/; www.durbin.senate.gov/download/the-credit-card-competition-act-of-2023_-one-pager

keting targeted to their large number of low-risk, long-tenure, high-spending cardholders that generate interchange revenue. By not sharing information, large incumbent lenders, that potentially hold market power from informational rents, may be expected to be making it more difficult for competitors to successfully target their profitable customers by raising their competitor's costs of acquiring new consumers. Our empirical findings that the lowest residual types are the ones sharing information are consistent with a different domain: investors sharing information. Goldstein et al. (2025)'s theory explains that less informed investors non-reciprocally share information with more informed investors, as this reduces the latter's price impact as it can trade less aggressively on its own information, whereas the more informed investors do not share information as this would reduce their private informational advantage and profits.

5.3 Effect of Trended Data on New Account Openings

The analysis in the previous section suggests that Trended Data was expected to be a competitive threat to profitable incumbent lenders by enabling their competitors to targeted marketing to acquire profitable consumers. In this section, we provide quantitative evidence that is consistent with this hypothesis, and the qualitative evidence from industry materials discussed in Section 3.2. Section 5.3.1 explains our research design, based on heterogeneous consumer exposure to Trended Data, and Section 5.3.2 shows our results.

5.3.1 Research Design

We identify the causal effect of Trended Data on new credit card openings by creating a measure of heterogeneous consumer exposure to this innovation that we define in Equation 9. A consumer, i, holds credit cards, $c \in \{1, ..., C\}$, with a furnisher, F_c, and each card has a statement balance, $b_{i,c}$. Our exposure measure, $EXPT_i$, shows the proportion of a consumer's 2012 credit card statement balances held with lenders who share actual payments information. The higher the share of balances held with furnishers where actual payments information is shared in 2012, the more information is revealed to the market on a consumer's behavioral type (e.g., spending and revolving behaviors) by Trended Data's introduction.

$$EXPT_i \equiv \frac{\sum_c 1\{F_c \in \text{Sharers}\} \times b_{i,c}}{\sum_c b_{i,c}} \tag{9}$$

We use this exposure measure to estimate the difference-in-differences with varying treatment intensity equation shown in Equation 10. We estimate an OLS regression with consumer fixed effects (γ_i) and year-quarter fixed effects (γ_t) and cluster standard errors at the consumer-level. Our parameters of interest are δ_τ which are the coefficients on the interaction between our exposure measure ($EXPT_i$) and year-quarter indicators (D_τ) after τ quarters, where our omitted group ($\tau = -1$) is Q4 2012, before Trended Data's launch. Our outcome of interest ($Y_{i,t}$) is whether the individual has any new credit card openings – an indicator of the competition for consumers whose information was about to be revealed. We use quarterly data from Q1 2011 to Q4 2016, and restrict to a balanced panel of 0.51 million consumers with $0 < EXPT_i < 1$ who hold two cards with positive balances in 2012. Figure 7 Panel A shows that the CDF of the exposure measure is smooth with mean 49.5% and median 49.2%.

$$Y_{i,t} = \sum_{\tau \neq -1} \delta_\tau \Big(D_\tau \times EXPT_i \Big) + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{10}$$

5.3.2 Empirical Results

Figure 7 Panel B shows that consumers who are more exposed to Trended Data are more likely to open new credit card accounts for up to two years after introduction, with Table 6 showing a subset of these coefficients after 0, 5, 10, and 15 quarters. In 2013 Q4, we estimate that going from 0% to 100% exposure causes a 0.42 percentage point (95% C.I. 0.22 to 0.61) increase in credit card openings. This increase is statistically and economically significant, it represents a 13% increase relative to the Q4 2012 mean of 3.22% of consumers opening any new credit cards in a quarter. We interpret this average increase as indicating the potential of innovations, such as Trended Data, to reduce adverse selection and to increase credit access. After two years, as the breakdown in information sharing occurs, the effect dissipates to be insignificant from zero. Internet Appendix Figure E9 shows the robustness of this result to studying consumers with three cards.

5.4 Discussion

Given our results, we now discuss whether the breakdown of information sharing is best understood as a coordination failure – a natural explanation for the phenomenon we document. If this were the result of a prisoner's dilemma, the only Nash equilibrium would be for all lenders not to share information, even if all lenders would be better off by coordinating to share information. In games with multiple equilibria, there may be a coordination failure leading lenders to a pareto-dominated equilibrium, even though lenders would be better off coordinating to reach an alternative equilibrium.

The breakdown in information sharing does not appear to simply be a coordination failure. An industry body – the Consumer Data Industry Association (CDIA) – exists to facilitate and coordinate information sharing, but was unable to prevent the breakdown, or undo it in the ten years since, even as it successfully coordinates the sharing of many other types of information. Further evidence comes from the fact that at least two large credit card lenders have never shared this information, even before Trended Data (Consumer Financial Protection Bureau, 2023). When Consumer Financial Protection Bureau (2023) asked lenders for their rationale for not sharing information, one of these said "Not required to do so. Not consistently furnished nor adequately studied", and another said "Not required, furnishing is voluntary. Doesn't believe cost of furnishing is worth it". The responses of these lenders to the CFPB are consistent with lenders considering that the costs of sharing information outweigh the benefits.

Our empirical evidence indicates that lenders have heterogeneous payoffs from sharing information and Trended Data made not sharing information a dominant strategy for some incumbent lenders. Trended Data changed the payoffs of sharing information: it reduces a lender's private information and increases the risk of its profitable customers being targeted by existing competitors or new entrants. The only lenders willing to share information are those with few high-quality accounts at risk of being targeted. Such lenders may either be indifferent about sharing, or they may share information for other reasons: incentivizing positive consumer behaviors, technological benefits, not-profit motives, or a lack of sophistication. One lender who previously shared information suggested in its response to the Consumer Financial Protection Bureau (2023) that *if* data access was reciprocal ("give-to-get") it may share actual payments information. However, discussions with industry participants reveal that the credit reporting agencies are unwilling to set these terms as it would limit their ability to sell this product to a broader market, and would set a precedent that may affect their other products. Even if the agencies did introduce reciprocity, there is no indication that *all* large lenders would start sharing actual payments information. Overall, we view the lack of information sharing as a financial friction that maintains the status quo levels of both information asymmetry and competition in the market.

6 Effects of Mandating Information Sharing: Evidence from Credit Card Limits

The previous sections of this paper document the breakdown of voluntary information sharing and examine the reasons and implications of this event. The natural next question is: What would happen if lenders were mandated to share information? As actual payments information has not been mandated, we instead learn from a prior historical event: the Federal Trade Commission (FTC) mandating lenders to share information on credit card limits.[18] Not sharing credit limit information is generally expected to make consumers *appear* more utilized and higher risk than they are. Such strategic withholding of information benefits the incumbent lender, as it makes it harder for consumers to get competitive credit offers from other lenders. In the 1990s, credit limit information was rarely shared, but a combination of regulatory pressure and credit reporting agencies threatening to limit access to any of their data unless lenders shared credit limit information resulted in most, but not all, lenders sharing this information by the early 2000s (Hunt, 2005). From discussions with those in the industry, we understand it would not be credible for credit reporting agencies to threaten to shut off credit card lenders' access to credit reporting data unless they share actual payments information. The FTC mandate results in the remaining lenders also sharing this information.

6.1 Research Design

We produce causal estimates of the effects of mandating sharing of credit card limit information using a difference-in-differences design with varying treatment intensity. In November 2011 ($t = 0$), we observe that a small number of lenders start sharing credit card limit information on consumers' credit card accounts, shown in Internet Appendix Figure F1. Credit card limits are important information as 20% to 30% of a consumer's credit score is determined by their credit utilization: credit card statement balance divided by credit card limit. We exploit an institutional detail of how credit card utilization is calculated when credit limits are not shared to produce a consumer-level measure of heterogeneous exposure to lenders' decision to start sharing information. This is a new source of variation in US credit reports, where prior literature focuses on the removal of negative information, such as bankruptcy flags, as reviewed in Gibbs et al. (2024). We use variation in how much new information is revealed to the market. We do so by calculat-

[18] www.ftc.gov/news-events/news/press-releases/2009/07/agencies-issue-final-rules-accuracy-credit-report-information-allowing-direct-disputes

ing consumer-level (i) heterogeneous exposure, $EXPL_i = \frac{r_i - h_i}{r_i}$, as the difference between the *revealed* credit limits, $r_i \equiv \sum_c r_{i,c}$, and the credit limits that could be *inferred* based on the already observable information, $h_i \equiv \sum_c h_{i,c}$, where c is each card held by a consumer. For each of a consumer's credit cards, we calculate $r_{i,c}$ as the credit limits shared in October 2011 and, for accounts not sharing this information, we use the November 2011 credit limit. When a credit card account does not share the credit limit information, utilization is calculated using the highest balance historically recorded on the account, which is then used as an input into credit scores (Hunt, 2005). Therefore, for each credit card, we calculate $h_{i,c}$ as the credit limits shared in October 2011 and, for accounts not sharing this information, we use the highest balance historically recorded on the account in October 2011. We then aggregate these card-level calculations to produce a consumer-level exposure measure, $EXPL_i$. See Internet Appendix F for additional details.

Figure 8 Panel A shows that the distribution of our exposure measure is smooth with a mean of 17% and median of 14%. A higher exposure value means that a consumer's credit limits are higher than historical data shared would indicate. In such cases, revealing a consumer's credit card limit information is expected to lower their utilization, increase their credit scores, and increase their credit access. This approach is conceptually similar to Liberman et al. (2019) and Foley et al. (2022), which estimate predicted probabilities of default, with and without information in Chilean credit reporting data.

We use this exposure measure to estimate the difference-in-differences with varying treatment intensity equation specified in Equation 11. We estimate an OLS regression on a balanced panel of 1.09 million consumers with fixed effects for consumer (γ_i) and year-quarter (γ_t). Our parameters of interest are δ_τ, which are the coefficients on the interaction between our exposure measure, $EXPL_i$, and year-quarter indicators, D_τ, after τ quarters, where the omitted group is the quarter before information revelation (August 2011 to October 2011). Standard errors are clustered at the consumer-level.

$$Y_{i,t} = \sum_{\tau \neq \text{-}1} \delta_\tau \Big(D_\tau \times EXPL_i \Big) + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{11}$$

6.2 Empirical Results

Table 7 shows that moving from 0% to 100% exposure significantly increases credit scores by 22.3 points relative to baseline mean of 776, with a 95% C.I. of 22.4 to 22.9 points, after one quarter. Figure 8 Panel B shows that this effect is persistent, but declines in magnitude over time, reducing to 13.8 points after seven quarters, with a 95% C.I. of 13.4 to 14.3 points, shown in Internet Appendix Table F1. How does this information revelation affect credit access and competition? We evaluate this by considering the role of "inside" and "outside" lenders with different information sets (e.g., Petersen and Rajan, 1995; Sutherland, 2018). The inside lenders are the lenders who start sharing credit limit information, but already observe their own consumers' credit limits and credit risks. The outside lenders are those that already share credit limit information and potentially update their priors on consumers given the information newly shared by the inside lenders.

The release of information immediately and persistently increases competition, as measured by switching from inside to outside lenders. Table 7 shows that moving from 0% to 100% exposure significantly *decreases* the number of new credit cards opened with inside lenders by 52% after one quarter, point estimate -0.024 cards and a 95% C.I. of -0.029 to -0.019 cards. For the outside lenders, at the same time, we find a 46% *increase* in the number of new credit cards opened, with a point estimate of 0.064 cards and a 95% C.I. of 0.058 to 0.071 cards. These effects combine to cause a significant 22% overall *increase* in the total (i.e., the sum across inside and outside lenders) number of new cards opened after one quarter, with an estimate of 0.040 cards and a 95% C.I. of 0.032 to 0.048 cards. Figure 8 Panel C shows some attenuation in these results over time, however, they remain persistent and significant after seven quarters, shown in Internet Appendix Table F1. Results are similar when measuring any new credit cards opened in a quarter, shown in Table 7 and Internet Appendix Table F1.

Table 7 shows that moving from 0% to 100% exposure similarly significantly decreases the value of new credit card limits opened with inside lenders after one quarter by 74%, with a point estimate of $-\$507$ and a 95% C.I. of $-\$605$ to $-\$408$. It increases the value of new credit card limits with an outside lender after one quarter by 58%, with a point estimate of \$778 and a 95% C.I. of \$691 to \$864. This leads to an overall increase in total value of new credit card limits, combined across inside and outside lenders, after one quarter of \$268 with a 95% C.I. of \$67 to \$137. Figure 8 Panel D shows that these effects on the value of credit limits for newly-opened credit cards for inside and outside lenders persist over time, however, the effect on total new limits attenuates to become insignificant from zero after seven quarters, see Internet Appendix Table F1 for estimates.

We interpret our results as showing that the potential threat of increased competition explains why particular lenders are reluctant to voluntarily share information, and as demonstrating that mandating information sharing can increase competition. This is important since prior work documents how the credit card market has persistently high returns on assets in excess of adjusting for risk (Internet Appendix B, and also see Ausubel, 1991; Agarwal et al., 2015, 2018; Grodzicki, 2023; Herkenhoff and Raveendranathan, 2024; Nelson, 2025; Herkenhoff and Morelli, 2024). Therefore, increasing competition to reduce mark-ups from informational rents may be a desirable policy.

7 Conclusions

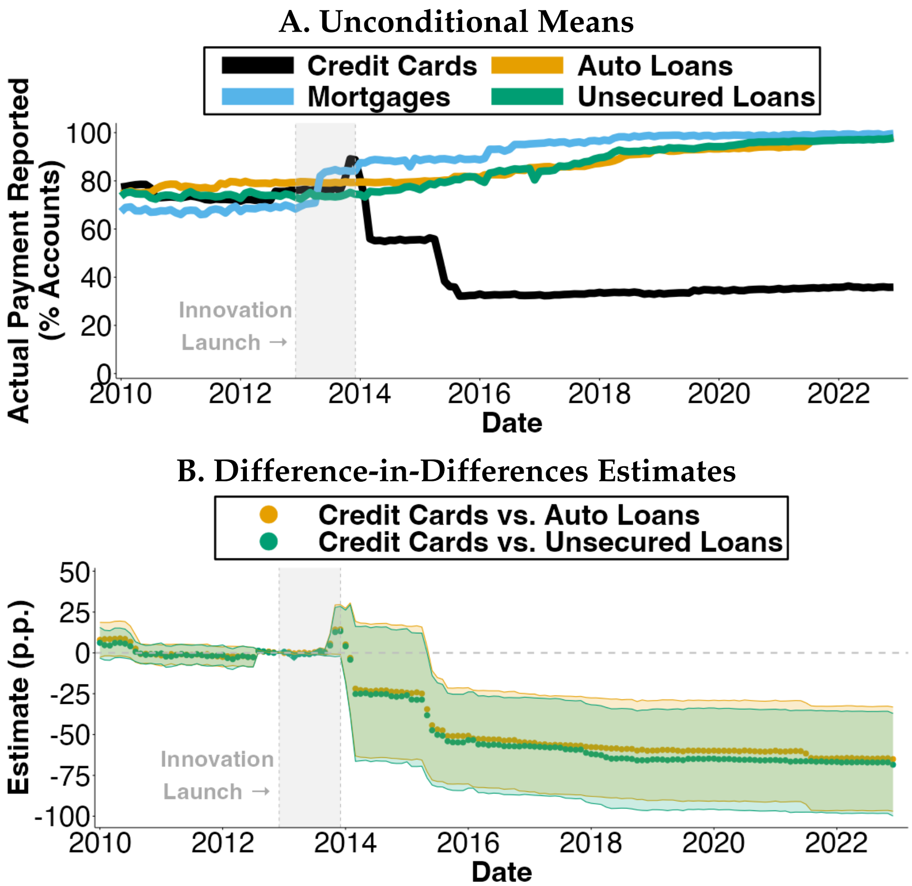
We document the fragility of information sharing. We show how, in the economically important and developed US credit card market, an innovation enabling the targeting of profitable customers pushes incumbent lenders beyond their limit to voluntarily share information. This results in 165 million US consumers missing information about their credit card actual payments on their consumer credit reports. This missing information leads to mis-measurement of credit card behaviors and limits the ability of lenders to predict profitability and compete for profitable customers. Our results are consistent with the innovation being a particular competitive threat to more profitable incumbent lenders. We then show how mandating sharing credit card information can increase competition. Together, this evidence supports a policy to mandate information sharing, similar to one that the UK consumer financial protection regulator is considering for the UK market.[19]

In the process of understanding information sharing, we reveal two new insights for understanding the credit card market: the importance of spending and card tenure. We show that lenders face a second source of uncertainty separate from default risk: the amount of credit card spending generating interchange revenue. We document a new fact. Credit card tenure varies across and within the credit score distribution. This fact indicates a need to evaluate credit card profitability over a card's lifetime, and these two insights together help to understand how high-credit-score consumers can generate enough interchange net of rewards over their card's lifetime to be profitable to lend to. Credit card lenders therefore want to acquire high-spending, long-tenure credit cardholders.

[19] www.fca.org.uk/publications/market-studies/ms19-1-credit-information-market-study

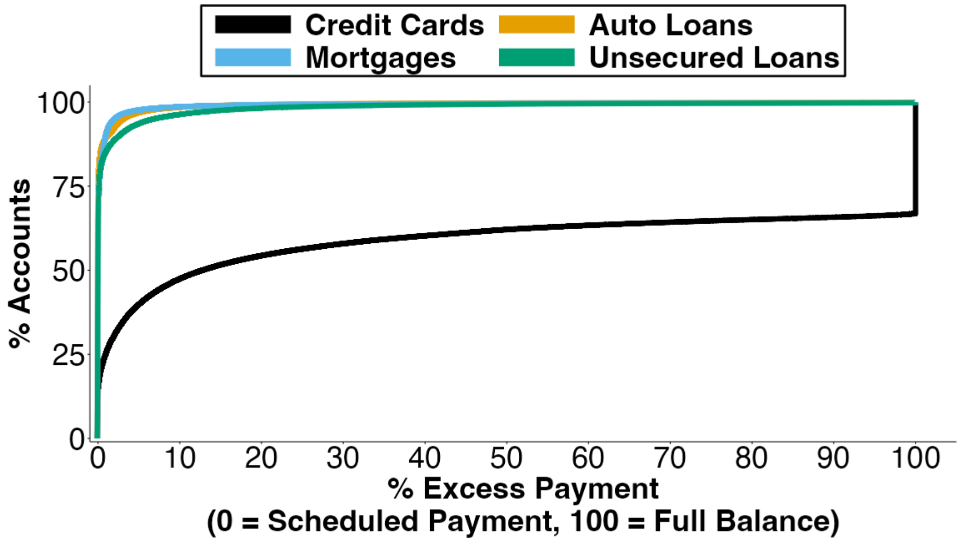
8 Figures and Tables

Figure 1: Coverage of Actual Payments Information in Consumer Credit Reports



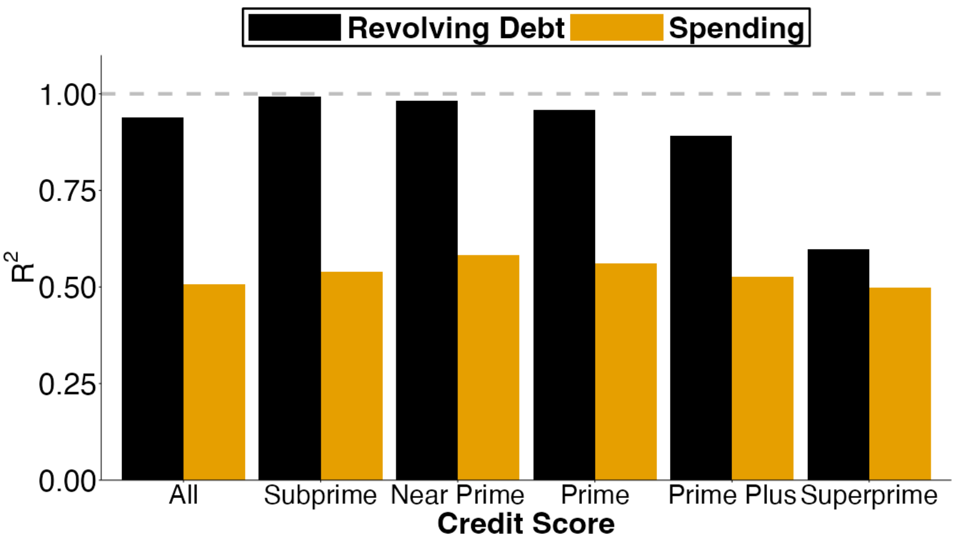
Notes: BTCCP data. 2013 is shaded in gray to denote the period when Trended Data was launched. Panel A shows, for each consumer credit product, the fraction of accounts in consumer credit reports sharing actual payment amounts. In the numerator of this calculation, accounts with actual payment amounts that are non-zero and non-missing are given a value of one, and accounts with zero or missing are given a value of zero. Both the numerator and the denominator of this calculation restricts to open accounts with non-zero balances and which have been updated in the last year. Panel B shows difference-in-differences estimates of sharing actual payment amounts for credit cards relative to auto loans (orange) and unsecured loans (green). Estimates are from OLS regression specified in Equation 1 on aggregated data with one observation per furnisher credit product per year-month (with weights applied to the number of accounts) with fixed effects for credit products and year month and December 2012 is the omitted group from the interaction between credit card indicator and year month indicator. Data is a balanced panel 2010 to 2022. 95% confidence intervals from standard errors clustered at the furnisher level. Panel B estimated for 6,068 (Credit Cards vs. Auto Loans) and 6,279 (Credit Cards vs. Unsecured Loans) furnisher portfolios.

Figure 2: CDF of Actual Payments in Excess of Scheduled Payments



Notes: BTCCP data, December 2012. CDF of non-zero and non-missing actual payments by credit product for non-delinquent accounts with non-zero balances, non-zero and non-missing scheduled payment amounts, balances greater than scheduled payment amounts, and actual payments greater than or equal to the scheduled payment amount. X-axis shows excess payment calculated as actual payments less scheduled payment amount as a percentage of balance less scheduled payment amount. In this calculation where payments are equal to or in excess of the full balance they are assigned a value of 100%. For credit cards, scheduled payment amount is the minimum amount due and balance is statement balance. For installment loans, scheduled payment amount is the regular payment due, and the balance is the amount outstanding. The scheduled payment amount for mortgages can include taxes and other fees, such as to homeowner associations. $N = 27.31$ *million credit card accounts,* $N = 5.37$ *million auto loan accounts,* $N = 5.56$ *million mortgage accounts, and* $N = 0.72$ *million unsecured loan accounts.*

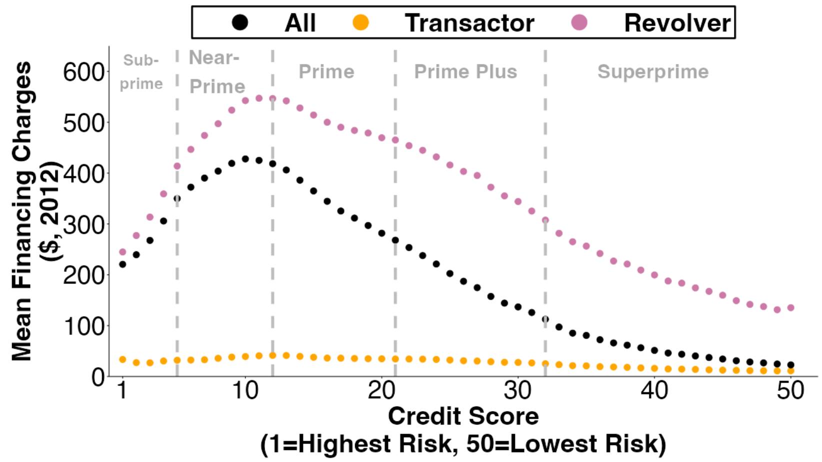
Figure 3: Measuring Credit Card Behaviors Without Actual Payments (AP) Information



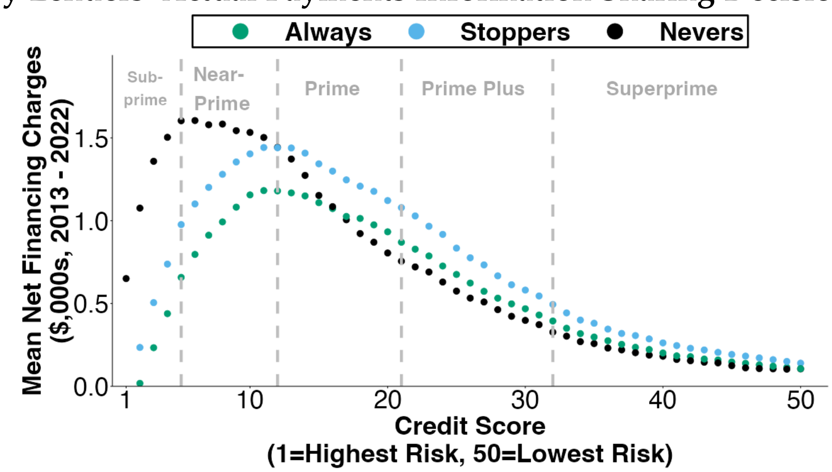
Notes: BTCCP data. R^2 from Equation 4 explaining credit card behaviors. Outcomes are Revolving Debt in black and Spending in orange. Account-level data measured in December 2013. The model performance can be evaluated relative to a benchmark $R^2 = 1$ (horizontal gray dashed line) if actual payments information is observed. OLS regressions include current statement balance, previous statement balance, the difference between these conditional on being positive, and indicators for non-zero current and previous statement balances. Each bar shows results of a separate regression for all credit scores ($N = 4.006$ million credit card accounts), and each credit score segment: subprime (the lowest credit score group with scores between 300 and 600, $N = 0.546$ million), near prime (scores between 601 and 660, $N = 0.561$ million), prime (scores between 661 and 720, $N = 0.697$ million), prime plus (scores between 721 and 780, $N = 0.819$ million), and superprime (the highest credit score group with scores of at least 781, $N = 1.384$ million).

Figure 4: Estimated Credit Card Financing Charges

A. Financing Charges (2012) By Credit Card Behaviors

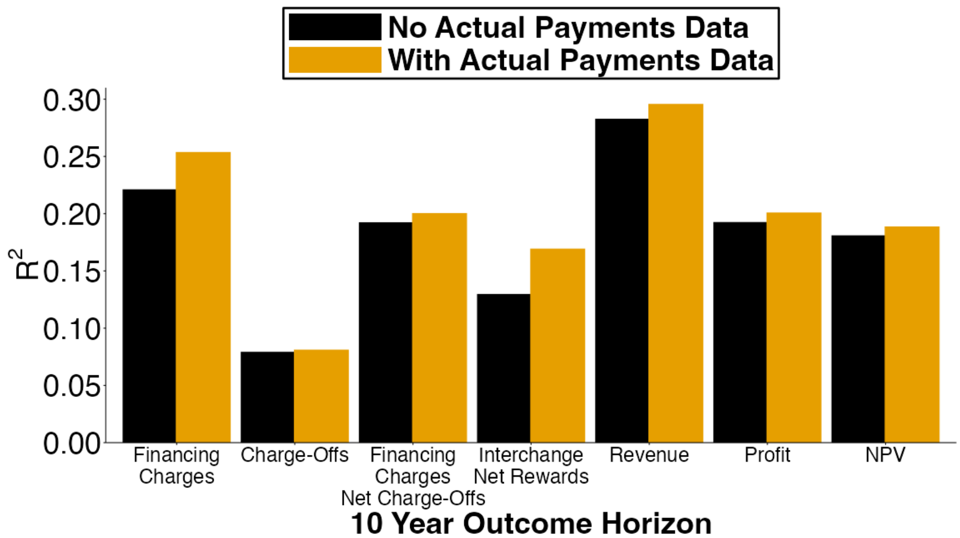


B. Financing Charges Net of Charge-Offs (2013 - 2022) By Lenders' Actual Payments Information Sharing Decisions



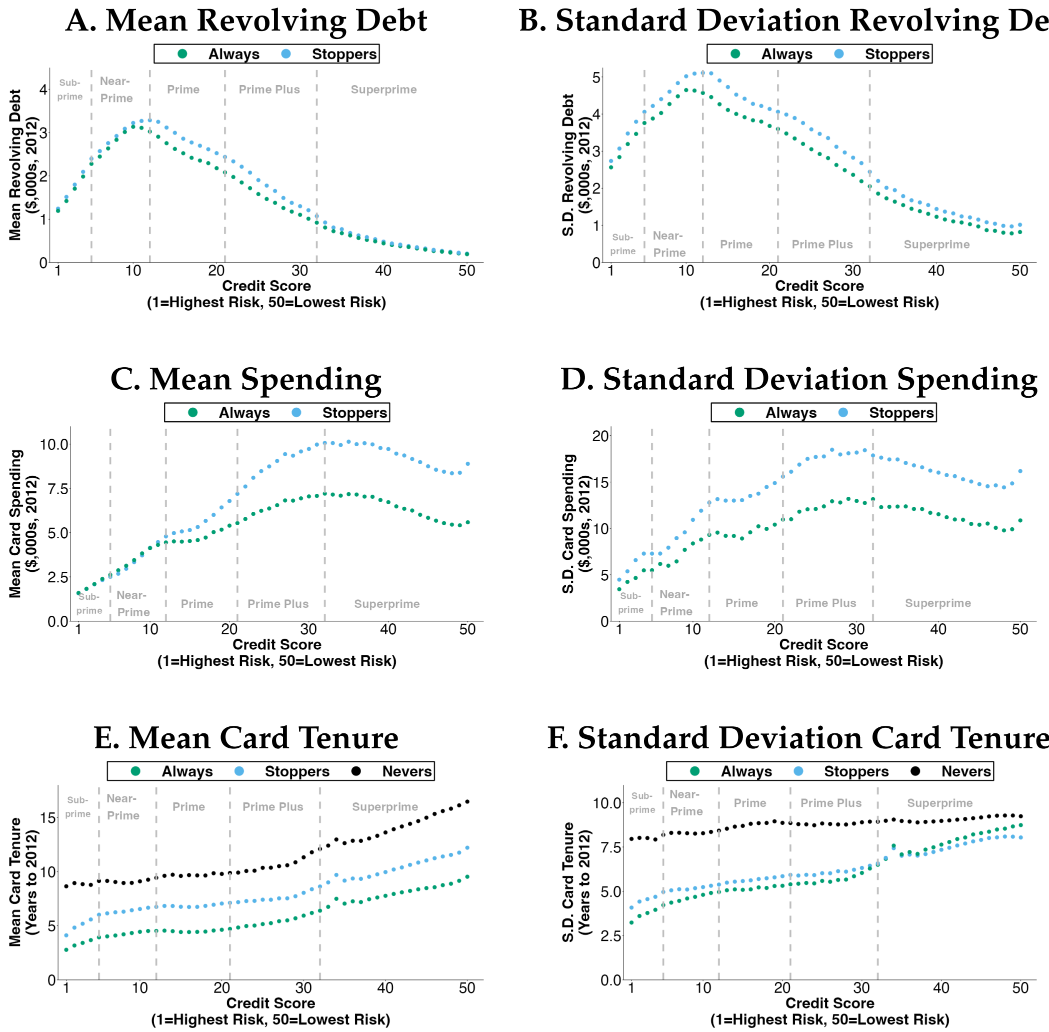
Notes: BTCCP data. Figures shows mean estimates conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Financing charges (the sum of interest and fees) are estimated as described in section D.1. Panel A shows 2012 financing charges splitting by their 2012 card behaviors: transactors pay their statement balance in full, and revolvers pay less than their full statement balance. Panel B shows financing charges accumulated across 2013 to 2022 net of charge-offs over this same time horizon with results split by classifying credit card furnishers by their sharing of information on actual payments information as described in paper section 2.2 and Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure 5: Marginal Value of Actual Payments (AP) Information for Predicting Lifetime Profits and its Components



Notes: BTCCP data. Figures use data to December 2012 to predict account-level credit card profitability where predictive performance is measured by out-of-sample R^2. Results are shown, in black, without actual payments information and, in green, with actual payments information. Figure shows predictions of lifetime profits and its components over a ten year horizon. Out-of-sample predictions from $N = 3.135$ million $Always$ credit card accounts. Data sample as described in paper section 2.2 and Table 5 notes.

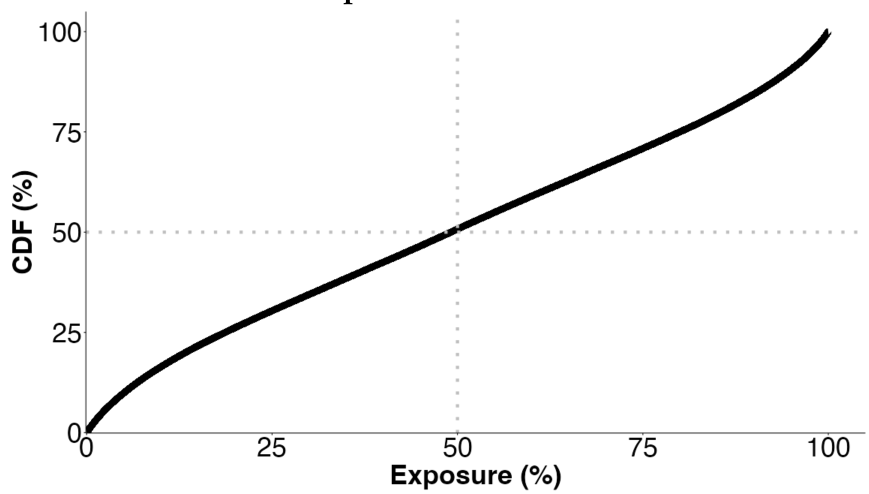
Figure 6: Credit Card Behaviors Conditional on Credit Score By Lenders' Actual Payments Information Sharing Decisions



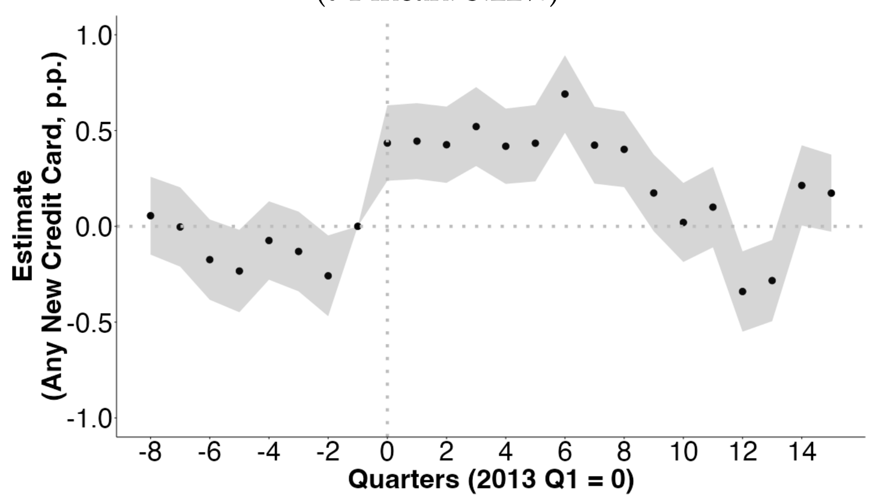
Notes: BTCCP data. Figure shows credit card behaviors (y-axis) conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A, C, and E shows means and Panels B, D, and F show standard deviations. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 and Table 5 notes. Revolving Debt and Spending is unobserved for $Nevers$ as these do not share actual payments information required to calculate such behaviors. Credit card revolving debt is 2012 mean value and credit card spending is total 2012 value and both are shown in thousands of dollars. Card tenure is shown in years to 2012. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure 7: Effects of Trended Data on Any New Credit Card Account Opening

A. CDF Exposure to Trended Data

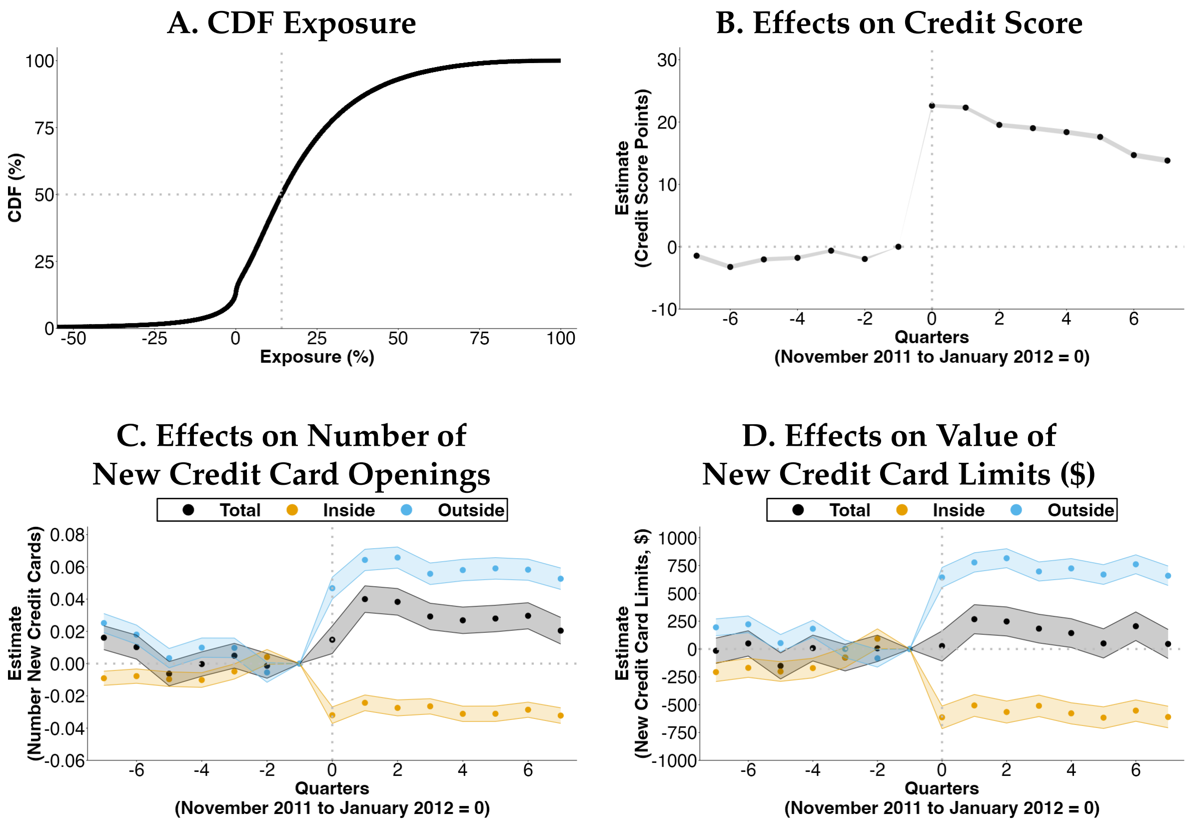


B. Estimates of Effects of Trended Data on Any New Credit Card Opening
(t-1 mean: 3.22%)



Notes: BTCCP data. Panel A shows CDF of exposure. Exposure is (pre-Trended Data) share of 2012 credit card balances held with furnishers who share actual payments information. Panel B shows difference-in-differences with varying intensity estimates in percentage points (p.p.) where the outcome is any new credit card account openings in a quarter. Difference-in-differences estimates are from balanced panel of 0.51 million consumers, with observations Q1 2011 to Q4 2016, with $0 < EXPT_i < 1$*, and holding two cards both of which have positive balances in 2012. Estimates from OLS regression specified in Equation 10 with consumer and calendar year-quarter fixed effects and interaction term between exposure and calendar year-quarter where Q4 2012 is omitted category and standard errors are clustered at the consumer level with 95% Confidence intervals displayed.*

Figure 8: Effects of Mandating Credit Card Limit Information Sharing



Notes: BTCCP data. Panel A shows CDF of our exposure measure, defined as $EXPL_i = \frac{r_i - h_i}{r_i}$*, the difference between a consumers' revealed credit limit (*r_i*) and their inferred credit limit prior to new credit limit information being revealed (*h_i*). Panel B, C, and D show difference-in-differences with varying intensity estimates where the outcome is (B) credit score, (C) number of new credit card account openings in a quarter, and (D) value of of new credit card limits opened in a quarter ($). Panels C and D show outcomes by different colors when calculated separately for inside and outside lenders, total (the sum of outcomes across inside and outside lenders). See Table 7 for baseline means for each of these outcomes. Data is a balanced panel of 1.09 million consumers. Results are estimating OLS regression specified in Equation 11 with consumer and calendar year-quarter fixed effects and interaction term between exposure (*$EXPL_i$*) and calendar year-quarter indicators (*D_τ*), where the quarter before information revelation is the omitted category. Standard errors are clustered at the consumer level with 95% Confidence intervals displayed.*

Table 1: Difference-in-Differences Estimates of Actual Payments Information Sharing for Credit Cards Relative to (1) Auto Loans and (2) Unsecured Loans

	(1)	**(2)**
$D_{Dec\ 2015} \times CRED_p$	-0.5093	-0.5483
	(0.1501)	(0.1504)
$D_{Dec\ 2022} \times CRED_p$	-0.6507	-0.6847
	(0.1629)	(0.1602)

Notes: BTCCP data. Table shows difference-in-differences estimates of sharing actual payments information for credit cards relative to auto loans (column 1) and unsecured loans (column 2). The outcome is the fraction of accounts in consumer credit reports with a payment reported in the last month where there are are non-zero and non-missing actual payments. Estimates are from OLS regression specified in Equation 1 on aggregated data with one observation per lender credit product per year-month (with weights applied to the number of accounts) with fixed effects for credit products and year month and December 2012 is the omitted group from the interaction between credit card indicator and year month indicator. Data is a balanced panel 2010 to 2022. Standard errors are shown in parenthesis are clustered at the furnisher level. Table shows two estimates – the interaction between credit card indicator and (a) the December 2015 indicator; (b) the December 2022 indicator. Columns (1) and (2) estimated for 6,068 (Credit Cards vs. Auto Loans) and 6,279 (Credit Cards vs. Unsecured Loans) furnisher portfolios respectively.

Table 2: Marginal Value of Actual Payments Information for Predicting Lifetime Profitability on Credit Cards, Auto Loans, and Unsecured Loans

	R^2 **Predicting Lifetime Profitability**		
Model	**Credit Cards**	**Auto Loans**	**Unsecured Loans**
1. Baseline	0.1919	0.1925	0.3508
2. Baseline + Actual Payments	0.2003	0.1928	0.3511
Percentage Change in R^2	+4.4%	+0.2%	+0.0%

Notes: BTCCP data. Table uses data to December 2012 to predict lifetime profitability (to 2022) on credit cards, auto loans, and unsecured loans where performance is measured by out-of-sample R^2. Predictive performance is shown in a baseline compared to with adding actual payments information as predictors. $N = 3.135$ million credit card accounts, $N = 3.212$ million auto loan accounts, and $N = 0.436$ million unsecured loan accounts for lenders sharing actual payments information.

Table 3: Marginal Value of Actual Payments Information for Predicting Credit Card Profitability as Measured by R^2

Outcome	Horizon (Years)	Baseline (R^2)	Baseline + Actual Payments (R^2)	Percentage Change
Interchange Net of Rewards	1	0.4006	0.6139	+53.2%
	10	0.1291	0.1687	+30.7%
Financing Charges Net of Charge-Offs	1	0.2174	0.2219	+0.2%
	10	0.1917	0.1997	+4.2%
Net Present Value	10	0.1803	0.1881	+4.3%

Notes: BTCCP data. Table uses data to December 2012 to predict components of credit card profitability. Table shows out-of-sample R^2. Predictive performance is shown in a baseline compared to with adding actual payments information as predictors. Predictions from $N = 3.134$ million $Always$ accounts (tested out-of-sample on $N = 3.135$ million accounts).

Table 4: Marginal Value of Actual Payments Information for Predicting Credit Card Profitability as Measured by Top-Ranked Predicted Portfolio Values

Outcome	Horizon (Years)	Baseline ($)	Baseline + Actual Payments ($)	Percentage Change
Interchange Net of Rewards	1	$171	+$42	+24%
	10	$473	+$63	+13%
Financing Charges Net of Charge-Offs	1	$1,391	+$14	+1%
	10	$4,959	+$140	+3%
Profit	10	$5,157	+$143	+2.8%
Net Present Value	10	$4,772	+$131	+2.7%

Notes: BTCCP data. Table uses data to December 2012 to predict components of credit card profitability. Table shows out-of-sample portfolio values from sorting predictions of each outcome and choosing top-ranked 100,000 accounts. Baseline shows mean account value ranking accounts by predictions without using actual payments information as predictors. Change with actual payments shows the percentage change in portfolio value relative to this baseline when instead ranking by predictions using actual payments information as predictors. Predictions from $N = 3.134$ million $Always$ accounts (tested out-of-sample on $N = 3.135$ million accounts).

Table 5: Credit Card Portfolio Means and Standard Deviations, Residual of Credit Score, By Lenders' Actual Payments Information Sharing Decisions

	Always	Stoppers	Nevers
Tenure	71.0	97.6	136.5
(S.D.)	(73.8)	(75.5)	(106.0)
Credit Limit	8,902.2	9,793.4	9,757.4
(S.D.)	(6,687.7)	(8,484.3)	(9,238.6)
Statement Balance	2,004.3	2,294.8	2,576.5
(S.D.)	(3,405.9)	(3,842.4)	(4,130.1)
Proxy Spending	2,486.2	2,800.2	3,286.2
(S.D.)	(4,036.2)	(4,987.6)	(6,998.7)
Financing Charges	130.1	235.0	156.5
(S.D.)	(351.3)	(534.5)	(440.8)
Revolving Debt	1,538.1	1,707.6	N/A
(S.D.)	(3,047.7)	(3,413.6)	
Spending	5,228.3	6,896.5	N/A
(S.D.)	(10,257.8)	(14,345.9)	
Accounts (%)	18.2%	47.2%	31.5%
Statement Balances (%)	16.6%	46.8%	35.3%

Notes: BTCCP data. Table shows means (standard deviations in parenthesis) for residual credit card portfolio characteristics as of December 2012 where data is residual on values of credit score from an OLS regression and then the population means are added back to the means to ease interpretation. Card tenure is measured in months. Proxy spending is measured by change in balances conditional on being non-negative. Financing charges are estimated based on our methodology described in section D.1. Results are split by classifying credit card furnishers by their sharing of actual payments information. The last two rows show the shares of the number of outstanding credit card accounts and the value of outstanding credit card statement balances by each type of furnisher. These data exclude furnishers who do not have at least 10,000 active credit cards (i.e. their portfolio is representative of least 100,000) in both December 2012 and in December 2015. ***Always*** *are furnishers sharing actual payment amounts information for more than 75% of their active credit cards in both December 2012 and December 2015.* ***Stoppers*** *are furnishers sharing actual payments amounts information for more than 75% of their active credit cards in December 2012 and for less than 10% in December 2015.* ***Nevers*** *are furnishers sharing actual payment amounts information for less than 10% of their active credit cards in both December 2012 and December 2015. The remaining furnishers are* ***Others*** *excluded from the table: these are 3.1% of accounts and 1.3% of statement balances.*

Table 6: Effects of Trended Data on Any New Credit Card Account Opening (Percentage Points)

	Estimate (S.E.)
$D_0 \times EXPT_i$	0.4347
	(0.1004)
$D_5 \times EXPT_i$	0.4338
	(0.1015)
$D_{10} \times EXPT_i$	0.0202
	(0.1052)
$D_{15} \times EXPT_i$	0.1732
	(0.1026)
Baseline Mean	3.22

Notes: BTCCP data. Each row of table shows results from separate regressions with the same specifications but varying outcomes. Exposure ($EXPT_i$) is (pre-Trended Data) share of 2012 credit card balances held with furnishers who share actual payments information. Table show Difference-in-differences estimates are from balanced panel of 0.51 million consumers, with observations Q1 2011 to Q4 2016, with $0 < EXPT_i < 1$, and holding two cards both of which have positive balances in 2012. Results are estimating the OLS regression specified in Equation 10 with consumer and calendar year-quarter fixed effects, and interaction term between exposure ($EXPL_i$) and calendar year-quarter indicators (D_τ), where Q4 2012 is the the omitted category. Table shows δ_τ estimates from the interactions between the exposure measure and the indicator after $\tau \in \{0, 5, 10, 15\}$ quarters after treatment ($D_\tau \times EXPL_i$). Standard errors are shown in parenthesis from clustering at the consumer level. Estimates and standard errors are in percentage points, with the baseline mean of 3.22%.

Table 7: One Quarter Effects of Mandating Credit Card Limit Information Sharing

	Estimate (S.E.)	Baseline Mean
Credit Score	22.32 (0.16)	776.04
Any New Credit Card Opening: Inside	−0.0089 (0.0008)	0.0208
Any New Credit Card Opening: Outside	0.0313 (0.0014)	0.0723
Any New Credit Card	0.0221 (0.0015)	0.0897
Number New Credit Cards Opening: Inside	−0.0243 (0.0025)	0.0462
Number New Credit Cards Opening: Outside	0.0643 (0.0034)	0.1394
Total Number New Credit Cards	0.0340 (0.0042)	0.1856
Value New Credit Card Limits: Inside	−$506.6 ($50.1)	$680.4
Value New Credit Card Limits: Outside	$777.7 ($44.2)	$1,346.2
Total Value New Credit Card Limits	$267.7 ($66.6)	$2,025.5

Notes: BTCCP data. Each row of table shows results from separate regressions with the same specifications but varying outcomes. Our exposure measure, defined as $EXPL_i = \frac{r_i - h_i}{r_i}$, the difference between a consumers' revealed credit limit (r_i) and their inferred credit limit prior to new credit limit information being revealed (h_i). Table show difference-in-differences with varying intensity estimates. Data is a balanced panel of 1.09 million consumers. Results are estimating OLS regression specified in Equation 11 with consumer and calendar year-quarter fixed effects and interaction term between exposure ($EXPL_i$) and calendar year-quarter indicators (D_τ), where the quarter before information revelation is the omitted category (August 2011 to October 2011). Table shows δ_1 estimates from the interaction between the exposure measure and the indicator one quarter after treatment ($D_1 \times EXPL_i$), See Internet Appendix Table 7 for δ_7 estimates, and for Figure 8 for δ_τ estimates over time. Standard errors are shown in parenthesis from clustering at the consumer level.

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9 Internet Appendix accompanying *"Unraveling Information Sharing in Consumer Credit Markets"*

Contents:

A. Credit Reporting Legal Requirements

B. Credit Card Industry Statistics

C. Actual Payments Information

D. Consumer Credit Profitability

E. Selection in Credit Card Lenders Sharing Information

F. Mandating Sharing Credit Card Limit Information

A Credit Reporting Legal Requirements

This appendix shows credit reporting legal requirements based on relevant public extracts (from Title 12 Chapter X CFR §1022.40-43 and Appendix E to Part 1022) of the Fair Credit Reporting Act (FCRA) amended by the Fair and Accurate Credit Transactions (FACT) Act.

"PART 660 — DUTIES OF FURNISHERS OF INFORMATION TO CONSUMER REPORTING AGENCIES

§660.2 Definitions.

For purposes of this part and Appendix A of this part, the following definitions apply:

(a) ***Accuracy*** means that information that a furnisher provides to a consumer reporting agency about an account or other relationship with the consumer correctly:

(1) Reflects the terms of and liability for the account or other relationship;

(2) Reflects the consumer's performance and other conduct with respect to the account or other relationship; and

(3) Identifies the appropriate consumer.

(e) ***Integrity*** means that information that a furnisher provides to a consumer reporting agency about an account or other relationship with the consumer:

(1) Is substantiated by the furnisher's records at the time it is furnished;

(2) Is furnished in a form and manner that is designed to minimize the likelihood that the information may be incorrectly reflected in a consumer report; and

(3) Includes the information in the furnisher's possession about the account or other relationship that the Commission has:

(i) Determined that the absence of which would likely be materially misleading in evaluating a consumer's creditworthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living; and

(ii) Listed in section I.(b)(2)(iii) of Appendix A of this part.

§660.3 Reasonable policies and procedures concerning the accuracy and integrity of furnished information.

(b) **Guidelines.** Each furnisher must consider the guidelines in Appendix A of this part in developing its policies and procedures required by this section, and incorporate those guidelines that are appropriate.

Appendix A to Part 660—Interagency Guidelines Concerning the Accuracy and Integrity of Information Furnished to Consumer Reporting Agencies

The Commission encourages voluntary furnishing of information to consumer reporting agencies. Section 660.3 of this part requires each furnisher to establish and implement reasonable written policies and procedures concerning the accuracy and integrity of the information it furnishes to consumer reporting agencies. Under § 660.3(b), a furnisher must consider the guidelines set forth below in developing its policies and procedures. In establishing these policies and procedures, a furnisher may include any of its existing policies and procedures that are relevant and appropriate. Section 660.3(c) requires each furnisher to review its policies and procedures periodically and update them as necessary to ensure their continued effectiveness.

I. Nature, Scope, and Objectives of Policies and Procedures

(a) **Nature and Scope.** Section 660.3(a) of this part requires that a furnisher's policies and procedures be appropriate to the nature, size, complexity, and scope of the furnisher's activities. In developing its policies and procedures, a furnisher should consider, for example:

  (1) The types of business activities in which the furnisher engages;

  (2) The nature and frequency of the information the furnisher provides to consumer reporting agencies; and

  (3) The technology used by the furnisher to furnish information to consumer reporting agencies.

(b) **Objectives.** A furnisher's policies and procedures should be reasonably designed to promote the following objectives:

  (1) To furnish information about accounts or other relationships with a consumer that is accurate, such that the furnished information:

    (i) Identifies the appropriate consumer;

    (ii) Reflects the terms of and liability for those accounts or other relationships; and

    (iii) Reflects the consumer's performance and other conduct with respect to the account or other relationship;

  (2) To furnish information about accounts or other relationships with a consumer that has integrity, such that the furnished information:

(i) Is substantiated by the furnisher's records at the time it is furnished;

(ii) Is furnished in a form and manner that is designed to minimize the likelihood that the information may be incorrectly reflected in a consumer report; thus, the furnished information should:

(A) Include appropriate identifying information about the consumer to whom it pertains; and

(B) Be furnished in a standardized and clearly understandable form and manner and with a date specifying the time period to which the information pertains; and

(iii) Includes the credit limit, if applicable and in the furnisher's possession;

(3) To conduct reasonable investigations of consumer disputes and take appropriate actions based on the outcome of such investigations; and

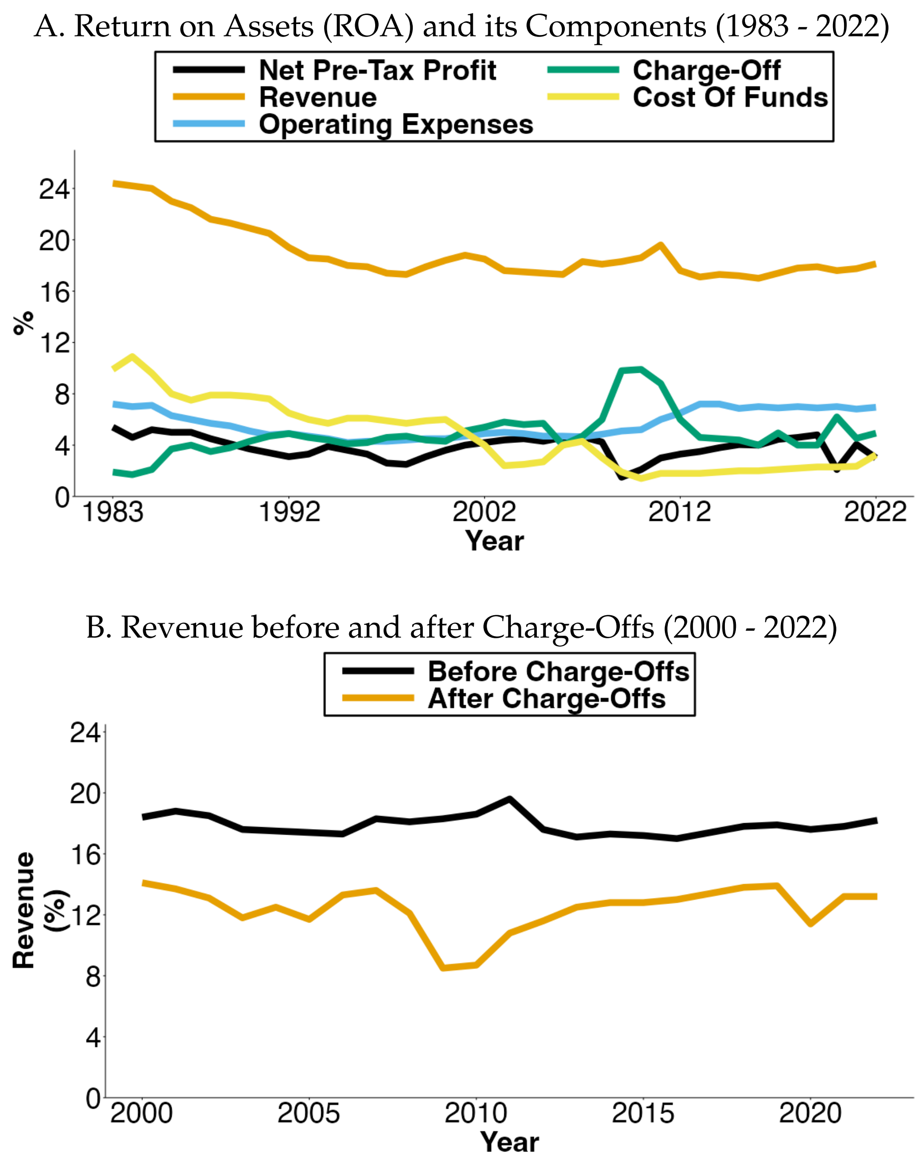
(4) To update the information it furnishes as necessary to reflect the current status of the consumer's account or other relationship, including, for example:

(i) Any transfer of an account (e.g., by sale or assignment for collection) to a third party; and

(ii) Any cure of the consumer's failure to abide by the terms of the account or other relationship."

B Credit Card Industry Statistics

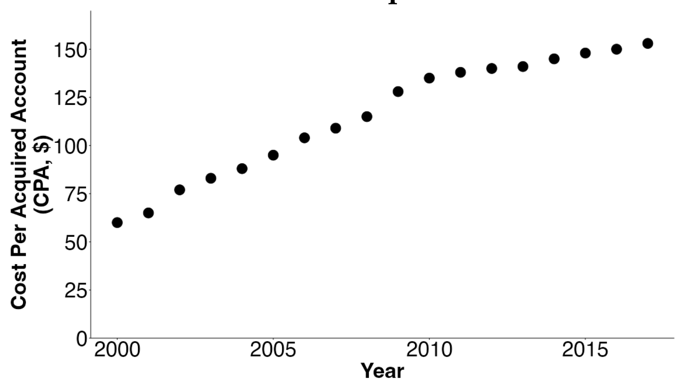
Figure B1: Credit Card Profitability



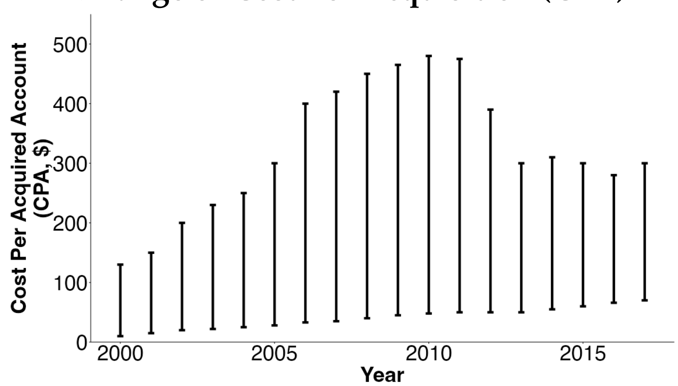
Notes: R.K.Hammer data. Percentages of credit card revolving balances. In Panel B revenues are total revenues (interest, consumer fees, interchange fees) before and after charge-offs as an industry measure of risk adjusting revenue.

Figure B2: Costs of Acquiring New Credit Card Account (2000 - 2017)

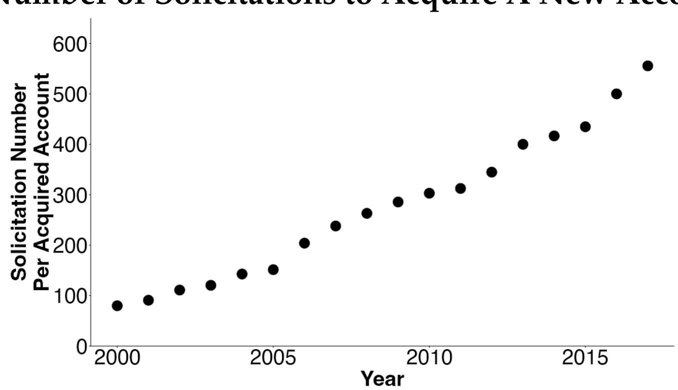
A. Mean Cost Per Acquisition (CPA)



B. Range of Cost Per Acquisition (CPA)



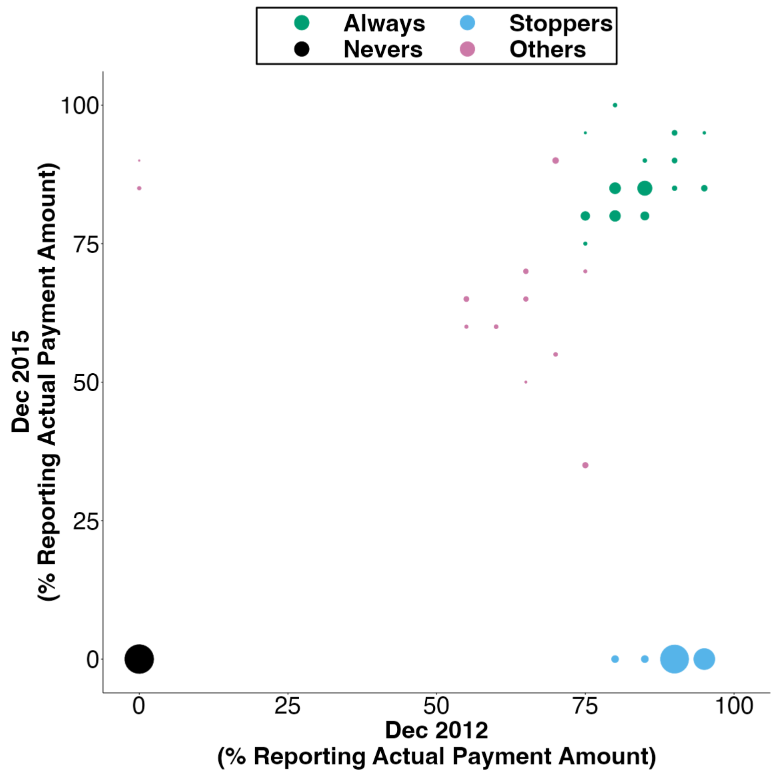
C. Number of Solicitations to Acquire A New Account



Notes: R.K.Hammer data. These are costs for acquiring new credit card accounts including marketing and underwriting costs.

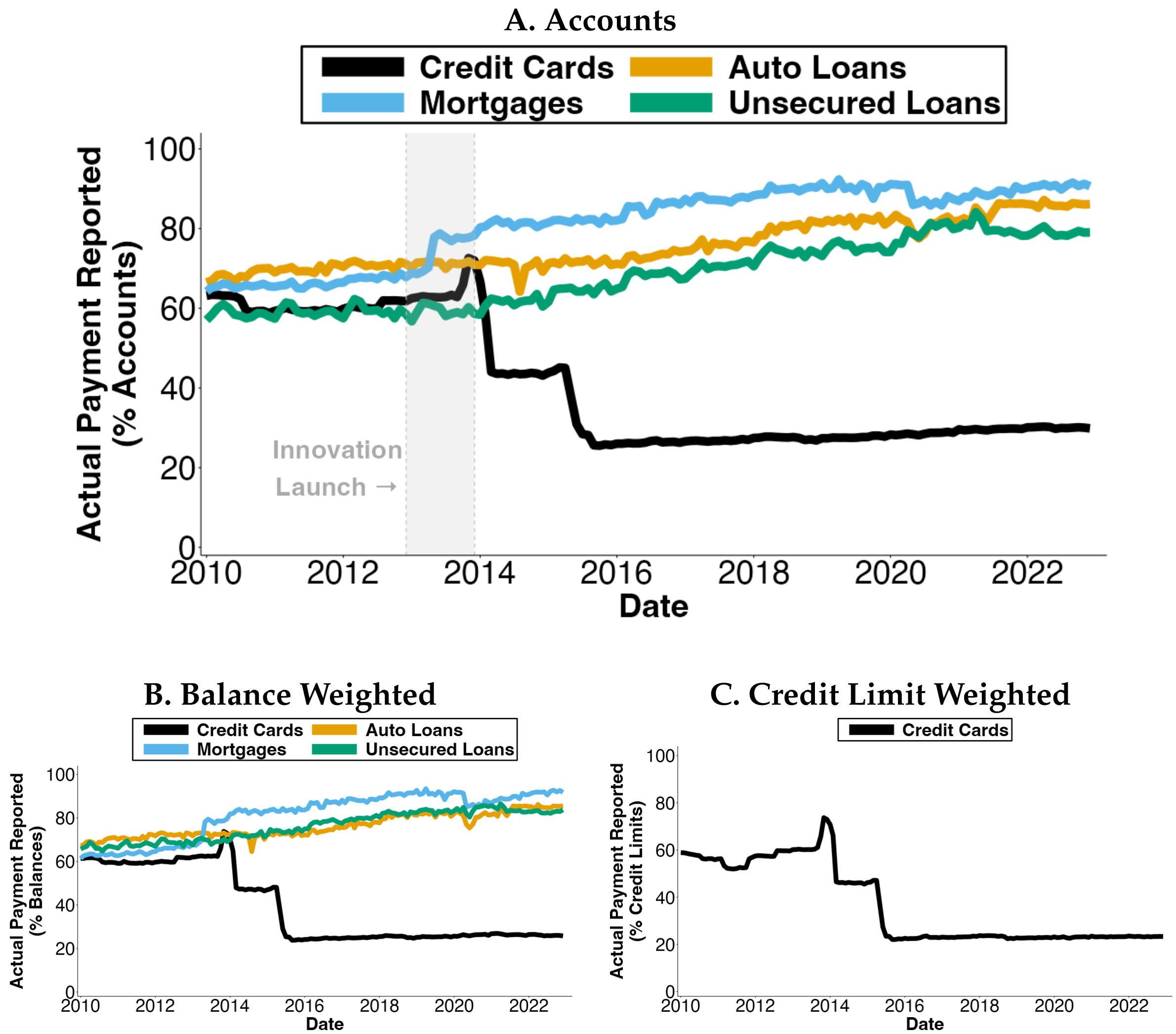
C Actual Payments Information

Figure C1: Actual Payments Information Sharing in Consumer Credit Reports by Furnishers from 2012 to 2015



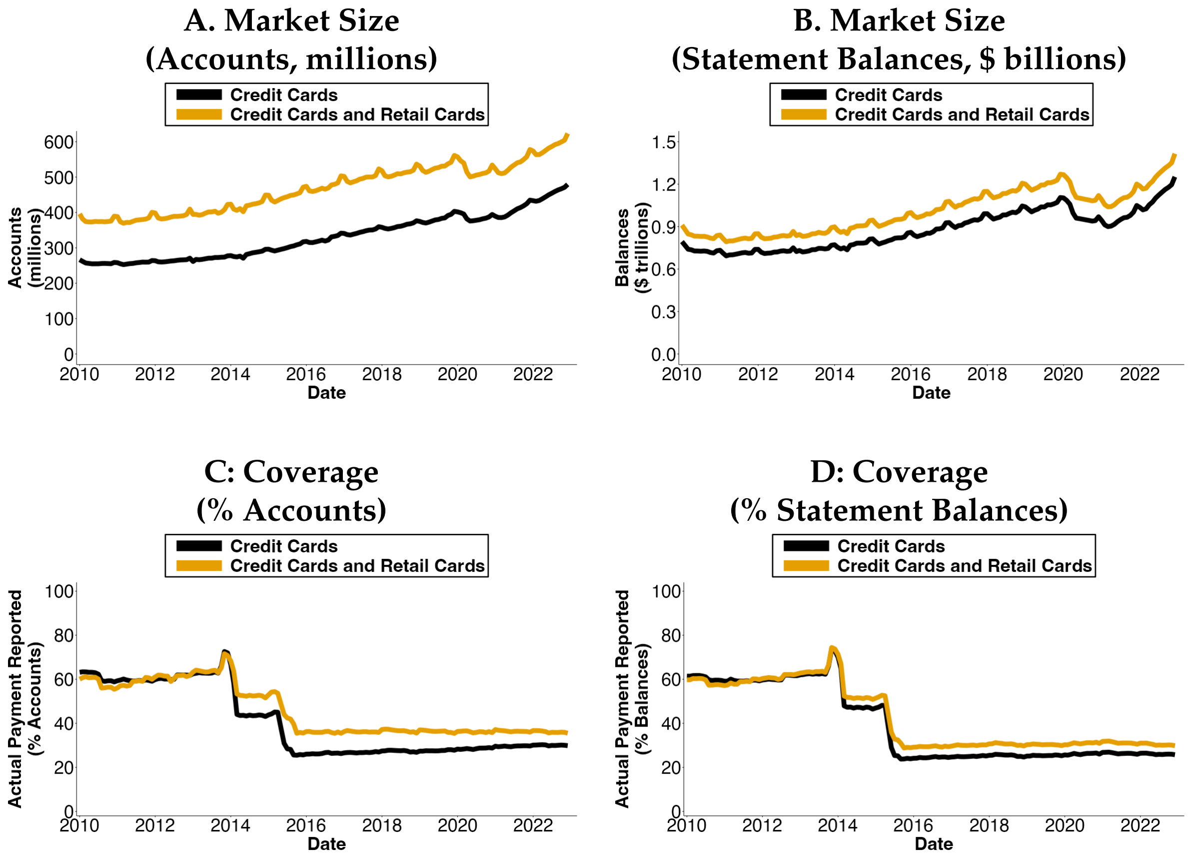
Notes: BTCCP data. This figure shows, for each consumer credit product, the fraction of accounts in consumer credit reporting data reporting actual payments in December 2012 (x-axis) and December 2015 (y-axis). In the numerator of this calculation, accounts with actual payments that are non-zero and non-missing are given a value of one, and accounts with zero or missing are given a value of zero. Both the numerator and the denominator of this calculation restricts to accounts with positive balances and that are not delinquent. Results are split by classifying credit card furnisher by their sharing of actual payments as described in paper section 2.2 or Table 5 notes. Dots are shown in five percentage point intervals aggregating furnishers in these intervals. Sizes of dots correspond to the total number of credit card accounts 2012 to 2015. This excludes furnishers that have fewer than 10,000 active credit cards (i.e., their portfolio is representative of fewer than 100,000 cards) in both December 2012 and in December 2015.

Figure C2: Robustness of Coverage of Actual Payments Information in Consumer Credit Reports



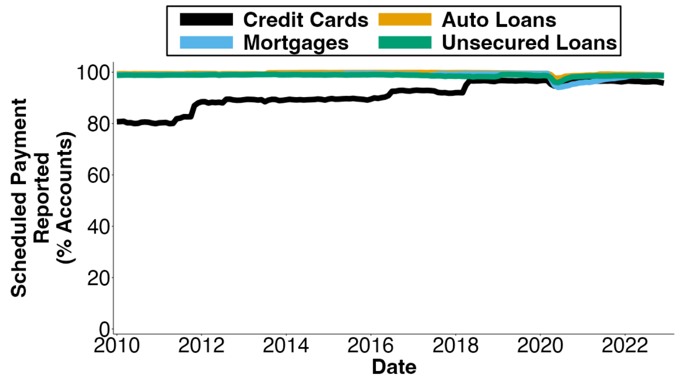
Notes: BTCCP data. In Panel A 2013 is shaded in gray to denote the period when Trended Data was launched. This figure shows the fractions of consumer credit reports with actual payments information. The numerator of these calculations are the number of accounts (Panel A) / value of balances (Panel B) / value of credit limits (Panel C) for accounts with actual payments information that are non-zero and non-missing. The denominator of this calculation is the total number of accounts (Panel A) / value of balances (Panel B) / value of credit limits (Panel C). Both the numerator and the denominator of these calculations restrict to open accounts with non-zero balances and which have been updated in the last year.

Figure C3: Robustness of Coverage of Actual Payments Information in Consumer Credit Reports to Inclusion of Retail Cards



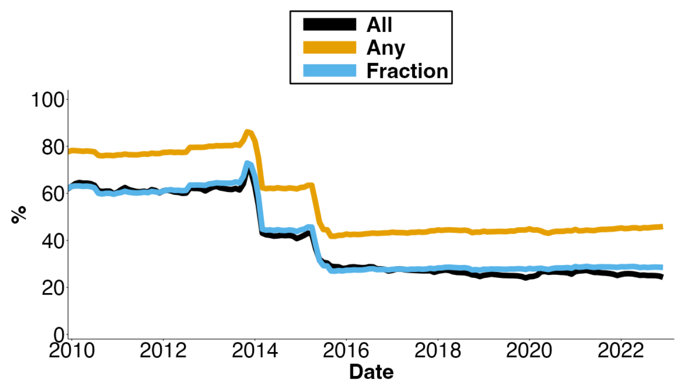
Notes: BTCCP data. These panels compare (general purpose) credit cards to combining these with retail (private label) credit cards. Panels A and B show how market sizes are affected as measured by number of accounts (Panel A) and outstanding statement balances (Panel B). Panels C and D show the fraction of accounts (Panel C) / balances (Panel D) with actual payment amounts in consumer credit reports that are reported as non-zero and non-missing. All panels restrict to open accounts with non-zero balances and which have been updated in the last year.

Figure C4: Coverage of Scheduled Payment Amounts in Consumer Credit Reports



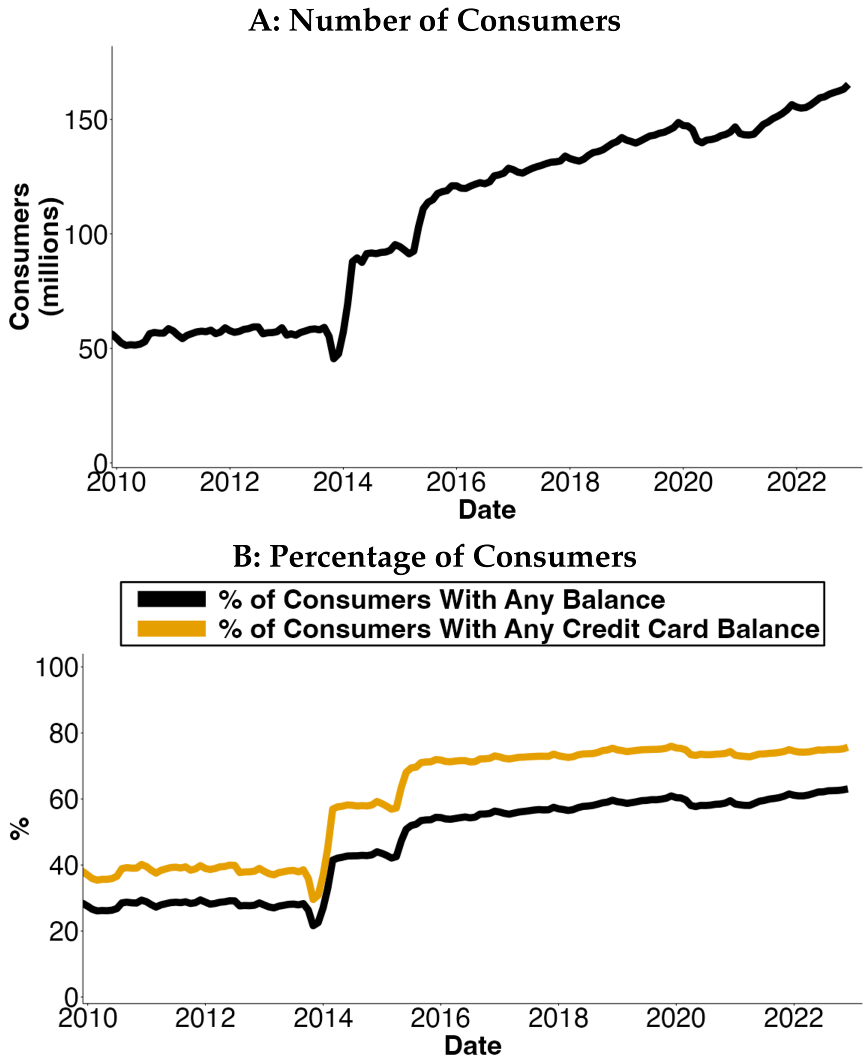
Notes: BTCCP data. Figure shows, for each consumer credit product, the fraction of accounts in consumer credit reports reporting non-zero and non-missing credit card scheduled payment amounts. These calculations restrict to open accounts with non-zero balances and which have been updated in the last year.

Figure C5: Credit Cardholders Without Credit Card Actual Payment Information in Consumer Credit Reports on: All Credit Card Accounts (black), Any Credit Card Account (orange), Fraction of Credit Card Accounts (blue)



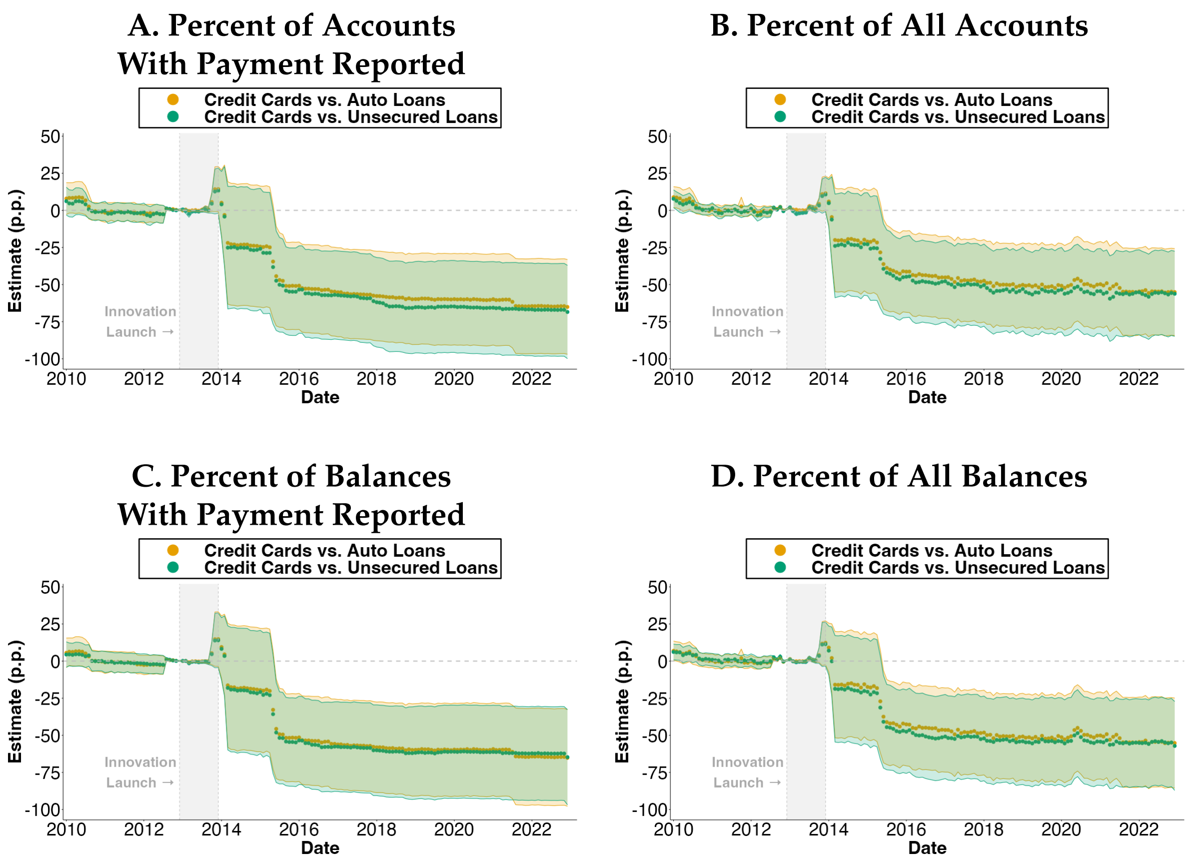
Notes: BTCCP data. The orange line shows the fraction of credit cardholders in consumer credit reports where credit card actual payments are zero or missing on at least one credit card account. The black line shows the fraction of credit cardholders in consumer credit reports where credit card actual payments are zero or missing on all their credit card accounts. The blue line shows, for credit cardholders, the mean proportion of credit cards where credit card actual payments are zero or missing. The denominator for all lines are the number of credit cardholders. The figure restricts to credit cardholders with non-zero credit card balances (which are open and which have been updated in the last year). The figure restricts to accounts which are open with non-zero balances and which have been updated in the last year.

Figure C6: Consumers without Credit Card Actual Payments Information in Consumer Credit Reports



Notes: BTCCP data. Panel A shows the number of consumers in consumer credit reports where credit card actual payments are zero or missing on at least one credit card account. Panel B shows the fraction of consumers in consumer credit reports where credit card actual payments are zero or missing on at least one account (which has a non-zero balance and which has been updated in the last year). The black line uses as a denominator all consumers with non-zero balances on any credit product. The orange line uses as a denominator consumers with non-zero credit card balances. Both panels restrict to open accounts with non-zero balances and which have been updated in the last year)

Figure C7: Difference-in-Differences Estimates of Actual Payments Information Sharing in Consumer Credit Reports for Credit Cards Relative to Auto Loans and Unsecured Loans



Notes: BTCCP data. 2013 is shaded in gray to denote the period when Trended Data was launched. Figure shows difference-in-differences estimates of sharing actual payment amounts for credit cards relative to auto loans (black, blue) and unsecured loans (orange, green). The outcome for black and orange lines is the fraction of accounts in consumer credit reports sharing actual payment amounts. The outcome for blue and green lines is the fraction of outstanding balances in consumer credit reports sharing actual payments information. Panels A and C condition on accounts where a payment date is recorded in the last month, Panels B and D show all accounts. Estimates are from OLS regression specified in Equation 1 on aggregated data with one observation per lender credit product per year-month (with weights applied to the number of accounts) with fixed effects for credit products and year month and December 2012 is the omitted group from the interaction between credit card indicator and year month indicator. Data is a balanced panel 2010 to 2022. 95% confidence intervals from standard errors clustered at the furnisher level. Panels A and C estimated for 6,068 (Credit Cards vs. Auto Loans) and 6,279 (Credit Cards vs. Unsecured Loans) furnisher portfolios. Panels B and D estimated for 6,968 (Credit Cards vs. Auto Loans) and 7,582 (Credit Cards vs. Unsecured Loans) furnisher portfolios.

Table C1: Illustrative Example of a Credit Card Account in Consumer Credit Reporting Data When Lender Reports Actual Payments Information (Months 1 to 3) and Stops Reporting Actual Payments Information (Months 4 to 6)

Month	Credit Limit	Balance	Scheduled Payment	Actual Payments	Payment Status
1	\$20,000	\$2,700	\$53	\$2,700	OK
2	\$20,000	\$2,200	\$43	\$2,700	OK
3	\$20,000	\$2,700	\$53	\$2,200	OK
4	\$20,000	\$2,300	\$46	\$0	OK
5	\$20,000	\$5,200	\$104	\$0	OK
6	\$20,000	\$8,700	\$174	\$0	OK

Notes: Yellow highlighted cells denote when lender stops reporting actual payments information. All other information remains reported. Some lenders may report actual payments as missing for all accounts, other lenders report it as \$0.

Table C2: Robustness of Difference-in-Differences Estimates of Actual Payments Information Sharing for Credit Cards Relative to (1) Auto Loans and (2) Unsecured Loans

	(1)	**(2)**
$D_{Dec\ 2015} \times CRED_p$	-0.4233	-0.4687
	(0.1436)	(0.1438)
$D_{Dec\ 2022} \times CRED_p$	-0.5624	-0.5830
	(0.1529)	(0.1501)

Notes: BTCCP data. Table shows difference-in-differences estimates of sharing actual payment amounts for credit cards relative to auto loans (column 1) and unsecured loans (column 2). The outcome is the fraction of accounts in consumer credit reports with a payment reported in the last month where there are are non-zero and non-missing actual payment amounts. Estimates are from OLS regression specified in Equation 1 on aggregated data with one observation per lender credit product per year-month (with weights applied to the number of accounts) with fixed effects for credit products and year month and December 2012 is the omitted group from the interaction between credit card indicator and year month indicator. Data is a balanced panel 2010 to 2022. Standard errors show in parenthesis are clustered at the furnisher level. Table shows two estimates – the interaction between credit card indicator and (a) the December 2015 indicator; (b) the December 2022 indicator. Columns (1) and (2) estimated for 6,968 (Credit Cards vs. Auto Loans) and 7,582 (Credit Cards vs. Unsecured Loans) furnisher portfolios respectively.

D Consumer Credit Profitability

D.1 Financing Charges

Financing Charges are defined as the sum of interest (r_t) and consumer fees (f_t). The most common consumer fees are late fees. Other consumer fees include annual card fees, over credit limit, and foreign exchange fees. Late and annual fees are typically fixed amounts that do not vary with balances. The CFPB estimates credit card financing charges to be $117 bn in 2019: 80% is interest revenue ($94.4 bn), and 20% ($23.6 bn) is consumer fees – primarily late fees ($14 billion, 11% of financing charges), annual fees (approximately $5bn) with the remainder being mainly balance transfer fees and cash advance fees.[20] Agarwal et al. (2023) estimates financing charges as $99.6 bn in 2019.

We estimate financing charges using an insight that credit card minimum payments are deterministically calculated. Each month the minimum payment amount due (m_t) on a credit card is typically determined by the formula shown in Equation 12. This is the maximum of two components. The first component is a floor dollar amount $\$\mu$. If balances are below this floor amount then balance rather than the floor is owed, however, this is not an economically important case given how low the floor amounts are. The second component is the sum of (i) a percentage $\theta\%$ of B_t: the statement balance before financing charges: $B_t \equiv b_t - r_t - f_t$, and (ii) financing charges ($r_t + f_t$). This formula does not vary with cardholder behavior and it is rare for firms to change their minimum payment formula on existing cards.

$$m_t = \max\left\{\$\mu,\ \theta\%\, B_t + r_t + f_t\right\} \tag{12}$$

Lenders use this minimum payment formula as it is the easiest way to comply with the Office of the Comptroller of the Currency's (OCC) safety and soundness regulations requiring non-negative amortization. Discussions with industry participants have told us other regulators and lenders often apply such regulations even if lenders are not supervised by the OCC. Nelson (2025) reports approximately 90 percent of outstanding credit card balances are held by 17 to 19 large and mid sized lenders who are supervised by the OCC or the CFPB. Some credit unions (credit unions in total are only approximately five percent of the market) and small, subprime lenders capitalize interest and fees and therefore our methodology may produce biased estimates for this small segment.

We find $\$\mu$ and $\theta\%$ in data through a process of manual review of the 84 furnishers we study. For each credit card furnisher, we find the values of μ and θ that matches the lower

[20] https://files.consumerfinance.gov/f/documents/cfpb_consumer-credit-card-market-report_2021.pdf; https://files.consumerfinance.gov/f/documents/cfpb_credit-card-late-fees_report_2022-03.pdf

set of the observed combinations of m_t and b_t. If we find the correct solution, transacting months should be upside errors (observing a minimum payment amount greater than our formula would predict) from fees (or trailing interest) – which are flat amounts not varying with balances – but extremely rarely downside errors (observing a minimum payment amount less than our formula would predict). These parameters can also be found algorithmically for each furnisher with similar results. In an algorithmic approach, focusing on transacting months (which requires observing actual payments information) helps to find these parameters because doing so removes observations which may contain interest in the observed minimum payment.

The values of $\$\mu$ and $\theta\%$ vary across lenders although when we examine a sample of credit card agreements in the CFPB's credit card agreement database they commonly take a small number of values.[21] The most common combination of parameters we find is $\mu^* = \$25$ and $\theta^* = 1\%$ and the most common θ^* is 1%. These are in line with the CFPB's credit card agreement database which contains details of new agreements from Q3 2011 and the CFPB's consumer credit market report which discussed minimum payment rules in 2015.[22] Given μ^* and θ^*, this produces a predicted minimum payment amount $\hat{m}_t^{interim}$ that would be due before financing charges.

$$\hat{m}_t^{interim} \equiv \max\left\{\$\mu^*,\ \theta^*\%\, b_t\right\} \tag{13}$$

Once we have worked out the minimum payment rules we can apply these across all revolving and transacting months and estimate financing charges. We make an interim estimate of financing charges $\widehat{(r_t + f_t)}^{interim}$ in Equation 14 as the difference between the minimum payment amount we observe (inclusive of financing charges) and the predicted amount. Since our earlier step applied θ to statement balances *after* including financing charges (i.e., b_t) whereas the correct formula applies it *before* financing charges (i.e., B_t), this interim financing charges estimate is slightly off when financing charges are non-zero (but will be correct when these are zero). We correct for this by subtracting our interim estimate from statement balances. Equation 15 then gives us our estimate of financing charges $\widehat{(r_t + f_t)}$ as the difference between the observed minimum payment (including financing charges) to the deterministic predicted amount we would expect without financing charges.[23] As these are estimated measures they are subject to measurement error. Our data only contains non-negative integers and therefore some error comes from

[21] www.consumerfinance.gov/credit-cards/agreements/

[22] https://files.consumerfinance.gov/f/201512_cfpb_report-the-consumer-credit-card-market.pdf

[23] This step could be iterated further but doing so makes no substantive difference because credit reporting data is reported as integers and so we stop the iteration at this stage.

rounding. How may this impact our results? If we choose the incorrect μ this only matters for very low balance account months. If we choose the incorrect θ, then this matters for high balance account months.

$$\widehat{(r_t + f_t)}^{interim} \equiv m_t - \hat{m}_t^{interim} \tag{14}$$

$$\widehat{(r_t + f_t)} \equiv m_t - \hat{m}_t^* \quad \text{, where } \hat{m}_t^* \equiv \max\left\{\$\mu^*,\ \theta^*\%\left(b_t - \widehat{(r_t + f_t)}^{interim}\right)\right\} \tag{15}$$

If one is willing to impose additional structure on the duration of borrowing, one could estimate effective interest rates, work out a card's interest rate, and decompose interest from the fee component (given the common fees such as late fees are not proportional to balances and do not occur in most months). Furthermore currently we estimate financing charges at the furnisher-level but with sufficient data an analogous method can be applied at the individual card-level to capture intra-furnisher heterogeneity in minimum payment formulae.

D.2 Charge-Offs

Charge Offs (c_t) are defined as the amount of credit card debt written-off. For profitability we need to calculate financing charges net of charge-offs. We measure charge-off using the manner of payment status: a variable consistently reported as a key input into the standardized credit scoring models firms rely on (FICO and VantageScore). We calculate the amount charged-off based on the outstanding balance in the month preceding an account reaching 120+ days past due. The month preceding is used as some furnishers report the outstanding balance as zero once they update the status of an account as being severely delinquent.[24] We discount this balance by 12.75% to allow for some delinquent debt being cured or later recovered in the collections process, this is based on CFPB estimates that 17% of delinquent loans are recovered within 4 years, with 8% recovered within first two years, and this recovery has 25% of costs.[25] An alternative approach we investigated was to use a variable that records the amount charged-off. However, this variable appears inconsistently reported across furnishers (e.g., some large portfolios have zero charge-offs which appears implausible) possibly due to different debt collections practices. The humped-shaped pattern in net financing charges is consistent with Nelson (2025) and our discussions with industry participants. Agarwal et al. (2015) shows a dip in the middle of

[24] Many severely delinquent accounts become impossible to follow as the debt may be consolidated, transferred to a different furnisher, or moved into collections, without their anonymized trade identifier.

[25] www.consumerfinance.gov/data-research/research-reports/consumer-credit-card-market-2022/

the distribution which we attribute to the particularly unusual time period their sample covering the Great Recession and their measures are point-in-time whereas ours cover most of a card's lifetime.

D.3 Interchange Net of Rewards

Interchange Net of Rewards (i_t) is interchange revenue (the amount of merchant fees generated by credit card spending transactions) less rewards expense (the amount credit card lenders pay in rewards to cardholders for spending). Unlike other sources of income that credit card lenders receive from the cardholder, interchange is received from merchants. Credit cards offer rewards to cardholders to incentivize them for spending on the card. These rewards can take a variety of forms including cashback, air miles, and points. Both interchange revenue and rewards expenses are proportional to the amount of spending on a credit card. Interchange revenue and rewards expenses are both higher for "reward" credit cards.

For the $Always$ group we observe actual payments, so we can estimate spending and interchange net of rewards for all years. For the $Stoppers$ group, we observe spending for 2013, but not in subsequent years, and therefore impute spending in years 2014 to 2022 based on the 2013 values, and impute it as zero if the card's statement balances is zero. For the $Nevers$ group actual payments are unobserved and therefore we cannot accurately impute spending.

We assume 0.5% spending is interchange net of rewards. Of course, the choice of what constant to apply to spending makes no difference when evaluating predicting interchange net of rewards, it only matters for considering the relative weight to apply to interchange net of rewards when predicting overall profits. Broadly we expect our approach is conservative for evaluating the importance of interchange net of rewards to profitability. Our approach captures the heterogeneity in the amount of spending but will underestimate the variance in net interchange that arises due to consumers holding different types of cards with different mark-ups. This assumption follows closely to Agarwal et al. (2015, 2018) who use a 2 percent interchange revenue and 1.4 percent rewards and fraud expense and Wang (2024) who assess merchant fees at 2.25 (MasterCard and VISA interchange revenue of 1.75) and rewards expense of 1.30. Mark-ups are higher on reward cards and such cards are more used by high credit score consumers (Agarwal et al., 2023). Interchange revenue in 2009 ranges from 1 to 3 percent.[26] Agarwal et al. (2023) assume 1.5 and 2.5 percent for standard and reward cards respectively.

[26] www.gao.gov/assets/gao-10-45.pdf

Agarwal et al. (2024) estimates mean rewards of $4.69 in their main sample and $13.34 per reward card ($160.08 annualized) which is close to the CFPB's estimates of $167 in annual rewards per rewards account in 2019 up from $139 in 2015. The CFPB estimates rewards expenses have increased 84% from 2015 to 2019 as more consumers hold reward cards, and also their rewards have become more generous, although more have annual fees.[27] Interchange fees in 2019 are approximately $50 bn – doubling since 2012.[28] Agarwal et al. (2023) reports the largest banks earnt $41.3 bn in interchange revenue and $34.8 bn in rewards expenses. Interchange revenue varies across issuers. One estimate uses 10-K reports for four (JP Morgan Chase, American Express, Capital One, Discover) of the six largest lenders and find rewards expenses (including partner payments) increased from $21.7 bn in 2019 to $33.1 bn in 2022 and across all six the interchange fees net of these increasing from $28.7 bn in 2018 to $31.9 bn in 2022.[29] An industry estimate from 2017 shows that American Express earnt $60.43 interchange revenue per active account compared to $34.09 for Capital One, $21.13 for JP Morgan Chase, and $17.40 for Discover.[30]

D.4 Discount Rate

For discounting lifetime profits to calculate net present value we apply a discount rate of 2% each year. This is based on R.K.Hammer and Agarwal et al. (2018), where costs of funds is estimated to be under 2%.

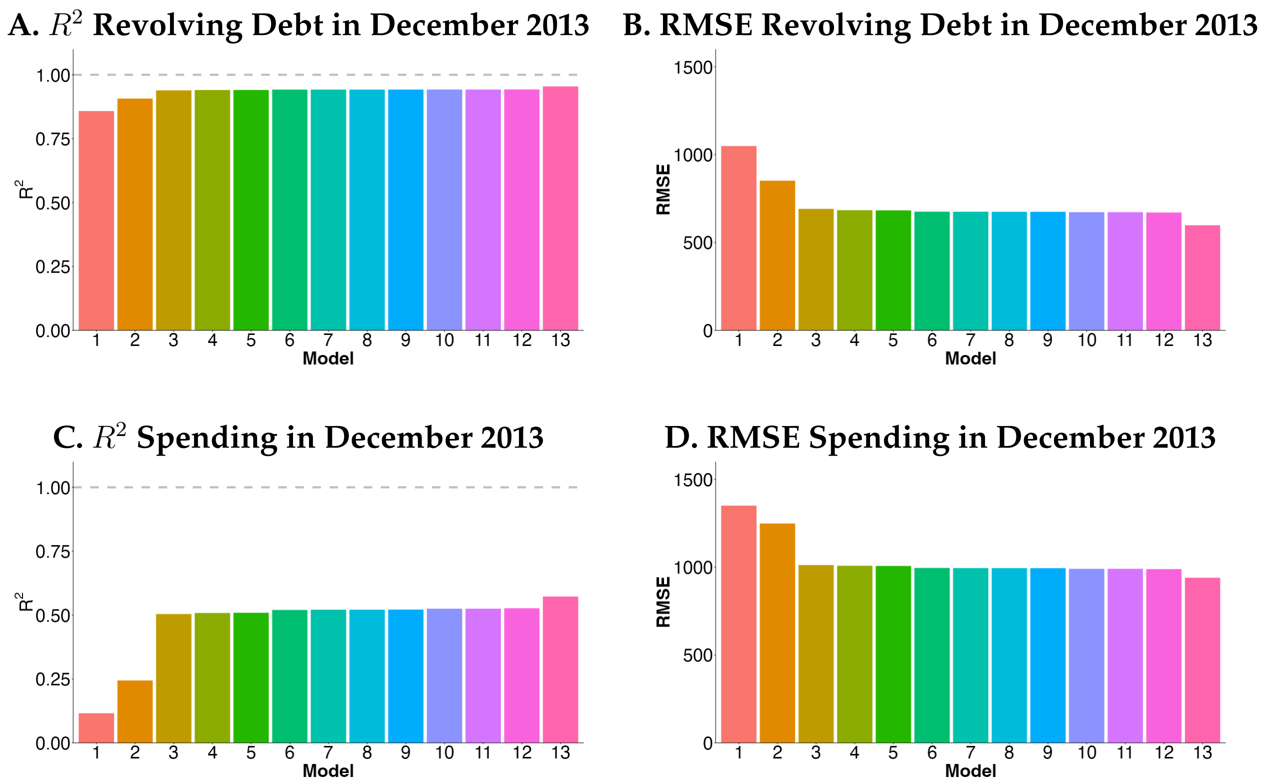
[27] https://files.consumerfinance.gov/f/documents/cfpb_consumer-credit-card-market-report_2019.pdf

[28] www.wsj.com/articles/the-credit-card-fees-merchants-hate-banks-love-and-consumers-pay-11592731800; www.fool.com/the-ascent/research/credit-card-company-earnings/

[29] www.lendingtree.com/credit-cards/study/reward-payments/

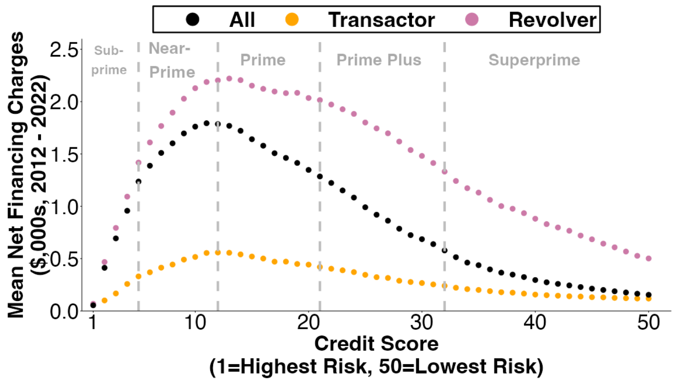
[30] www.valuepenguin.com/how-do-credit-card-companies-make-money

Figure D1: R^2 and Root Mean Squared Error (RMSE) Measurement Error in Estimating Contemporaneous Account-Level Credit Card Behaviors in December 2013



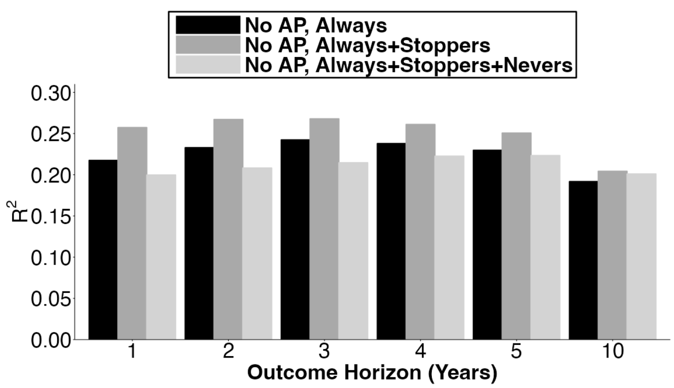
Notes: BTCCP data. Uses December 2013 data for furnishers sharing actual payments to explain contemporaneous account-level credit card behaviors. Figure shows results of OLS regressions where performance is evaluated by R^2 in Panels A and C and by root mean squared error (RMSE) in Panels B and D . Outcomes in Panels A and B are credit card revolving debt and outcomes in Panels C and D are credit card spending. Models 1 to 14 increase in complexity. Model 1 includes current balance, model 2 adds lag balance, model 3 adds change in balance conditional on greater than zero. Models 4 to 11 incrementally add in additional account-level variables: (4) credit score, (5) scheduled payment, (6) utilization and credit limit (7) tenure, (8) IRS zipcode income, (9) birth year, (10) state, (11) furnisher identifier. Model 12 adds in balance variables from other credit cards held by the consumer (Statement Balances, Changes in Statement Balances, Number, Limits, Utilizations). Model 13 includes lags for months 1 to 12, 18 and 24 for the trends of balances and changes in balances conditional on being greater than zero. $N = 4.006$ *million credit card accounts in each regression.*

Figure D2: 2012 to 2022 Financing Charges Net of Charge-Offs



Notes: BTCCP data. Figure shows mean estimates conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Financing charges are estimated as described in section D.1. Figure shows financing charges accumulated across 2012 to 2022 net of charge-offs with results split by classifying accounts by whether the revolved or transacted the majority of months in 2012. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

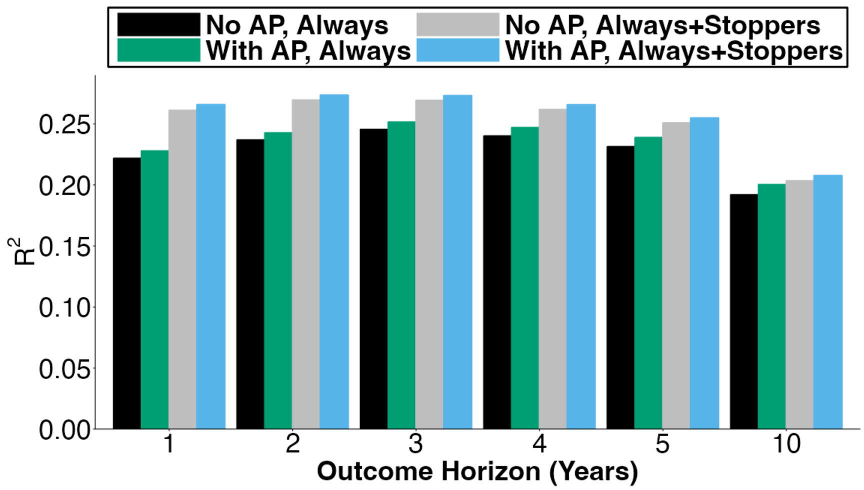
Figure D3: Predicting Financing Charges Net of Charge-Offs Without Actual Payments Information



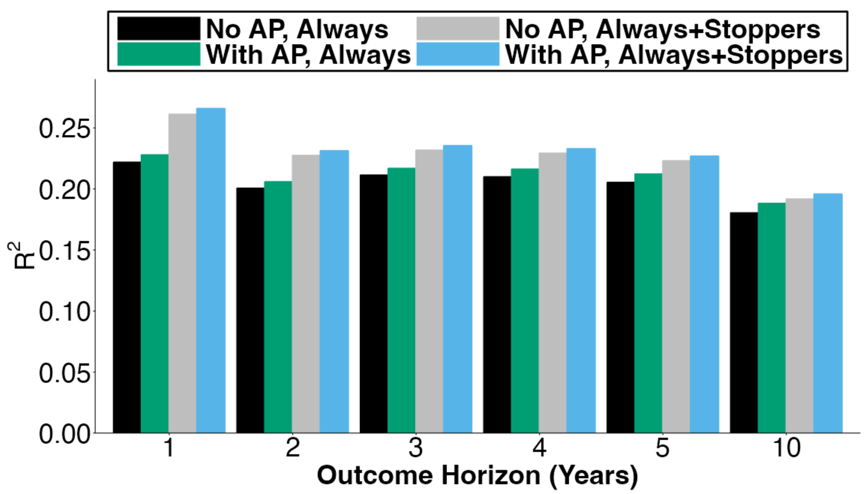
Notes: BTCCP data. Figures use data to December 2012 to predict credit card financing charges net of charge-offs at the account-level over one to ten year horizons. Predictive performance is measured by out-of-sample R^2. Predictive performance is shown without actual payments information. Performance is shown for three samples: $Always$, $Always + Stoppers$, $Always + Stoppers + Nevers$ as described in paper section 2.2 and Table 5 notes. Out-of-sample predictions from $N = 3.135$ million $Always$ credit card accounts, $N = 11.018$ million $Always + Stoppers$ credit card accounts, and $N = 14.927$ million $Always + Stoppers + Nevers$ credit card accounts.

Figure D4: Marginal Value of Actual Payments (AP) Information for Predicting Credit Card Profits over 1 to 10 Year Time Horizons

A. Profit

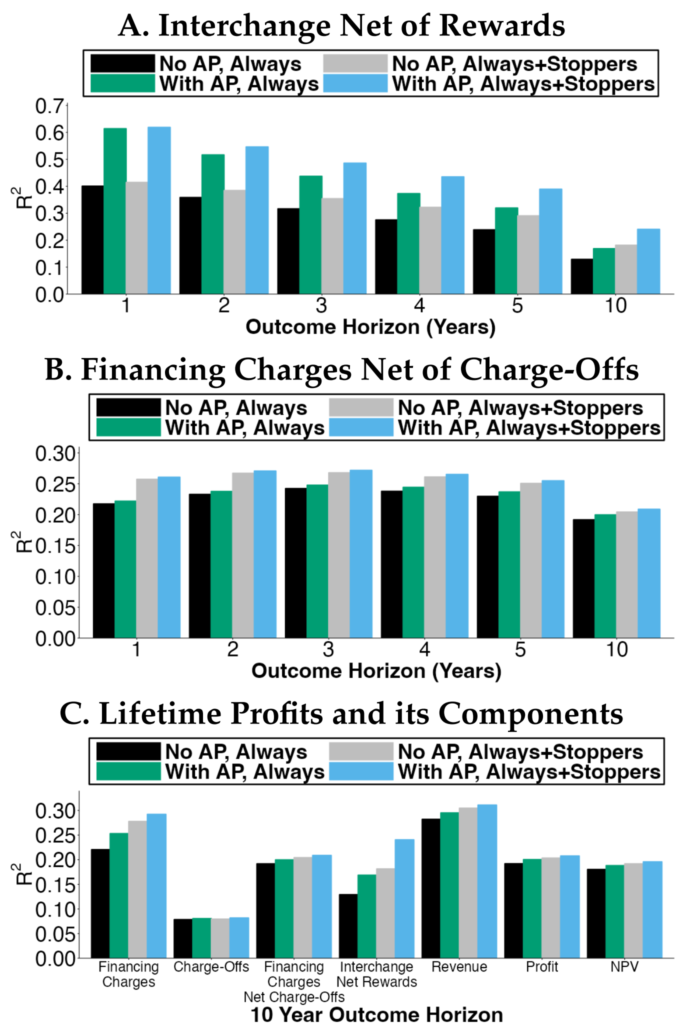


B. Net Present Value (NPV)



Notes: BTCCP data. Figures use data to December 2012 to predict account-level credit card profitability where predictive performance is measured by out-of-sample R^2. Results are shown without (black, gray) and with (green, blue) actual payments information. Performance is shown for two samples: $Always$ (black, green) and $Always + Stoppers$ (gray, blue) as described in paper section 2.2 and Table 5 notes. Spending beyond a one year horizon is imputed for $Stoppers$ but observed for $Always$. Panel A shows predictions of profit over one to ten year horizons. Panel B shows predictions of net present value (NPV) over one to ten year horizons. Out-of-sample predictions from $N = 3.135$ million $Always$ credit card accounts, and $N = 11.018$ million $Always + Stoppers$ credit card accounts.

Figure D5: Marginal Value of Actual Payments (AP) Information for Predicting (A) Interchange Net of Rewards, (B) Financing Charges Net of Charge-Offs, (C) Lifetime Profits, For Different Samples (Always, Always+Stoppers)



Notes: BTCCP data. Figures use data to December 2012 to predict account-level credit card profitability where predictive performance is measured by out-of-sample R^2. Results are shown without (black, gray) and with (green, blue) actual payments information. Performance is shown for two samples: $Always$ (black, green) and $Always + Stoppers$ (gray, blue) as described in paper section 2.2 and Table 5 notes. Spending beyond a one year horizon is imputed for $Stoppers$ but observed for $Always$. Panel A shows predictions of interchange net of rewards over one to ten year horizons. Panel B shows predictions of financing charges net of charge-offs over one to ten year horizons. Panel C shows predictions of lifetime profits and its components over a ten year horizon. Out-of-sample predictions from $N = 3.135$ million $Always$ credit card accounts, and $N = 11.018$ million $Always + Stoppers$ credit card accounts.

Table D1: Robustness of Marginal Value of Actual Payments Information for Predicting Credit Card Profitability as Measured by R^2 to Always+Stoppers Data Sample

Outcome	Horizon (Years)	Baseline (R^2)	Baseline + Actual Payments (R^2)	Percentage Change
Interchange Net of Rewards	1	0.4145	0.6188	+49.3%
	10	0.1814	0.2405	+32.6%
Financing Charges Net of Charge-Offs	1	0.2573	0.2607	+1.3%
	10	0.2042	0.2087	+2.2%
Profit	10	0.2033	0.2077	+2.1%
Net Present Value	10	0.1917	0.1958	+2.2%

Notes: BTCCP data. Table uses data to December 2012 to predict components of credit card profitability. Table shows out-of-sample R^2. Predictive performance is shown in a baseline compared to with adding actual payments information as predictors. Spending beyond a one year horizon is imputed for $Stoppers$ but observed for $Always$. Predictions from $N = 11.014$ million $Always + Stoppers$ accounts (tested out-of-sample on $N = 11.018$ million accounts).

Table D2: Robustness of Marginal Value of Actual Payments Information for Predicting Credit Card Profitability as Measured by Top-Ranked Predicted Portfolio Values to Always+Stoppers Data Sample

Outcome	Horizon (Years)	Baseline ($)	Baseline + Actual Payments ($)	Percentage Change
Interchange Net of Rewards	1	$319	+$80	+25%
	10	$531	+$94	+18%
Financing Charges Net of Charge-Offs	1	$2,600	+$7	+0%
	10	$7,954	+$98	+1%
Profit	10	$7,966	+$105	+1.3%
Net Present Value	10	$7,424	+$95	+1.3%

Notes: BTCCP data. Table uses data to December 2012 to predict components of credit card profitability. Table shows out-of-sample portfolio values from sorting predictions of each outcome and choosing top-ranked 100,000 accounts. Baseline shows mean account value ranking accounts by predictions without using actual payments information as predictors. Change with actual payments shows the percentage change in portfolio value relative to this baseline when instead ranking by predictions using actual payments information as predictors. Predictions from $N = 11.014$ million $Always + Stoppers$ accounts (tested out-of-sample on $N = 11.018$ million accounts).

E Selection in Credit Card Lenders Sharing Information

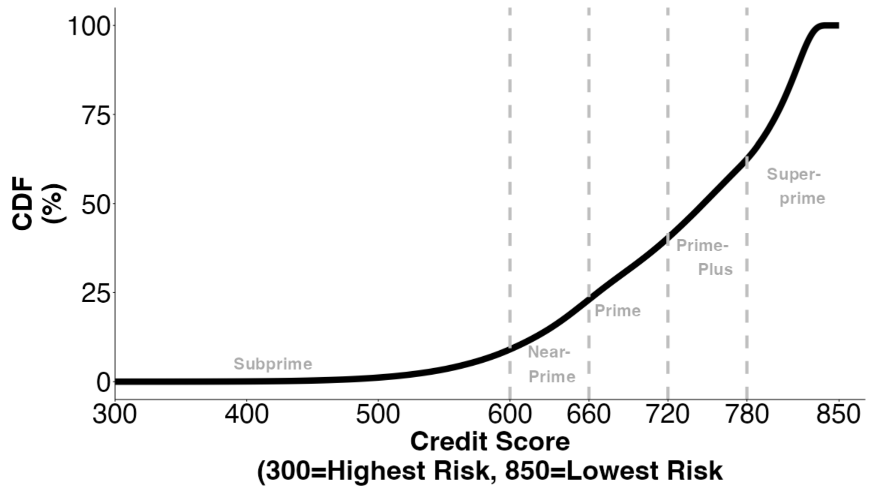
Table E1: Summarizing Selection in Credit Card Portfolios

	Always	**Stoppers**	**Nevers**
Credit Score	720.73	719.70	744.23
(S.D.)	(87.10)	(89.61)	(76.16)
Tenure	68.52	95.18	141.21
(S.D.)	(76.65)	(79.13)	(109.75)
Credit Limit	8,574.75	9,460.33	10,403.06
(S.D.)	(7,626.41)	(9,487.96)	(9,446.22)
Statement Balance	2,077.10	2,351.69	2,456.91
(S.D.)	(3,535.00)	(3,954.01)	(4,323.95)
Utilization	36.26	39.08	29.49
(S.D.)	(38.75)	(39.97)	(35.24)
Proxy Spending	2,454.67	2,752.78	3,369.77
(S.D.)	(4,059.19)	(5,044.94)	(7,917.64)
Accounts (%)	18.2%	47.2%	31.5%
Statement Balances (%)	16.6%	46.8%	35.3%

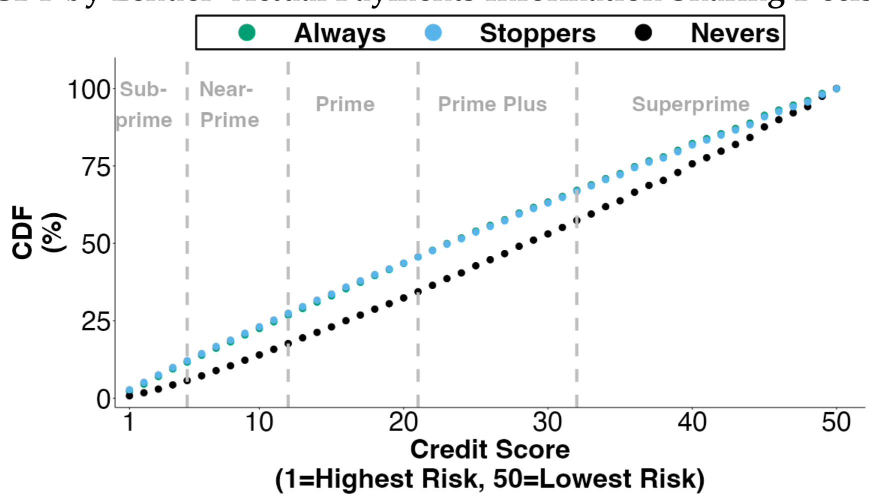
Notes: BTCCP data. Table shows means (standard deviations in parenthesis) for credit card portfolio characteristics as of December 2012. Card tenure is measured in months. Proxy spending is measured by change in balances conditional on being non-negative. Financing charges are estimated based on our methodology described in section D.1. Results are split by classifying credit card furnishers by their sharing of actual payments information on . The last two rows show the shares of the number of outstanding credit card accounts and the value of outstanding credit card statement balances by each type of furnisher. These data exclude furnishers who do not have at least 10,000 active credit cards (i.e., their portfolio is representative of least 100,000) in both December 2012 and in December 2015. ***Always*** *are furnishers sharing actual payment amounts information for more than 75% of their active credit cards in both December 2012 and December 2015.* ***Stoppers*** *are furnishers sharing actual payments amounts information for more than 75% of their active credit cards in December 2012 and for less than 10% in December 2015.* ***Nevers*** *are furnishers sharing actual payment amounts information for less than 10% of their active credit cards in both December 2012 and December 2015. The remaining furnishers are* ***Others*** *excluded from the table: these are 3.1% of accounts and 1.3% of statement balances.*

Figure E1: CDF of Credit Score

A. CDF

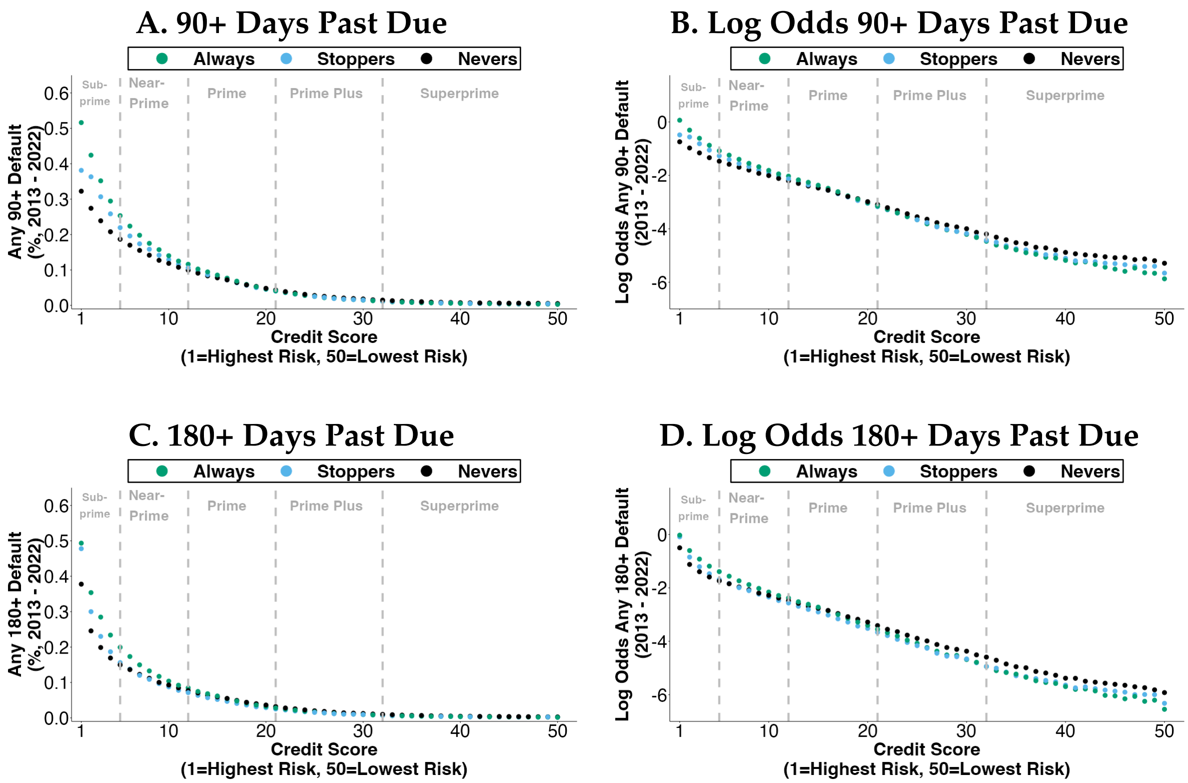


B. CDF by Lender' Actual Payments Information Sharing Decision



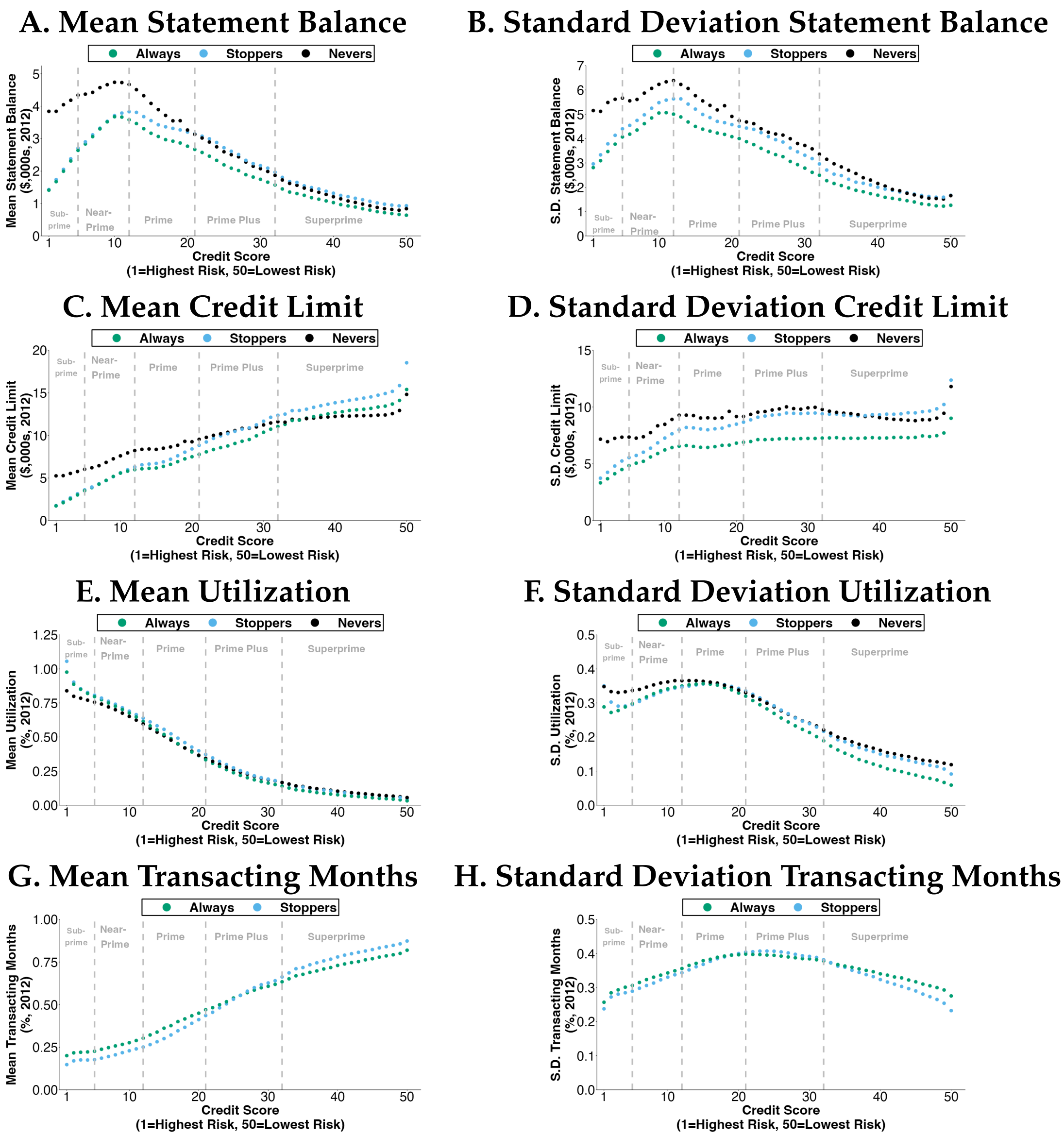
Notes: BTCCP data. Panel A shows CDF and Panel B shows CDF by 50 quantiles where thresholds are defined globally and fixed across classifications. Results in Panel B are split by classifying credit card furnishers by their sharing of actual payments information as described in paper section 2.2 or Table 5 notes. Gray dotted lines divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores).

Figure E2: Credit Card Default Rates Conditional on Credit Score



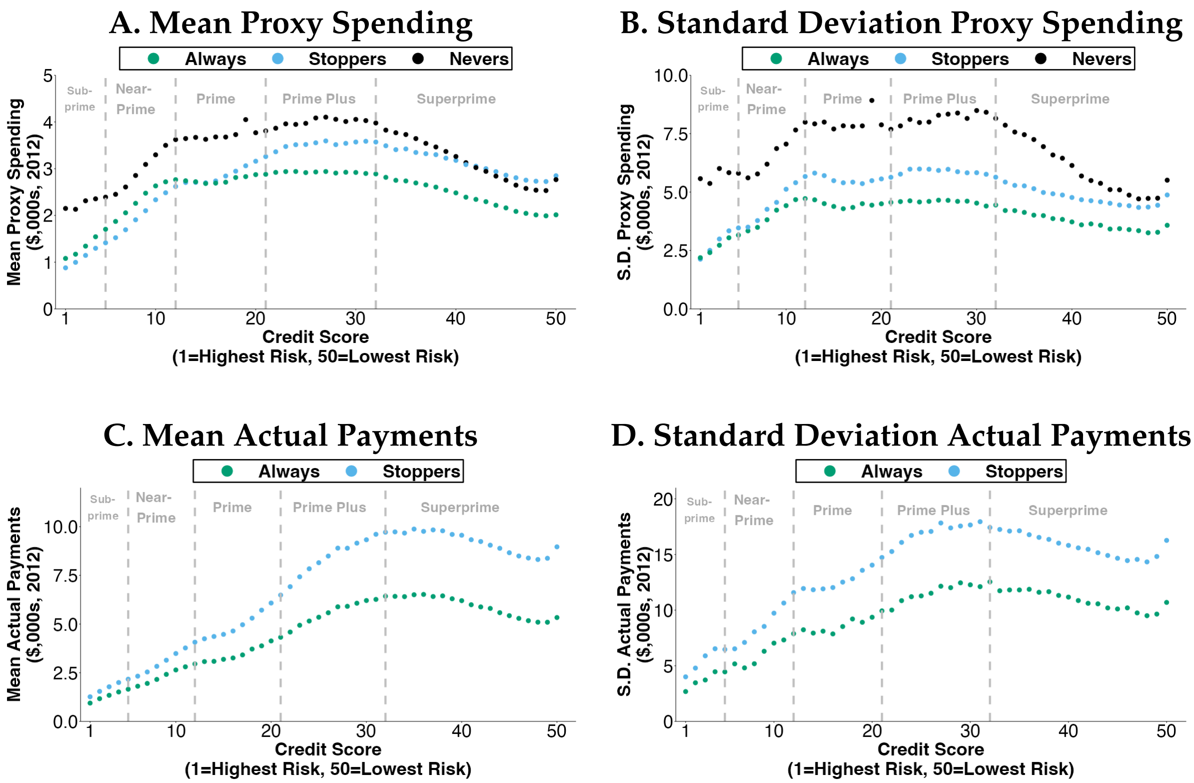
Notes: BTCCP data. Figure shows fraction of credit cards in December 2012 that become delinquent at any point 2013 to 2022 (y-axis) conditional on 50 quantiles of credit score (x-axis). Panel A shows delinquency defined as any 90 or more days past due (DPD) and Panel B shows this in log odds. Panel C shows for 180 or more DPD and Panel D shows this in log odds. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E3: Credit Card Behaviors Conditional on Credit Score



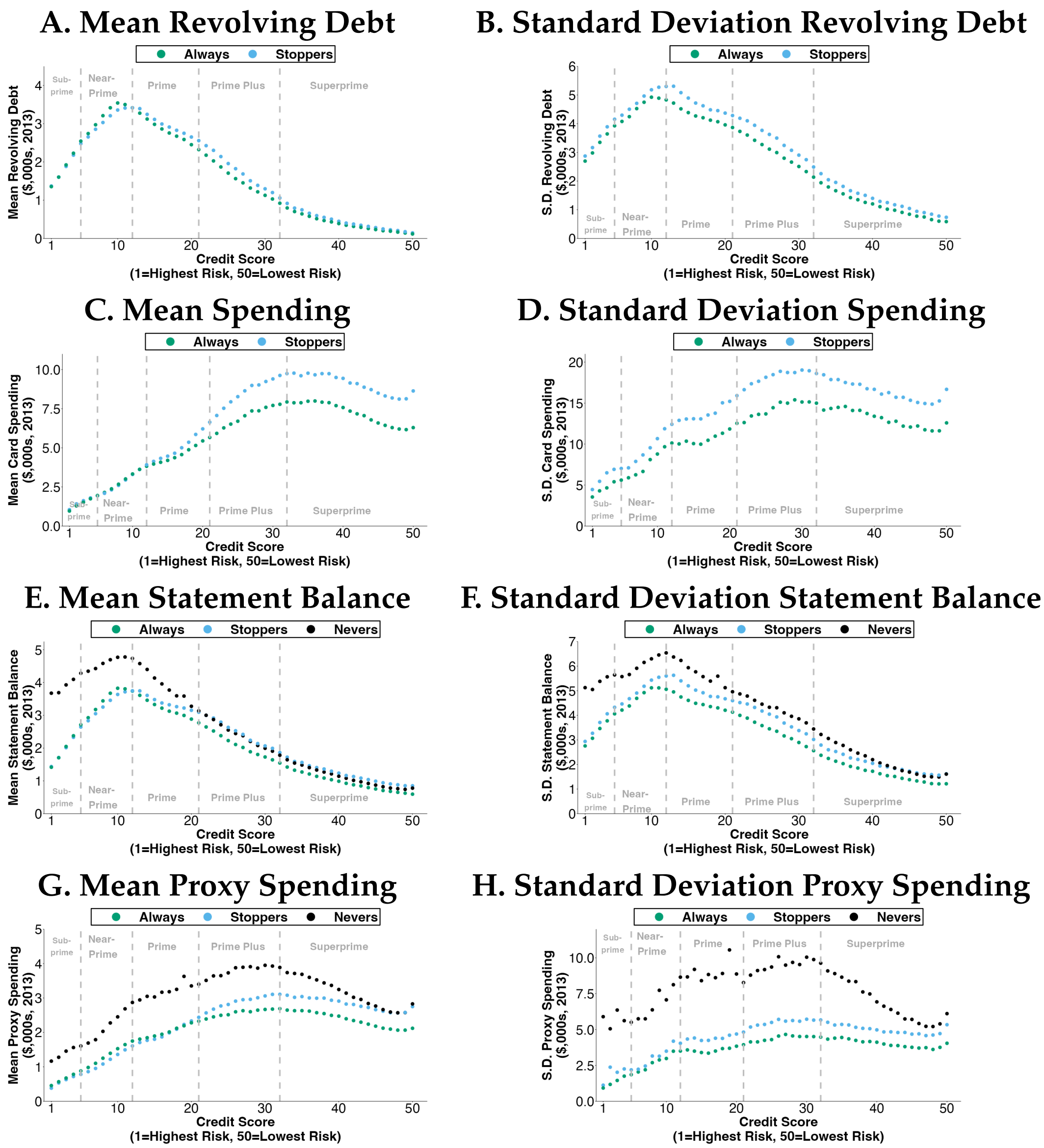
Notes: BTCCP data. Figure shows credit card behaviors conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A, C, E, and G show means. Panels B, D, F, and H show standard deviations. Utilization rate is calculated by statement balance divided by credit limit. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E4: Credit Card Spending Behaviors Conditional on Credit Score



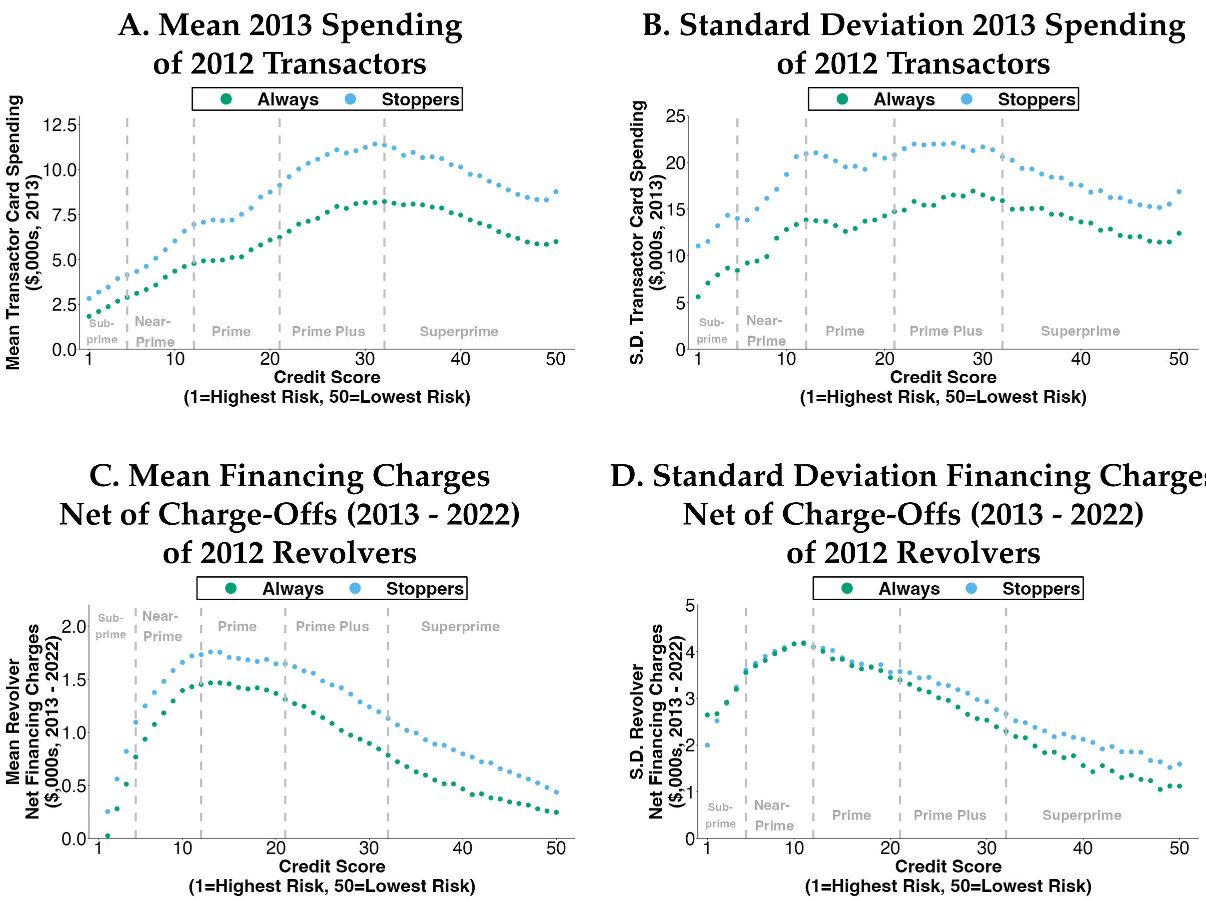
Notes: BTCCP data. Figure shows credit card spending behaviors (y-axis) conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A and C show means. Panels B and D show standard deviations. Proxy spending is calculated by change in statement balance where counted as zero if negative. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E5: 2013 Credit Card Behaviors Conditional on Credit Score



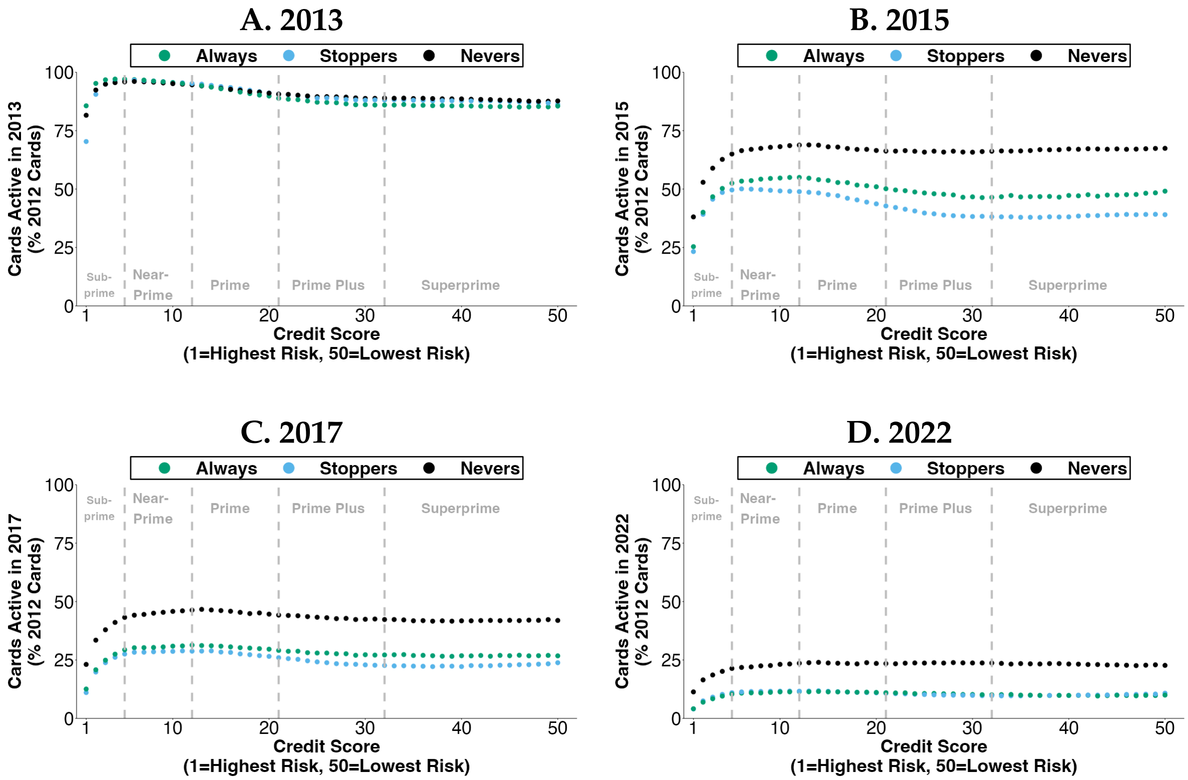
Notes: BTCCP data. Figure shows credit card behaviors (y-axis) conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A, C, E, and G show means. Panels B, D, F, and H show standard deviations. Proxy spending is calculated by change in statement balance where counted as zero if negative. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E6: Credit Card Behaviors of Transactors and Revolvers Conditional on Credit Score



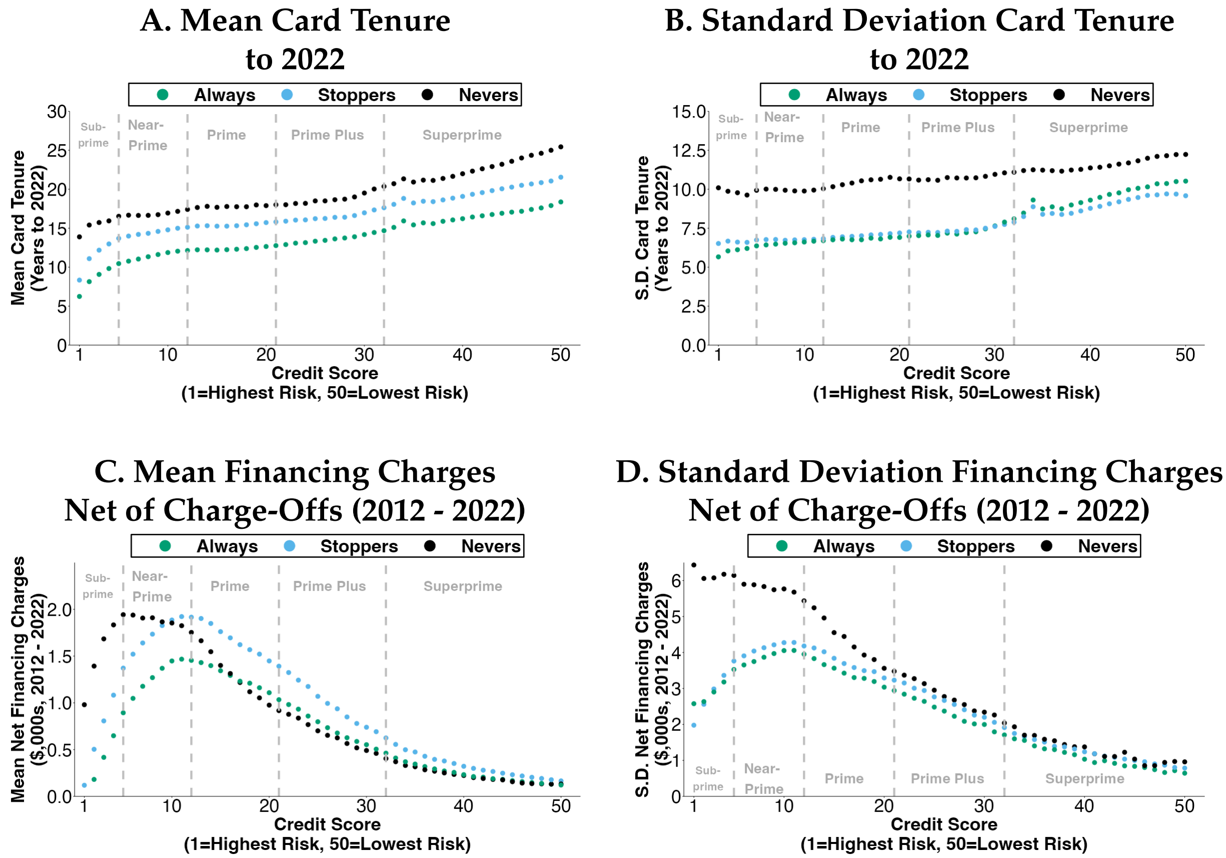
Notes: BTCCP data. Figure shows credit card behaviors (y-axis) conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A and C show means. Panels B and D show standard deviations. Panels A and C show 2013 spending for accounts transacting the majority of months in 2012. Panels B and D show 2013 to 2022 financing charges net of charge-offs for accounts revolving the majority of months in 2012. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E7: Credit Card Activity Rates Conditional on Credit Score



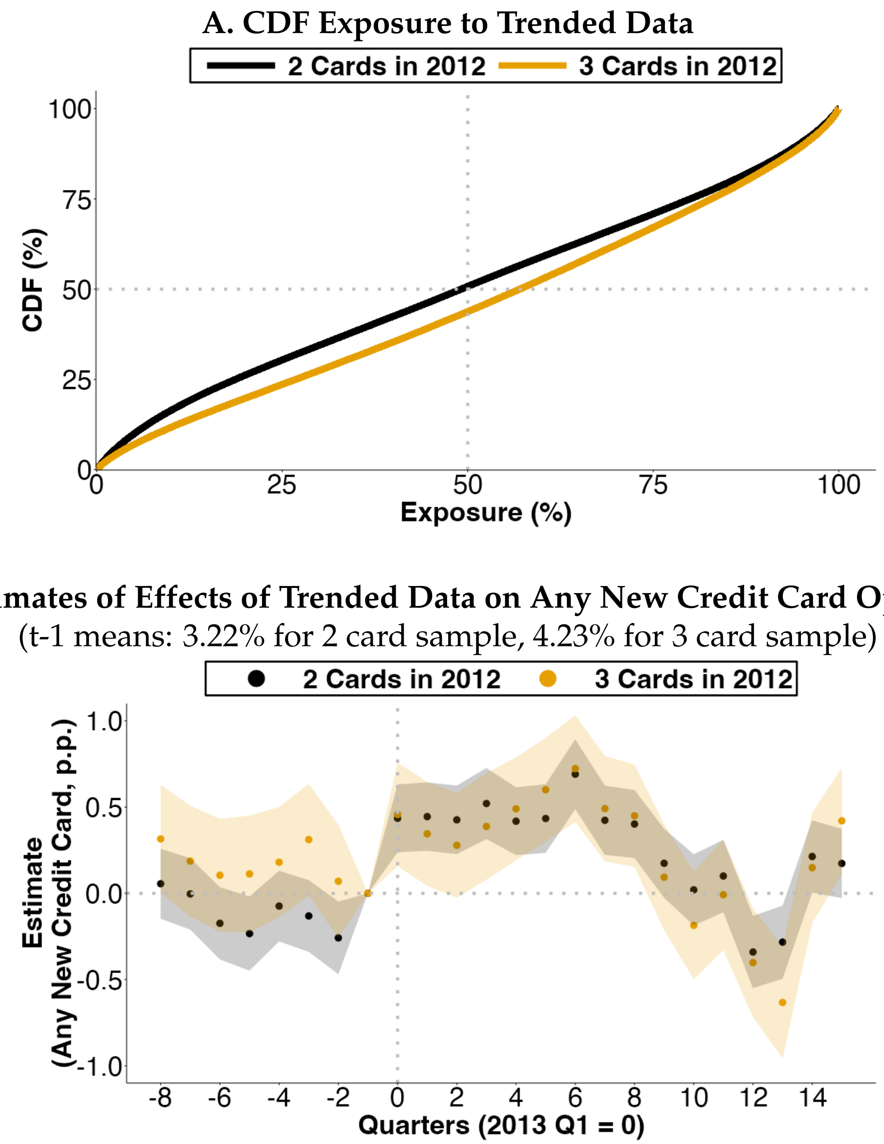
Notes: BTCCP data. Figure panels shows fraction of credit cards in December 2012 that remain active over different horizons. Panel A by 2013, B by 2015, C by 2017, and D by 2022. These are presented conditional on 50 quantiles of credit score (x-axis). A card is active if it remains open with a non-zero statement balance and is not 90+ day past due and has been updated in the last year. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E8: Credit Card Tenure to 2022 and Financing Charges Net of Charge-Offs (2012 to 2022) Conditional on Credit Score



Notes: BTCCP data. Figure shows credit card behaviors (y-axis) conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Panels A and C show means. Panels B and D show standard deviations. Panels A and B show card tenure to 2022. Panels C and D show financing charges net of charge-offs from 2012 to 2022. Results are split by classifying credit card furnishers by their sharing of information on actual payment amounts as described in paper section 2.2 or Table 5 notes. Credit score quantile thresholds are defined globally and fixed across classifications. Gray dotted lines show quantiles which divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores) fall in the distribution.

Figure E9: Effects of Trended Data on Competition for 2 and 3 Card Samples



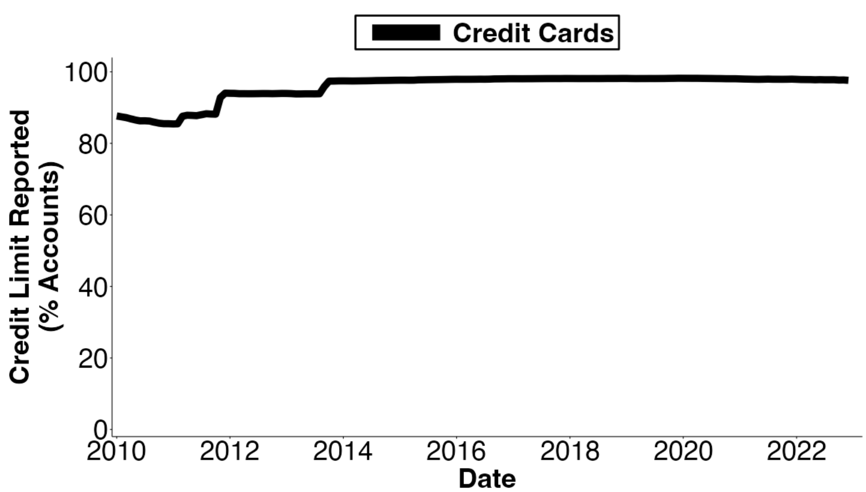
Notes: BTCCP data. Panel A shows CDF of exposure. Exposure is (pre-trended data) share of 2012 credit card balances held with furnishers who share actual payments information. Panel B shows our difference-in-differences with varying intensity estimates in percentage points (p.p.) where the outcome is any new credit card account openings in a quarter. Difference-in- differences estimates from balanced panel of consumers Q1 2011 to Q4 2016, with $0 < EXPT_i < 1$*, and holding two (black) / three (orange) cards both of which have positive balances in 2012. The two card sample is 0.51 million consumers and the three card sample is 0.29 million consumers. OLS regression with consumer and calendar year-quarter fixed effects and interaction term between exposure and calendar year-quarter where Q4 2012 is omitted category and standard errors are clustered at the consumer level.*

F Mandating Sharing Credit Card Limit Information

We do not observe an increase in credit card limit information sharing on July 2010, when the policy becomes effective, but observe an increase in November 2011 and a smaller one in 2013, shown in Figure F1 below. We therefore expect the CFPB's inception in July 2011 led to these rules being enforced. We isolate which anonymized furnishers revealed information on credit card limits by taking data from October 2011 and November 2011 and compare their credit card tradelines with credit limit information shared in November 2011 that did not share this information in October 2011. We use this to label furnishers as either "insiders", who reveal information in November 2011, and "outsiders", who learn about about the information revealed.

Information is revealed for approximately 30% of these furnishers' open cards, 39% of outstanding balances, and 36% of their consumer base. These revealed accounts are a non-random subset of the furnisher's accounts. Revealed accounts have, on average, higher credit scores (775 vs. 736), higher credit limits ($16,363 vs. $9,461), higher statement balances ($2,622 vs. $1,903), and shorter card tenures (7.4 vs. 8.7 years), compared to accounts with the same furnishers that shared credit card limit information in October 2011.

Figure F1: Coverage of Credit Card Limits in Consumer Credit Reports



Notes: BTCCP data. Figure shows the fraction of credit card accounts in consumer credit reports with non-zero and non-missing credit card limits.These calculations restrict to open accounts with non-zero balances and which have been updated in the last year.

Table F1: Seven Quarter Effects of Mandating Credit Card Limit Information Sharing

	Estimate (S.E.)	Baseline Mean
Credit Score	13.82 (0.22)	776.04
Any New Credit Card Opening: Inside	-0.0132 (0.0008)	0.0208
Any New Credit Card Opening: Outside	0.0254 (0.0014)	0.0723
Any New Credit Card	0.0122 (0.0016)	0.0897
Number New Credit Cards Opening: Inside	-0.0322 (0.0025)	0.0462
Number New Credit Cards Opening: Outside	0.0526 (0.0034)	0.1394
Total Number New Credit Cards	0.0204 (0.0042)	0.1856
Value New Credit Card Limits: Inside	$-$\$610.4 (\$49.4)	\$680.4
Value New Credit Card Limits: Outside	\$658.2 (\$44.6)	\$1,346.2
Total Value New Credit Card Limits	\$45.6 (\$66.5)	\$2,025.5

Notes: BTCCP data. Each row of table shows results from separate regressions with the same specifications but varying outcomes. Our exposure measure, defined as $EXPL_i = \frac{r_i - h_i}{r_i}$, the difference between a consumers' revealed credit limit (r_i) and their inferred credit limit prior to new credit limit information being revealed (h_i). Table show difference-in-differences with varying intensity estimates. Data is a balanced panel of 1.09 million consumers. Results are estimating OLS regression specified in Equation 11 with consumer and calendar year-quarter fixed effects and interaction term between exposure ($EXPL_i$) and calendar year-quarter indicators (D_τ), where the quarter before information revelation is the omitted category (August 2011 to October 2011). Table shows δ_7 estimates from the interaction between the exposure measure and the indicator seven quarters after treatment ($D_7 \times EXPL_i$). Standard errors are shown in parenthesis from clustering at the consumer level.