Unraveling Information Sharing
in Consumer Credit Markets

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Abstract

We study the breakdown of information sharing in US consumer credit markets. We document a 53 percentage point decrease in credit cards sharing actual payments information with credit bureaus between 2013 and 2022, without any decrease for other credit products. Decreased information sharing is an unintended response of credit card lenders to credit bureaus' innovation. We show the innovation uses credit card actual payments information to reveal heterogeneous credit card behaviors that predict components of profitability: spending drives interchange and revolving debt drives financing charges. The credit card lenders that stop sharing information have higher profitability and higher spending customers who are attractive for competitors to target. Our results demonstrate the sensitivity of information sharing to innovations enabling targeting of profitable customers. We then provide empirical evidence that mandating information sharing increases switching in line with increasing competition.

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1 Introduction[1]

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, credit reporting agencies ("credit bureaus") act as financial 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"). Between 2013 and 2022, we find the fraction of credit card accounts that shared actual payments information with credit bureaus *decreased* by 53 percentage points (Figure 1). None of the six largest credit card lenders share actual payments information and none plan to voluntarily do so (CFPB, 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 an "unraveling" in the spirit of classical information economics (e.g., Akerlof, 1970; Rothschild and Stiglitz, 1976; Roth and Xing, 1994).

The timing of this information sharing breakdown follows an innovation created by

credit bureaus. 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 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 the credit bureaus 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 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 contract terms (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 evaluate the value of observing actual payments information for predicting consumer credit profits and its components. We construct a model of lifetime credit card profits and find that actual payments information increases the ability to predict (measured by R^2), at the account-level over a ten year horizon, interchange revenue (the transaction fees credit card lenders receive from merchants when a consumer spends on their card) net of rewards by 31% and 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 makes it easier for credit card lenders to target profitable cardholders, especially high spending ones, to acquire. In contrast, in auto loans or unsecured loans, observing actual payments information does little to predict profits and so lenders are willing to keep sharing such information without an increased threat of competition.

The selection of credit card lenders by their actual payments information sharing decisions is consistent with the innovation being a particular competitive threat to some

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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 variance compared to lenders who keep sharing information. 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 keep sharing information have portfolios with the worst types on multiple dimensions (the "lemons" in Akerlof, 1970).

We show 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 more exposed consumers open relatively more new credit cards after the innovation. We interpret such switching prompts incumbents to respond by reducing information sharing.

If lenders do not voluntarily share information, how would mandating information sharing affect markets? Sharing of actual payments information is not mandatory. We instead learn from studying the effects of a prior historical event: the Federal Trade Commission mandating sharing of credit card limit information.[2] We use a difference-in-differences design with varying treatment intensity by how much 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 to which their information is revealed to. We interpret these results as showing mandating information sharing can increase switching in line with increasing competition. The US Consumer Financial Protection Bureau is investigating the lack of actual payments information sharing (CFPB, 2023) and our research findings supports a policy to mandate information sharing.

Our main contribution is empirically documenting the fragility of information sharing. 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, it can be beneficial for firms to voluntarily share information with their competitors through fi-

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[2]Prior research examines the effects of consumer credit reports having additional information added (e.g., Foley et al., 2022) or information removed (e.g., Musto, 2004; Bos et al., 2018; Liberman et al., 2019; Dobbie et al., 2020; Gross et al., 2020; Jansen et al., 2022; Fulford and Nagypál, 2023) and how to design credit reporting systems focusing on the length of histories to remember (e.g., Elul and Gottardi, 2015; Bhaskar and Thomas, 2017, 2019; Chatterjee et al., 2020; Blattner et al., 2023; Kovbasyuk and Spagnolo, 2023).

nancial intermediaries (e.g., Diamond, 1984; Ramakrishnan and Thakor, 1984) but it is theoretically ambiguous whether they do (e.g. Pagano and Jappelli, 1993; Raith, 1996; Bouckaert and Degryse, 2006). 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 incumbency position by stopping sharing information as doing so undermines technological innovations that pose a competitive threat.[3]

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 a second source of uncertainty: how much a credit 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. This card lifetime perspective helps to understand why credit card lenders lend to and heavily concentrate their marketing towards high credit score consumers (e.g., CFPB, 2021) given these generate little-to-no revenue from financing charges. But it makes sense given 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.[4] These insights advance research on the supply of credit cards (e.g., Ausubel, 1991; Agarwal et al., 2018), credit card rewards (e.g., Agarwal et al., 2023b), and payment systems (e.g., Evans and Schmalensee, 2004; Mukharlyamov and Sarin, 2019; Wang, 2023).[5]

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

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[3]For example, Amazon US used to share details of what a consumer purchased in order confirmation emails but stopped doing so following advances in scraping technology that could use this information for targeted marketing. Amazon UK continues to share this information — potentially due to stricter data protection laws. Apple stopped sharing information on device locations following advances in tracker technology that could be used for targeted marketing. Many firms have stopped sharing information following AI developments such as ChatGPT. For examples, Twitter / X used to provide free API access to its data but stopped doing so and Google has restricted the dissemination of its research.

[4]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."

[5]Prior literature on the credit card market includes Ausubel (1997, 1999); Agarwal et al. (2010b,a, 2015a,b); Stango and Zinman (2016); Han et al. (2018); Keys and Wang (2019); Ru and Schoar (2020); Galenianos and Gavazza (2022); Grodzicki (2023a,b); Herkenhoff and Raveendranathan (2023); Nelson (2023).

2 Background and Data

2.1 Consumer Credit Reporting

Consumer credit reporting agencies ("credit bureaus") — Equifax, Experian, and TransUnion in the US — are financial intermediaries created as a coordination mechanism for lenders to share information about their borrowers with each other. Credit reporting data record information on consumers' borrowing histories. This 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). The consumer credit agencies' technology is to ingest, collate, and store data from a large number of lenders and then produce variables on consumers that are value-added for lenders (and non-lenders). For example, consumer credit reporting data are used to construct credit scores such as FICO and VantageScore.

Lenders demand this information as it helps to reduce adverse selection (e.g., Bouckaert and Degryse, 2006; Blattner et al., 2023) and moral hazard (e.g., Padilla and Pagano, 1997, 2000; Gehrig and Stenbacka, 2007).[6] US consumer credit reports – and credit scores derived from them – are used for managing credit risk, marketing, and screening.[7] 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 will tailor their product offers (studied in Stango and Zinman, 2016; Han et al., 2018; Ru and Schoar, 2020). Furthermore, credit reports are also used to incentivize timely payment of other household bills, such as medical and utility bills, and to help screen applicants in labor, insurance, and housing markets (e.g., Dobbie et al., 2020; Bartik and Nelson, 2023).

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[6]Moral hazard and adverse selection are empirically challenging to distinguish without experimental data such as Karlan and Zinman (2009). Positive correlation tests between interest rates and default (e.g., Chiappori and Salanie, 2000) may be neither necessary nor sufficient if there are multiple sources of information asymmetry (e.g., Finkelstein and McGarry, 2006; Einav et al., 2021). Information sharing games may have multiple equilibria and, which equilibrium outcome occurs is ambiguous (e.g., Pagano and Jappelli, 1993; Raith, 1996; Bouckaert and Degryse, 2006). Decisions of lenders to share information are a repeated game, and the more information shared, the greater the network effects of credit reporting data (e.g., Hunt, 2002).

[7]We study on the US, but the data contents, legal requirements, and industry practices of credit reporting vary around the world (e.g., Jappelli and Pagano, 2002). See Barron and Staten (2003); Hunt (2005) for a history of US credit reporting.

Sharing information is voluntary and access to information is non-reciprocal. In the US, there is no law requiring lenders to share information with credit reporting agencies.[8] 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) regulate *how* information should be shared (Online Appendix A). This requires that information shared with credit bureaus 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.

Although they are not required to share information, lenders have strong incentives to voluntarily share information. 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 the lending decision of one lender can affect the repayment of another lender's loan. This interdependence means 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 such benefits against the risks of increased competition. More specifically, by sharing their private information with competitors, lenders may be risking giving away a competitive advantage that exists due to the private information they hold and enabling competitors to target their profitable customers. This can explain why some credit market segments do not voluntarily share information at all. For example, most buy now pay later (BNPL), payday loans, and some subprime

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[8]The data contents, legal requirements, and industry practices of credit reporting vary around the world (e.g., Jappelli and Pagano, 2002). See Barron and Staten (2003); Hunt (2005) for a history of US credit reporting.

auto loans are not reported.[9]

Why would lenders be willing to voluntarily non-reciprocally share information? One explanation can be found in Bouckaert and Degryse (2006) which provides a theoretical framework for the conditions under which lenders voluntarily and non-reciprocally share all, partial, or no information with their competitors. In Bouckaert and Degryse (2006), 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.[10] Another possible explanation is that voluntary information sharing is the strategic response within a repeated game of lenders with regulators. Once a lender grows large enough, regulatory pressure to voluntarily share information can accumulate – as most recently seen with the CFPB pressuring BNPL lenders to do so. 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 the University of Chicago Booth TransUnion Consumer Credit Panel (BTCCP) data (TransUnion, 2023).[11] BTCCP is anonymized consumer credit reporting data from a US consumer credit reporting agency: TransUnion. 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.

BTCCP contains information at the consumer level (e.g., credit scores) and at the trade-line level (i.e., monthly observations for each of the consumer's credit accounts (e.g., auto

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[9]The main unobserved segment of the auto loan market are high interest rate loans from "buy-here-pay-here" auto dealerships and small finance companies (Low et al., 2021). The main unobserved segment of the unsecured loan market are small-value products such as interest-free buy now pay later (BNPL) loans (e.g., Guttman-Kenney et al., 2023b) and high interest rate payday loans (e.g., Gathergood et al., 2019). BNPL lenders such as Klarna and payday lenders report in the UK but not in the US. We understand this is due to a combination of greater regulatory pressure to do so in the UK and also lower competitive risk. The UK limits on marketing prevent credit card (or other lenders) using consumer credit reporting information to target marketing to target profitable BNPL or payday lending consumers.

[10]See Padilla and Pagano (1997, 2000); Marquez (2002); Bouckaert and Degryse (2004); Dell'Ariccia and Marquez (2004, 2006); Hauswald and Marquez (2003, 2006); Gehrig and Stenbacka (2007); Schenone (2010).

[11]Examples of published research using BTCCP include Kluender et al. (2021); Guttman-Kenney et al. (2022); Keys et al. (2022); Yannelis and Zhang (2023). For a guide and review of consumer credit reporting data see Gibbs et al. (2023).

loan, credit card, mortgages, unsecured loans). Importantly for our paper, BTCCP trade-line 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).[12]

BTCCP has anonymized consumer and tradeline identifiers enabling tracking these over time. It also contains anonymized identifiers for the firm reporting tradeline-level information. This enables us to observe 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 other 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. No individual consumers or individual lenders are identified in BTCCP.

We apply standard data restrictions following Gibbs et al. (2023). 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 (see Online Appendix B for a time series). In addition, when we study portfolios as of December 2012, we drop inactive credit cards: we drop cards that are closed, are 180+ days past due, or have no balance on the account in the last twelve months. We deal with outliers by top coding variables at their 99.99 percentiles (and for those that can have negative values also at their 0.01 percentiles).

Classifying Credit Card Lenders in BTCCP

BTCCP includes anonymized furnishers of data: this is the relevant unit of analysis as the data furnisher is the firm that makes decisions on what information to share. For predicting credit card profitability and understanding selection, we keep 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.[13]

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[12]BTCCP (and other consumer credit reporting datasets) do not contain variables showing the prices (e.g., interest rates, fee schedules) or revenues credit products generate. Regulatory datasets contain some of this information but have data access restrictions and, even for those with access, have some important limitations. The Federal Reserve's FR Y14-M credit card data, described in Agarwal et al. (2023b), does not have account-level data on interchange revenues, requires estimating rewards, covers a selected subset of the market (19 banks), cannot be linked to credit reports, and cannot link individual accounts across lenders. Similar challenges apply to the OCC's Credit Card Metrics dataset used in Agarwal et al. (2015b, 2018) and the CFPB's Credit Card Database used in Nelson (2023).

[13]Across our entire dataset there are 7,547 furnishers of credit cards and between 2012 and 2015 there are 5,533. In December 2012 there are 4,912 and in December 2015 there are 4,518. For our 84 furnishers, we

We examine these 84 credit card furnishers' sharing of actual payments information and classify them into four groups: *"Always"*, *"Stoppers"*, *"Nevers"*, and *"Others"* (Online Appendix Figure G1). *Always* (18% of accounts) are furnishers sharing actual payments information for more than 75% of their credit cards in both December 2012 and December 2015.[14] *Stoppers* (47% of accounts) are furnishers sharing actual payments information for more than 75 percent of their credit cards in December 2012 and for less than 10 percent in December 2015. *Nevers* (32% of accounts) are furnishers sharing actual payments information for less than 10 percent of their credit cards in both December 2012 and December 2015. *Others* contains the remaining furnishers (3% accounts).

Other Data

We refer to public data released by the US Consumer Financial Protection Bureau (CFPB) summarizing its findings from interviewing credit card lenders about their sharing of actual payments information CFPB (2023).

We also use credit card industry data from R.K.Hammer (a data source used in Jørring (2023)). These aggregated summary data are presented in Online Appendix C and show the profitability of this market and costs of acquisitions.

3 Unraveling Information Sharing

3.1 Describing Unraveling

The "actual payments" variable records information on the total amount of actual payments made on an account in the last month.[15] 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. Actual payments on credit card accounts are highly dispersed: a quarter are at or within one percentage point of the scheduled payment amount (the minimum payment due), a third are paying the full statement

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follow outcomes on these accounts even if the furnisher changes.

[14]A furnisher that shares information for its entire portfolio would not appear as exactly 100% sharing because some months will be accurately reporting a consumer making actual payments information of zero dollars. Most furnishers that do not have trivially-small portfolios share actual payments information for either exactly 0% or more than 75% and therefore our threshold choice does not affect results – it merely changes who is classified as *Always* or *Others*. If we added smaller credit card furnishers beyond the 84 in our sample they would generally be categorized in the *Always* or *Other* category.

[15]If a consumer makes multiple payments in a month then the actual payments variable is the sum of these.

amount (or more), and the remainder are spread in-between (Online Appendix Figure D1). Whereas for other consumer credit products, the majority are at or within one percentage point of the scheduled payment amount: 83% of mortgages, 69% of auto loans, 58% of unsecured loans.

Figure 1 Panel A shows the fraction of accounts in consumer credit reports where actual payments information is observed.[16] 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.[17] 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 card sharing actual payments information during 2013 due to one furnisher starting sharing this information. This one 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 bureaus and other information on these (e.g., credit limits, scheduled payment amounts).[18] 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 (Online Appendix D).[19]

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[16]We define actual payments information as observed if it is non-zero and non-missing. We classify zeros in this way because some lenders report zeros for all their accounts and therefore are missing. However, there will be some accounts that are zeros and therefore may not be exactly 100% reporting by this measure.

[17]Our results are not specific to TransUnion. CFPB (2020) find a consistent pattern in Experian data: a decline in actual payments information for credit cards from a peak of 88% in Q3 2013 to 40% from 2015 onwards. We understand our results also hold for Equifax data.

[18]See Online Appendix Figures Online Appendix Figures B1, D4, and I1. Complete coverage does not mean precisely 100% have non-zero amounts as some accounts will accurately have zero credit limits or zero scheduled payment amounts. Complete coverage is conditional on lenders who report information. CFPB (2020) reports "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".

[19]Not conditioning on the date of the last payment shows the same pattern but makes the baseline levels of coverage lower as some accounts with positive balances will have zero actual payments made because a zero payment was due or because a consumer missed a payment. Sometimes (general purpose) credit cards and retail credit cards (also known as private label credit cards) are grouped together and we find consistent results with such an approach. Retail credit cards are only able to be used at one merchant or a small group of merchants. This is in contrast to (general purpose) credit cards that are widely accepted by merchants. Retail credit cards are otherwise similar to credit cards and we do not examine them further

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 to 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.[20]

CFPB (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 (Nilson Research). 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 credit card lenders sharing actual payments information as of 2022 contains none of these six large credit card lenders. None of these lenders intend to voluntarily start sharing information and there are no material barriers preventing them doing so (CFPB, 2023). Other smaller lenders beyond these six large lenders may also have stopped sharing information during this time but this was not reported by the CFPB.[21] We refer to this breakdown of co-operative information sharing an "unraveling" in the spirit of classical information economics (e.g., Akerlof, 1970; Rothschild and Stiglitz, 1976; Roth and Xing, 1994) with a breakdown in the market for sharing information.[22]

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because it is a much smaller economic market with outstanding balances being approximately a tenth of the size of the credit card market (CFPB, 2021).

[20] The lack of information for a substantial number of consumers and a large fraction of accounts may have general equilibrium effects indirectly affecting the credit risk assessments and marketing decisions of other consumers. For example, some lenders may not purchase information on credit card actual payments due to its poor coverage and therefore this may impact decisions for consumers where this information is reported. See Liberman et al. (2019) and Fulford and Nagypál (2023) for studies of the general equilibrium effects of credit information in other contexts.

[21] Other smaller lenders in this market account for 19% of the market based on public data from Nilson Research. They are, in decreasing order market share: U.S. Bank, Wells Fargo, Barclays (who only offers co-branded cards), Navy FCU, Synchrony, USAA, Credit One, Goldman Sachs, and PNC. A tail of very small lenders account for the remaining 12% of the market.

[22] Akerlof (1970) shows how private information can mean a market with exogenous contracts unravels such that only the worst quality of good are traded in equilibrium. Rothschild and Stiglitz (1976) shows 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 economic

There is no decline in sharing actual payments information for installment loans: auto loans, mortgages, and unsecured loans. 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, 99.6% of mortgages, 97.9% of unsecured personal loans.

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, 2014

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, credit reporting agencies launched a new product: "Trended Data". This innovative new product created a 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 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 or whether the consumer had any delinquency in the last seven years. By linking data across multiple archives, Trended Data enables the creation of trended variables such as whether a consumer's total outstanding credit balances have trended up or down in the last year.

The part of Trended Data that is relevant to our study is that it uses histories of credit card statement balances and actual payments to 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. Trended Data measures are available to purchase for marketing. Doing so enables highly targeted marketing screening consumers based on their revolving and spending behaviors for consumers 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.[23] Lenders can purchase

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term unraveling is also 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. Doing so reduces the volume in the centralized process or, in the extreme, means no centralized process occurs.

[23]One lender who previously shared information suggested in its response to the CFPB (2023) that *if* data access was reciprocal ("give-to-get") it may share actual payments information. However, the credit reporting agencies are unwilling to set these terms as it would set a precedent and also limit their ability to sell this product to a broader market. And, even if the agencies did do so, there's no indication that *all* large lenders would start sharing actual payments information.

these data without sharing information 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 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"*. 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"*. Whereas for installment loans, Trended Data's value is in improving credit risk assessments. In the mortgage market, Fannie Mae is *"including Trended Data materially improved modeling of loan performance"* and from 2016 requires its use for underwriting. This is consistent with statements by Equifax, Experian, TransUnion, and also with both FICO and VantageScore who incorporate Trended Data into the latest versions of their credit scoring models (VantageScore 4.0 available from 2017 and FICO 10T available from 2020) both approved for use by the Federal Housing Finance Agency in 2022. This indicates 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. We find evidence of this: trends in credit card actual payments information improve the performance of consumer credit scores predicting not only credit card default but also installment loans defaults (Online Appendix Tables E1 and E2). The lack of credit card actual payments information for 165 million credit cardholders also means if these cardholders repay their credit card debt in full this positive behavior is unobserved in their credit report so does not improve their credit score (and may potentially disincentives 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., 2015b) and interest (e.g., Nelson, 2023). Pressures on these credit card revenue streams increased the relative importance of interchange revenue (e.g., Experian 2023). Substantial charge-offs incurred due to the 2008 financial crisis meant lenders increasingly shifted their focus away from short-term risky profits (e.g., TowerGroup 2010 Note) and so, as a lower risk source of revenue, interchange revenue becomes increasingly attractive. The 2010 Durbin Amendment also re-

stricted interchange fees on debit cards but not on credit cards (e.g., Mukharlyamov and Sarin, 2019). Banks therefore had increased incentives to attempt to shift their customers' spending to credit cards in order to earn higher interchange fees.

Technically, lenders could construct spending and revolving debt measures before Trended Data by purchasing historical account-level credit reporting data containing balances and actual payments. However, discussions with industry participants have confirmed in practice they did not. 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"*. 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 historically 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 credit reporting data is charged on a per-archive basis. Third, industry participants told us of concerns that using historical archives could 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). Unlike the US, it did not prompt an unraveling of sharing actual payments information for credit cards or other loans in either of these countries.[24] This is explained by different institutional arrangements. The UK has reciprocity in sharing information and data cannot be used for marketing but can *"only for the purposes of control of risk, fraud and over-indebtedness"* (terms of sharing are administered by the industry body "SCOR": the Steering Committee on Reciprocity). The UK caps interchange revenue meaning high spending consumers generate less revenue than they do in the US where there is no cap.[25] This means 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. Canada's credit reporting arrangements does not have reciprocity in data sharing as the US does. However, unlike the US, Canada does not al-

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[24]The same credit reporting agencies operate in these markets – Equifax, Experian, and TransUnion operate in the UK while Equifax and TransUnion in Canada – and the structure of the credit card market is analogous – indeed some lenders such as Capital One operate in all three markets. High and stable coverage of actual payments information means researchers using consumer credit reporting data from Canada or the UK can study credit card payment behaviors across a consumer's credit card portfolio (e.g., Adams et al., 2022; Guttman-Kenney et al., 2023a; Allen et al., 2023).

[25]In the EU and UK, credit cards operating via MasterCard or VISA have caps on interchange of 0.3%. As American Express is both a payment merchant and a credit card lender it is not directly capped.

low individual marketing of credit cards but only allows aggregated data on geographic areas to be used for targeting.[26] 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 then 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. CFPB (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 effects using the OLS regression in Equation 1 with one observation per furnisher's credit product portfolio (p), per year-month (t), including fixed effects for furnisher's credit portfolio (γ_p) and year-month (γ_t). We weight observations by the number of accounts in each furnisher's credit product portfolio. δ_τ are our parameters of interest showing the interaction between calendar year-month indicators (D_τ) and an indicator for a furnisher's credit card portfolio ($CRED_p$). The omitted time period is 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 and unsecured loans as control groups (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 markets are less disrupted by Trended Data than credit cards.[27]

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

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[26]Equifax Canada state "while the information from a single Equifax credit file can't be divulged, the average of credit behavio(u)r and scores of a particular neighbo(u)rhood can."

[27]For installment loans, the actual payments information is in the same credit archive as the corresponding scheduled payment and balance information. Whereas for credit cards, the actual payments observed in this month's credit archive correspond to the previous credit archive's scheduled payment and balance information (explained more in section 4.3). This means Trended Data's use of multiple archives reveals more for credit cards than for installment loans.

3.3.2 Empirical Results

Our difference-in-differences results in Figure 1 Panel B 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.[28] While sharing of credit card actual payments information changes little between 2015 to 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 statistically significant at the 1% level but we note that the standard errors after 2013 are wide (15 to 16 percentage points) as a result of clustering at the furnisher level where a small number of large credit card furnishers drive the overall results. 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

This section understands the unraveling by providing a conceptual framework for how profitability differs for credit cards compared to installment loans: auto loans and unsecured loans. These three markets have $3.4 trillion in outstanding balances in December 2022.[29] This framework enables us to then empirically evaluate the marginal value of actual payments information to predicting profitability. We show how actual payments information helps to measure heterogeneous credit card behaviors and helps to predict lifetime profitability.

4.1 Credit Card Profitability

Lenders' expectations of profitability determine which new credit card accounts to attempt to acquire. For acquired accounts, after their contract terms (e.g., interest rate, loan duration) are determined the lender remains uncertain about how a consumer will use the account and the profits the account will ultimately generate. Lenders may be better

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[28]Estimates in Online Appendix Table D1. Online Appendix Figure D7 and Table D2 shows results are robust to using our broader sample definition and weighting by balances.

[29]Online Appendix Figure B1 summarizes the market sizes over time and Online Appendix Table B1 summarizes the differences in product structures.

able to predict profitability if profits are less dependent on uncertain consumer behaviors. Lenders will also be better able to predict profitability if consumer behaviors driving profitability are more persistent over time. If so, historical data such as actual payments information can potentially be informative for predicting profits, and its components.

Two credit cards with identical product features can yield substantially different realized profits (Π_{POST}^{CRED}). This is because credit card profits have multiple, uncertain sources of revenues and costs which are all determined by credit cardholder behaviors after origination.

Given this uncertainty, lenders need to make decisions based on expected profitability: Π_{PRE}^{CRED} as shown in Equation 2. Expected profitability at time $t = 0$ depends on the information available at that time (X_0), primarily information in consumer credit reports. Profitability covers the duration of a card's life from opening at $t = 1$ and held until $t = T$. If a lender can observe how long a consumer currently holds a credit card for, they may be better able to predict a card's lifetime profitability. a represents the acquisition costs (including marketing and underwriting costs) incurred at $t = 0$, which are approximately \$140 and range from \$50 to \$390 in 2012 (R.K.Hammer, Online Appendix C). Other components of revenue and costs have an additive structure and are uncertain: i_t is interchange revenue net of rewards expense, r_t is interest revenue, f_t is consumer fee revenue (primarily late fees and annual fees), and c_t are the costs of charge-offs and fraud. This specification allows for profits to be discounted over time ($\delta < 1$) and if lenders are risk-averse (for example, due to regulation). Lenders also have other organizational-level costs such as costs of funds and operations separate from this account-level measure of profitability.[30]

$$\Pi_{PRE}^{CRED} = E_{t=0}[\Pi_{POST}^{CRED}|X_0] = E_{t=0}\Big[\sum_{t=1}^{T} \delta^t \Big(i_t + \alpha \ r_t + f_t - c_t \Big)|X_0\Big] - a \qquad (2)$$

Because cardholder behaviors are heterogeneous, the ability to predict cardholder behaviors is crucial to determining whether they are profitable to lend to and, if so, which type of credit card to market to a consumer (e.g., a low interest rate card or a high rewards card). Charge-offs are rare but costly events - being the largest costs lenders face and so credit scoring to predict the risk of default is the foundation for lending decisions. Interest revenue is generated proportionally from revolving debt (d_t), $r_t \propto d_t$, where revolving debt is the stock value of the balance remaining after deducting actual payments, i.e., the amount revolved from one statement to the next statement. For a given interest rate,

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[30]R.K.Hammer and Agarwal et al. (2018) estimate costs of funds of under 2% and organization costs of 7% to 8% in 2012.

higher interest revenue is generated from higher revolving balances and from revolving balances for longer durations. The amount of interchange revenue net of rewards expense is proportional to the amount of spending, $i_t \propto s_t$, where spending (s_t) is the flow value of new transactions from one statement to the next statement. 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.

Credit card lenders have different business models and risk tolerances such that they do not all want to lend to the same consumers. This means lenders are not only interested in predicting overall profitability but its component parts. Annual reports show the majority of the revenue generated by 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' 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.

Increasing the predictability of consumer-level profits enables lenders to reduce their costs by avoiding marketing to unprofitable consumers. 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 credit card products available 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 business models: in 2021 American Express spent $5.5 billion and Capital One spent $4.0 billion (public annual reports). Marketing pre-selected credit card offers through direct mail is overwhelmingly concentrated towards very low credit risk ("superprime" or "prime plus" credit score) consumers (CFPB, 2021).

Better prediction reduces the degree of adverse selection a lender faces and enables improved screening. Pre-selected credit offers are a form of screening. For example, a lender may send to a consumer a high rewards card that also has a high annual fee. Such offers screen for high-spending consumers and deters applications from high-risk consumers who can not afford the up-front annual payment. Pre-selected credit offers are highly targeted in their marketing design and contractual features to maximize profits across heterogeneous behavioral types of consumers (e.g., Ru and Schoar, 2020) and vary across the business cycle (e.g., Han et al., 2018).

4.2 Installment Loan Profitability

How does credit card profitability compare to that of installment loans? In this section, we analyze this question by studying installment loans: auto loans and unsecured loans. Equation 3 shows the profit equation for installment loans. Unlike with credit cards, there is no interchange revenue stream for these products. Installment loans also have uncertain consumer fee revenue (f_t). Auto loans and unsecured loans are products that have a fixed term, unlike the open-ended structure of credit cards. As with credit cards, there is uncertainty over whether installment loans will be unpaid and become charged-off (c_t). Auto loans are secured against the auto vehicle which means if the consumer stops paying, the lender can seize the asset to limit their losses. Credit cards and unsecured loans are not collateralized against an asset and therefore if a consumer stops paying, it may be more challenging for the lender to limit their losses.

At origination, installment loans typically have a fixed loan amount, duration, and scheduled monthly payment. This means that, in contrast to credit cards, interest revenue (r_t) is known. However, 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 (q_t) than originally scheduled (r_t) – although it is sometimes able to recoup some of this through charging prepayment fees.[31]

$$\Pi_{PRE}^{INST} = E_{t=0}[\Pi_{POST}^{INST}|X_0] = \sum_{t=1}^{T} \delta^t \Big(\alpha \, r_t - E_{t=0}[q_t|X_0] \Big) + E_{t=0}\Big[\sum_{t=1}^{T} \delta^t \Big(f_t - c_t \Big) | X_0 \Big] - a \quad (3)$$

4.3 Measuring Credit Card Behaviors

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 4 as the credit card statement balance ($b_{i,t-1}$) less actual payments ($p_{i,t}$) made against that 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" (also known as convenience users) who do not ($d_{i,t} = 0$). $b_{i,t-1}$ rather than $b_{i,t}$ is used in this

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[31]Grunewald et al. (2020) write *"In both the subprime and prime markets, prepayment risk is substantial"* in the auto loan market.

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.

$$d_{i,t} \equiv \begin{cases} b_{i,t-1} - p_{i,t} & \text{if } b_{i,t} - p_{i,t} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Credit card spending ($s_{i,t}$) is a flow measure of consumption defined in Equation 5 as 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. Spending behavior is important for lenders as credit card interchange revenue is a function of spending.

$$s_{i,t} \equiv \begin{cases} b_{i,t} - b_{i,t-1} + p_{i,t} & \text{if } b_{i,t} - b_{i,t-1} + p_{i,t} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

We evaluate how much error is added to the measurement of credit card behaviors when actual payments are unobserved. 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 6 where outcomes $Y_{i,t}$ are revolving debt and spending and 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 / highest credit risk group), near prime, prime, prime plus, and superprime (the highest credit score group / lowest credit risk group). We use data in December 2013 as the period of highest coverage of actual payments information and drop data from furnishers not sharing payments information. There is one observation per credit card account (i).

$$Y_{i,t} = \alpha + \beta_1 \, b_{i,t} + \beta_2 b_{i,t-1} + \beta_3 \tilde{\Delta} b_{i,t} + \beta_4 \mathbf{1}\{b_{i,t} > 0\} + \beta_5 \mathbf{1}\{b_{i,t-1} > 0\} + \varepsilon_{i,t} \tag{6}$$

Figure 2 summarizes our results for measuring revolving debt (Panel A) and spending (Panel B) without actual payments information. Across all credit scores, revolving debt is measured with an R^2 of 0.94: showing not observing actual payments increases measure-

ment error. R^2 is decreasing in credit score and is lowest for the superprime group where $R^2 = 0.60$.[32]

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 with an R^2 of 0.51 when actual payments are unobserved.[33] Adding other variables – credit score, zipcode income, scheduled payment, and trends in statement balances – does not change our findings (Appendix Table F1 and Figure F1).

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 wanting to use credit reporting data for measuring revolving credit card debt (e.g., Bornstein and Indarte, 2023; Fulford and Schuh, 2023) and measuring credit card spending as a consumption measure (e.g., Ganong and Noel, 2020; Gross et al., 2020).

4.4 Predicting Consumer Credit Profitability

4.4.1 Modeling Profitability

We now take our profitability equations to empirically examine the predictability of profitability and the marginal value of actual payments in such predictions. We begin by constructing measures of realized profits at the account level for multiple consumer credit products. Having developed empirical measures of profitability, we then perform an exercise in predicting account-level profits. We summarize our methodology in this and the subsequent subsection with more details provided in Online Appendix G.

Measuring realized profits for installment loans is fairly straightforward as we observe a loan's origination terms and charge-offs. Loan terms (loan origination amount A^{INST}, number of scheduled monthly payments N^{INST}, and the scheduled monthly payment amount M^{INST}) provide the scheduled financing charges ($M^{INST} \times N^{INST} - A^{INST}$).[34] We account for loan prepayment by subtracting a proportion of scheduled financing charges when the loan is repaid before its scheduled end date.

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[32] 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).

[33] 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).

[34] We note that for some loans, especially high credit score auto loans, this will imply a zero percent interest rate. Interest rates can also be calculated for mortgages (e.g., Shahidinejad, 2023) and installment loan products (e.g., Yannelis and Zhang, 2023).

Measuring realized profits for credit cards requires calculating financing charges, interchange net of rewards, and charge-offs. 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.

We introduce a new methodology to estimate credit card financing charges in credit reporting data despite these data not containing a variable for this or key product terms (e.g., interest rates). We do so using the formula in Equation 7 that credit card lenders use to calculate minimum payments. Its first component is a floor dollar amount $\$\mu$.[35] 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 ($r_t + f_t$).

$$M_t^{CRED} = \max \left\{ \$\mu, \ \theta\% \, B_t + r_t + f_t \right\} \tag{7}$$

Because minimum payments are deterministically calculated with this formula, observing statement balances and scheduled minimum payments (both inclusive of financing charges) suffices to work out 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 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.

Our methodology appears reasonable in several ways. The most common combination of parameters we find is $\$\mu = \$25$ and $\theta\% = 1\%$ and the most common θ is 1% which is in line with the CFPB's credit card agreement database. The mean of $211.06 in 2012 is close to prior research (e.g., Agarwal et al., 2015b, 2023b) using regulatory datasets with different samples and time periods.[36] Figure 3 Panel A shows we find a hump shape in financing charges by credit score as found in prior research (e.g., Nelson, 2023) and also find financing charges being higher for accounts revolving debt than those transacting debt: these findings are despite our methodology not using this information. If actual

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[35]If balances are below this floor amount then balance rather than the floor is owed. We ignore as this is not economically important given how low the floor amounts are.

[36]Our estimates would not be expected to exactly line up given those studies examine different time periods, different samples, and different datasets which may have different variable definitions. Agarwal et al. (2015b) finds mean annualized financing charges of $223.03 (April 2008 to December 2011). Agarwal et al. (2023b) finds mean financing charges of $17.02 in March 2019: which is $204.24 annualized.

payments are observed, researchers potentially can add additional assumptions to this methodology to separate financing charges into fees and interest, and also estimate effective interest rates.

4.4.2 Methodology for Predicting Profitability

Using data up to December 2012, we predict account-level outcomes ($Y_{i,2012+j}$) on 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 (Online Appendix Figure H7).

We show credit card results for lenders who *Always* share actual payments information, as these are the firms we observe outcomes data for their card's lifetime. We show our results are robust to including *Stoppers* (who stop sharing actual payments information) for whom we need to impute spending (classifications described in Section 2.2). We cannot evaluate the value of actual payments information for lenders that never share this information (*Nevers*).[37] For *Always* we observe actual payments so can estimate spending and interchange net of rewards for all years. For *Stoppers* 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.

Our baseline model in Equation 8 uses the vector ($X'_{i,2012}$) of predictors observed in December 2012. These include indicators for 100 credit score quantiles and credit scores interacted with other account-level information: up to three years of balances, delinquency, utilization rates, estimated financing charges, card tenure, and credit limits. In the case of installment loans, we interact credit score with: the origination amount, scheduled loan duration, and scheduled payment amount.[38] Importantly, $X'_{i,2012}$ does not include actual payments information.

$$Y_{i,2012+j} = X'_{i,2012}\beta + \varepsilon_{i,2022} \tag{8}$$

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[37] While we cannot evaluate actual payments information for lenders that never share this information, Online Appendix Figure G3 compares the baseline prediction of financing charges net of charge-offs.

[38] We examined different specifications of predictors and use the one that best predicts out-of-sample. As a result the specifications differ for auto loans, credit cards, and unsecured loans.

The comparison model in Equation 9 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.

$$Y_{i,2022} = X'_{i,2012}\beta + Z'_{i,2012}\lambda + \varepsilon_{i,2022} \tag{9}$$

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.

4.4.3   Results Predicting Profitability

Table 1 shows the out-of-sample R^2 from models without and with actual payments information to predict lifetime (10 year) profits on credit cards, auto loans, and unsecured personal loans. We find 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.[39] In contrast, actual payments information does not substantially improve the ability to predict lifetime profits for either auto loans or unsecured personal loans – 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.[40] This empirical finding helps to explain why installment loans are willing to keep sharing actual payments information after Trended Data is launched: doing so does not pose a competitive threat enabling competitors to target their profitable customers. While credit cards have a revenue stream directly dependent on spending – interchange – which 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.[41]

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[39] Online Appendix Figure G4 shows results hold for predicting profitability over 1 to 10 year time horizons. My calculation of low predictability of credit card profitability complements the wide cross-sectional dispersion in credit card borrowing costs previously found in Stango and Zinman (2016).

[40] Actual payments information may have limited ability to predict prepayment in auto loans as these loans may be prepaid when a car is sold or traded-in. In such cases, the actual payments information would only not be equal to the scheduled amount at the end of the agreement. Adverse selection due to default risk is present across consumer credit markets (e.g., Ausubel, 1991; Edelberg, 2004; Adams et al., 2009; Crawford et al., 2018) so also appears unlikely to explain differential sharing decisions for credit cards compared to installment loans.

[41] In addition pre-selected offers using credit reports are a common acquisition channel for credit cards but less natural for auto loans (as a loan is typically taken out at dealerships) and unsecured personal loans

How does actual payments information increase the ability to predict the components of credit card profitability? Figure 4 shows the out-of-sample R^2 for predicting (Panel A) interchange net of rewards and (Panel B) financing charges net of charge-offs, both over one to ten year horizons. Panel C shows the profitability components together for the ten year lifetime horizon. We also evaluate this in Table 2 by comparing the realized portfolio values of the top ranked 100,000 accounts when ranking accounts by their out-of-sample predictions made with and without using actual payments information. This shows actual payments increases the net present value of lifetime profits by 2.7%. Our prediction results may be a lower bound since 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.[42]

Actual payments information substantially improves the prediction of interchange net of rewards. Actual payments information increases the R^2 for predicting interchange net of rewards over a one year horizon by 0.401 to 0.614 and over a ten-year horizon by 0.129 to 0.169 (Figure 4 Panel A). Table 2 shows observing actual payments information increases the portfolio value of interchange net of rewards over a one-year horizon by 24% ($42 mean increase) and over a ten-year horizon by 13% ($63). Results are qualitatively similar for $Always + Stoppers$.[43] 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. Actual payments information increases the R^2 for predicting financing charges net of charge-offs over a one year horizon by 2.1% from 0.217 to 0.222 and over a ten year horizon by 4.2% from 0.192 to 0.200 (Figure 4 Panel A). Table 2 shows observing actual payments information increases the portfolio value of financing charges net of charge-offs over a one year horizon by 3% ($14 mean increase) and over a ten year horizon by 1% ($140). Results are similar using $Always + Stoppers$.[44] These predictive increases

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(which are long-term products taken out less frequently).

[42] If there is cross-subsidization, then greater prediction may also enable some lenders to acquire low risk but expected to profitable consumers to lower the risk of their overall credit card portfolio enabling them to lend more to higher expected profit but riskier consumers and so generate higher overall profits that are also more stable over the business cycle.

[43] Actual payments information increases R^2 from 0.415 to 0.619 on a one year horizon, where spending is observed for both $Always$ and $Stoppers$, and by 0.181 to 0.241 on a ten year horizon, where spending post-2013 is imputed for $Stoppers$. Portfolio values increase by 25% over a one year horizon and 18% over a ten year horizon.

[44] Actual payments information increases R^2 by 1.3% from 0.257 to 0.261 on a one year horizon, where spending is observed for both $Always$ and $Stoppers$, and by 2.2% from 0.204 to 0.209 on a ten year horizon,

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 small percentage uplifts are quantitatively important in levels.

Our results are likely to underestimate the importance of interchange revenue for three reasons. First, we assume a flat 0.5% margin of interchange net of rewards, however, rewards cards (most commonly at higher credit scores where high spenders are) have higher margins (Agarwal et al., 2023b). 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., 2023a,b; Han, 2023).[45] Third, our results do not include lenders who do not share actual payments information – in the next section we show these 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 better understand lenders' motivations for no longer sharing information. The decision of credit card lenders to share actual payments information is non-random: *Nevers* (who never share this information), compared to *Always* (who always share this information) or *Stoppers* (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 (Online Appendix Table H1).

5.1   Defaults

Can default risk explain differential information sharing decisions across credit card lenders? Adverse selection due to default risk is well-documented in prior literature in the credit card market (e.g., Ausubel, 1991; Agarwal et al., 2010b).[46] In our data, lenders that never share information (*Nevers*) have more creditworthy cardholders (mean 744) than *Always* or *Stoppers* (means around 720) (Online Appendix Table H1).

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where spending post-2013 is imputed for *Stoppers*. Portfolio values increase by $< 1\%$ over a one year horizon and 1% over a ten year horizon.

[45]Gelman and Roussanov (2023) shows consumers exogenously receiving a new credit card, without any rewards or promotion, causes higher total credit card spending and attribute this to mental accounting.

[46]Also see Jaffee and Russell (1976); Stiglitz and Weiss (1981); Stavins (1996); Ausubel (1999); Calem and Mester (1995); Calem et al. (2006); Adams et al. (2009); Karlan and Zinman (2009); Einav et al. (2012); Ambrose et al. (2016); Crawford et al. (2018); Blattner et al. (2023); DeFusco et al. (2022); Gupta and Hansman (2022); Matcham (2023); Nelson (2023).

We condition cards on their default risk in December 2012 and examine whether these cards 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 as one would expect from non-linear models such logistic regressions. Default rates conditional on credit score are generally similar across lenders with different information sharing decisions (Online Appendix Figure H2). Given this result, default risk is *not* the primary reason for 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.[47] We present results in two ways. First, Table 3 shows the residualized means and standard deviations in cardholder behaviors. We residualize using OLS regressions of outcomes on values of credit scores and adding back population means to ease interpretation ($Y_i - \widehat{Y}_i + \bar{Y}$). Second, Figure 5 (and additional Figures in Online Appendix H) shows the means and 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*).[48]

5.2.1 Revolving Behaviors

Table 3 shows the portfolios of lenders who stop sharing information (*Stoppers*) have 11% higher mean and 12% higher standard deviation residual revolving debt than those who keep sharing information (*Always*). Figure 5 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.

These differences in revolving behavior translate into *Stoppers* having more profitable portfolios (Figure 3 Panel B). Financing charges net of charge-offs (2012 - 2022) for *Stoppers* are 36% ($259) higher mean and 8% ($209) higher standard deviation than *Always* (mean $710, s.d. $2,691).

We do not observe revolving debt for the *Nevers*, and instead use statement balance

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[47]Examining non-default behaviors that do not go into the construction credit scores is conceptually similar to an unobservables test in Finkelstein and Poterba (2014).

[48]We use this approach to present results because the distribution of credit scores is uneven with low density mass for a large number of low credit score values but a high density for particular high credit score values: quantiles display how 60% of cards prime plus or superprime and a 38% of cards are superprime (CDFs in Online Appendix Figure H1).

as an observed but biased proxy for revolving debt. We find monotonicity (*Nevers > Stop-pers > Always*) in means and standard deviations, however, this relationship only holds for below median credit scores (Online Appendix Figure H3). The other way we infer *Nevers*'s revolving debt is comparing our *Always+Stoppers* estimates to public revolving debt estimates for from the Federal Reserve Bank of Philadelphia. This implies the *Nevers* revolve a slightly higher share of balances and have more accounts revolving debt than *Stoppers* or *Always*.[49]

5.2.2 Spending Behaviors

Figure 5 Panel D shows substantial dispersion in spending conditional on credit score: showing spending is a second source of uncertainty lenders experience beyond default risk. Differences in spending behaviors residual of default risk across lenders appear to most clearly explain differential information sharing decisions: with adverse selection into sharing information. Higher spending is important to lenders' business models as it generates higher interchange revenue. Table 3 shows *Stoppers*'s spending, residual of default risk, is 31% ($1,643) higher mean and 41% ($4,275) higher standard deviation than *Always* (mean $5,246, s.d. $10,345). Differences in standard deviations of spending between *Stoppers* and *Always* occur across the credit score distribution (Figure 5 Panel D) and differences for mean spending (Figure 5 Panel C) occur for prime, prime plus and superprime segments (i.e. those that often contain transactors). Part of the reason for this standard deviation being so high is consumers often hold multiple credit cards and so credit card lenders are competing to be "top of wallet": the main (or ideally only) card a consumer uses.[50]

How does the spending of $Nevers$ compare? *Nevers* have more cards held by high credit score consumers which would be, on average, expect to generate higher spending. We investigate this using a proxy for spending – change in statement balances conditional on being positive ($\tilde{\Delta}b_{i,t}$) – that we observe across *Always*, *Stoppers*, and *Nevers*. Equation 10 shows how this proxy measure is spending plus a non-random error term $\nu_{i,t}$ which is

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[49]FR Y-14K data for Q4 2012 estimate revolving debt is 77% of balances and 71% of accounts revolve debt. Aggregating *Always* and *Stoppers* in our data, we estimate revolving debt is 73% of balances and 63% of accounts revolve debt. We caveat that FR Y-14K data 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.

[50]Discussions with industry participants indicate a cardholder needs to spend at least $10,000 to $20,000 per year for several years to overcome their acquisition and other costs and become profitable on interchange revenue alone. Discussions mentioned how 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 long-duration contracts for it to be a worthwhile venture for the lender.

biased downwards as actual payments increase ($p_{i,t}$ can only be greater than or equal to zero) and 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. This measure (residual of default risk) shows *Nevers* have a higher mean and higher standard deviation than *Stoppers*, who in turn have a higher mean and a higher standard deviation than *Always* (Table 3).[51] 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).[52] If we calculate spending aggregating *Always* and *Stoppers* and multiply by their market share it would imply total spending of \$2.43 trillion and so indicates *Nevers*'s mean spending is higher than the rest of the market average.

$$\tilde{\Delta}b_{i,t} \equiv \begin{cases} b_{i,t} - b_{i,t-1} \equiv s_{i,t} - \underbrace{p_{i,t} + r_{i,t} + f_{i,t}}_{\nu_{i,t}} & \text{if } b_{i,t} - b_{i,t-1} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

5.2.3 Card Tenure

The longer a credit card is held for, the more private information a lender may hold, which they could use to extract information rents from the cardholder.[53] Holding a card for longer may indicate a consumer's switching costs have increased – potentially due to preferring that card to alternatives.

We document a new fact: card tenure varies across and within the credit score distribution as displayed in Figure 5 Panels E (mean card tenure) and F (s.d. card tenure). There's a clear pattern of adverse selection in information sharing decisions by card tenure. Table 3 shows *Nevers*'s card tenure, residual of default risk, has the highest means and s.d. (mean 136 months, s.d. 106 months) compared to *Stoppers* (mean 98 months, s.d. 76 months) and *Always* (mean 71 months, s.d. 74 months). Figure 5 Panel E shows this pattern exists in means across the distribution of credit scores, and the differences in s.d. between *Nevers* and *Always+Stoppers*.

Substantial differences in card tenure across the credit score distribution 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., 2015b) or

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[51]See Online Appendix Figures H4 and H5 for results by credit score.

[52]The Federal Reserve statistics are the sum of (general-purpose) credit cards and retail (private label) credit cards. For this comparison we therefore include data on retail credit cards where actual payments are observed.

[53]Sharpe (1990); Rajan (1992); Petersen and Rajan (1994); Von Thadden (2004); Nelson (2023)

a single point-in-time (e.g., Agarwal et al., 2023b). Given we find different segments of the credit score distribution, cards within these segments, and different credit card lender portfolios have substantially tenures the lifetime profitability of credit cards may differ from the profitability over a short, fixed horizon. For example, consider 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 to explain an otherwise puzzling fact that credit card lenders lend to and heavily concentrate marketing towards high credit score consumers (e.g., CFPB, 2021) despite those consumers frequently being transactors generating little-to-no revenue from financing charges (Figure 3 Panel B).[54] High credit score transactors' longer tenure can be mean their accounts are NPV > 0 on interchange – especially if they can find high spenders – and also avoids future acquisition costs.[55]

The portfolios of the credit card lenders remaining in the market for sharing actual payments information are the worst (the "lemons" in Akerlof, 1970) residual types 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.[56] Our results are consistent with *Nevers* and *Stoppers* holding information rents over other lenders: as incumbent lenders they are especially exposed to actual payments information in Trended Data being used for marketing targeted to their large number of low-risk, long-tenure, high spending cardholders that generate interchange revenue. By not sharing information, incumbent lenders with market power from informational rents make it more difficult for competitors to successfully target their

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[54]Similar aggressive competition for low risk consumers is also observed in other markets with adverse selection such as healthcare where it leads to higher an "(un)-natural monopoly" where a small number of firms profitably operate with high mark-ups (Kong et al., 2023).

[55]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. Online Appendix Figure H9 shows how interchange net of rewards increases with card tenure and is noticeably higher for the high credit score segments. Furthermore, given high credit score transactors are very low risk there is little-or-no risk-adjustment required.

[56]The greater dispersion among the part of the market not willing to share information may appear reminiscent of Hendren (2013) who finds greater dispersion explains which consumer segments are served by which insurance markets. However, these are different. In Hendren (2013) consumers are unable to access insurance because the dispersion from private information makes them unprofitable. Whereas in our case the dispersion appears to be for a profitable segment where lenders hide their profitable consumers to prevent targeting by their competitors.

profitable customers by raising their competitor's costs of acquiring new consumers.[57]

5.3 Effect of Trended Data on New Account Openings

Analyses in the previous section suggests that Trended Data was expected to be a competitive threat by enabling targeted marketing. In this section we provide evidence that is consistent with this hypothesis. In subsection 5.3.1 we explain our research design based on heterogeneous consumer exposure to Trended Data and then in subsection 5.3.2 we show 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 (Equation 11) to this innovation. 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 by Trended Data on a consumer's behavioral type (e.g., spending and revolving behaviors) in 2013.

$$EXPT_i \equiv \frac{\sum_c 1\{F_c \in \text{Sharers}\} \times b_{i,c}}{\sum_c b_{i,c}} \tag{11}$$

We use this exposure measure to estimate the difference-in-differences with varying treatment intensity equation shown in Equation 12. 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.[59] Figure 6 Panel A shows the CDF of the exposure measure is smooth with mean 49.5% and median 49.2%.

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[57]Industry data from R.K.Hammer (Online Appendix C2) shows the mean costs of acquisitions increasing over time because more solicitations are required to successfully acquire each new account. [58]

[59]Online Appendix H10 shows robustness to including consumers with three cards.

$$Y_{i,t} = \sum_{\tau \neq -1} \delta_\tau \Big(D_\tau \times EXPT_i \Big) + \gamma_i + \gamma_t + \varepsilon_{i,t} \qquad (12)$$

5.3.2 Empirical Results

Our results show 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 (Figure 6 Panel B). In 2013 Q4, we estimate 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 is a 13% increase relative to the Q4 2012 mean 3.22% rate of opening a new credit card 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 unraveling occurs, the effect dissipates to be insignificant from zero.

5.4 Discussion

Given our results we now discuss whether the unraveling of information sharing is best understood as a coordination failure – a natural explanation for the phenomenon we document and one that some lenders themselves suggest explains their own behavior. 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. In games with multiple equilibria, there may also be a coordination failure leading lenders to a pareto-dominated equilibrium, even though they would be better off coordinating to reach an alternative equilibrium. Unraveling does not appear to simply be a coordination failure. An industry body – the Consumer Data Industry Association (CDIA) – exists to facilitate and coordinate sharing but was unable to prevent the unraveling or undo it in the nine 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 (CFPB, 2023).[60] These lenders' responses to the CFPB (2023) are consistent with them considering that the costs of sharing information outweigh the benefits.[61]

Our empirical evidence indicates lenders have heterogeneous payoffs from sharing information and Trended Data made not sharing information a dominant strategy for

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[60]Although we note it remains possible for a coordination failure to only exist between the lenders who stopped sharing information, we view this as an unlikely explanation given the CDIA's existence.

[61]When CFPB (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.".

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.[62] The only lenders willing to share information are those with few high-quality accounts at risk of being targeted (i.e., without market power). They 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.[63] This lack of information sharing is 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

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 are mandated to share information? As actual payments information has not been mandated, we instead learn from a prior historical event: the the Federal Trade Commission (FTC) mandating lenders to share information on credit card limits. Not sharing credit limit information makes consumers *appear* more utilized and higher risk than they actually 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.[64] In the 1990s, credit limit information was commonly not 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).[65] The FTC mandate results in the remaining lenders also sharing this information.

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[62] A reduction in adverse selection can increase entry (e.g., Dell'Ariccia et al., 1999) and reduce the incumbent's voluntary sharing of information (e.g., Bouckaert and Degryse, 2006).

[63] Our empirical findings on the worst residual types being the ones sharing information is consistent with a different domain: investors sharing information. Goldstein et al. (2023)'s provides a theory for why less informed investors non-reciprocally share information with more informed investors (doing so reduces the latter's price impact as it can trade less aggressively on its own information) while the more informed investors do not share information (doing so would reduce their private informational advantage and reduce their profits).

[64] Giannetti et al. (2017) finds in Argentina incumbent banks strategically downgraded high quality firms or entrepreneurs in their public credit registry before such information was released to their competitors.

[65] From discussions with industry, we understand it would not be credible for credit reporting agencies to threaten to shut off credit card lenders' access to credit bureau data unless they share actual payments 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 a small number of lenders start sharing credit card limits information on consumers' credit card accounts (Online Appendix Figure I1).[66] 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.[67]

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.[68] We use variation in how much information is revealed by calculating consumer-level (i) heterogeneous exposure $EXPL_i = \frac{r_i - h_i}{r_i}$ as the percentage difference between the *revealed* credit limits ($r_i \equiv \sum_c r_{i,c}$) and credit limits that could be *inferred* based on information observed prior to the limits being revealed ($h_i \equiv \sum_c h_{i,c}$). For each of a consumer's credit cards (c) we calculate $r_{i,c}$ as the credit limits shared in October 2010 and, for accounts not sharing this information, we use the November 2010 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 2010 and, for accounts not sharing this information, we use the highest balance historically recorded in October 2010. We then aggregate these card-level calculations to produce a consumer-level exposure measure. Figure 7 Panel A shows the distribution of our exposure measure is smooth with a mean of 17% and median of 14%. A higher exposure value means 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,

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[66]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 (Online Appendix Figure Panel I1 A). We therefore expect the CFPB's inception in July 2011 led to these rules being enforced. In another context, Wang and Burke (2022) show payday lending regulations did not have effects when enacted but only had effects when enforced.

[67]Approximately 20% for VantageScore and 30% for FICO. Credit utilization may also be measured on revolving credit lines such as retail cards and home equity lines of credit for those with such accounts.

[68]Sources of variation in US credit reports are mainly concentrated on riskier subsamples of the population, exploiting the removal of negative information such as on bankruptcy (e.g., Musto, 2004; Dobbie et al., 2020; Gross et al., 2020; Jansen et al., 2022), medical debts in collections (e.g., Batty et al., 2022), public records (e.g., Fulford and Nagypál, 2023), defaults (e.g., Blattner et al., 2023), or the addition of information about natural disasters (e.g., Guttman-Kenney, 2023). See Gibbs et al. (2023) for a review of credit reporting data.

increase their credit scores, and increase their credit access.[69]

We use this exposure measure to estimate the difference-in-differences regression specified in Equation 13. We estimate an OLS regression on a balanced panel of 1.09 million consumers with consumer (γ_i) and year-quarter (γ_t) fixed effects and with standard errors clustered at the consumer level.[70] 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.

$$Y_{i,t} = \sum_{\tau \neq \text{-}1} \delta_\tau \Big(D_\tau \times EXPL_i \Big) + \gamma_i + \gamma_t + \varepsilon_{i,t} \tag{13}$$

6.2 Empirical Results

Figure 7 Panel B shows moving from 0% to 100% exposure significantly increases credit scores by 22.6 points (95% C.I. 22.4, 22.9) and this effect is persistent but declines in magnitude over time. This effect size can be evaluated relative to a baseline mean credit score of 776.

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, 1994, 1995; Schenone, 2010; Sutherland, 2018). The inside lenders are lenders who started sharing credit limit information but already knew about their own consumers' credit limits and credit risks. The outside lenders already share credit limit information and potentially learn about the consumer from updating their priors with the data newly shared by the inside lenders.[71]

This change in credit score increases competition with switching from inside to outside lenders. Figure 7 Panel C shows moving from 0% to 100% exposure significantly decreases the rate of opening any new credit card with an inside lender in a quarter by 56% (estimate -1.16 percentage points, 95% C.I. -1.32 to -1.00 percentage points). For outside lenders, at the same time we find a 32% (estimate 2.35 percentage points, 95% C.I. 2.08 to 2.62 percentage points) increase in the rate of opening any new credit card and causes a significant 14% overall increase in the number of new cards opened (estimate 1.24, 95% C.I. 0.93 to 1.54). Figure 7 Panel D shows this also significantly decreases the

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[69]This approach is conceptually similar to Liberman et al. (2019) and Foley et al. (2022) who estimate predicted probabilities of default with and without information in Chilean credit reporting data.

[70]Online Appendix I contains additional details on the sample.

[71]Outside lenders are measured with error – they may contain some portfolios of the inside lender using a different furnisher who already shared this information.

value of new credit card limits with an inside lender by 90% (estimate -$614, 95% C.I. -$715 to -$512 percentage points) and increases the value of new credit card limits with an outside lender by 48% (estimate $643, 95% C.I. $554 to $732). There is no significant overall increase in total new limits across inside and outside lenders combined (estimate $27, 95% C.I. -$108 to $162 relative to a baseline mean of $2,026) and therefore we expect outside lenders are attracting consumers through improved non-credit limit contract terms (e.g., lower interest rates, higher rewards). We interpret our results as showing the potential threat of increased competition explains why some lenders are reluctant to voluntarily share information and mandating information sharing can increase competition. This is important since the credit card market has persistently high returns on assets in excess of adjusting for risk and therefore increasing competition to reduce mark-ups from informational rents may be a desirable policy.[72]

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 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 with market power from informational rents.[73] We then show how mandating sharing credit card information can increase competition. This evidence together supports a policy to

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[72]See Online Appendix C and Herkenhoff and Raveendranathan (2023).

[73]Understanding the limits of information sharing due to the market power of incumbents – see Philippon (2015, 2019); Traina (2018); Grullon et al. (2019); De Loecker et al. (2020); Eeckhout and Veldkamp (2022) for studies of market power more broadly – may also inform on the limits of open banking *unless* it enables competitors to target incumbent's profitable customers.He et al. (2023) provides theory on the effects of open banking including showing the circumstances when it can leave consumers worse-off. Early empirical research into open banking adoption shows some consumer benefits (e.g., Babina et al., 2022; Nam, 2022). The UK was an early adopter of open banking but the potential competitive gains do not appear to have been realized: six years after its introduction fewer than 10% of UK consumers use it and the positions of incumbent lenders with market power appears little changed: Financial Times, 26 January 2023 and The (unmet) potential of Open Banking" Oxera report 4 July 2023. Open banking's effects may be limited if consumers remain with incumbents even when competitors offer improved terms. This may occur for a variety of reasons including privacy concerns of sharing information, concerns about the stability of FinTech lenders to lend to them, and behavioral frictions such as limited inattention which warrant research.

mandate information sharing as we expect it to reduce incumbents' informational rents and improve market efficiency by reducing information asymmetry.

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 lenders face a second source of uncertainty separate to 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. Lenders therefore want to acquire high-spending, long-tenure credit cardholders.

8 Figures and Tables

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

A. Unconditional Means

B. Difference-in-Differences Estimates
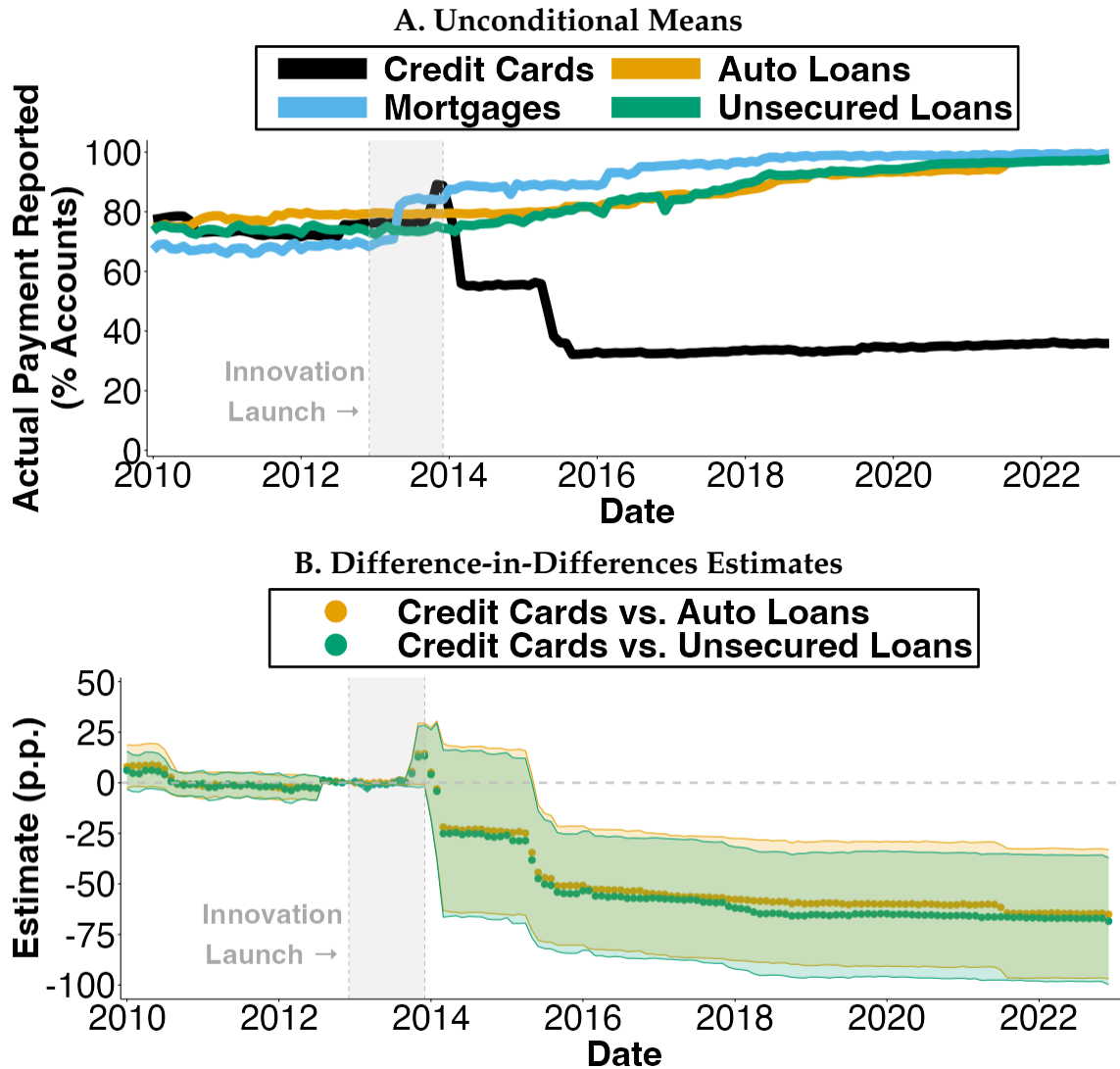
Notes: BTCCP data. 2013 is shaded in gray to denote the period when Trended Data was launched. Panel A shows, for each consumer credit product, the fraction of accounts in consumer credit reports sharing actual payment amounts. In the numerator of this calculation, accounts with actual payment amounts 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.

Figure 2: Measuring Credit Card Behaviors Without Actual Payments (AP) Information

A. Revolving Debt
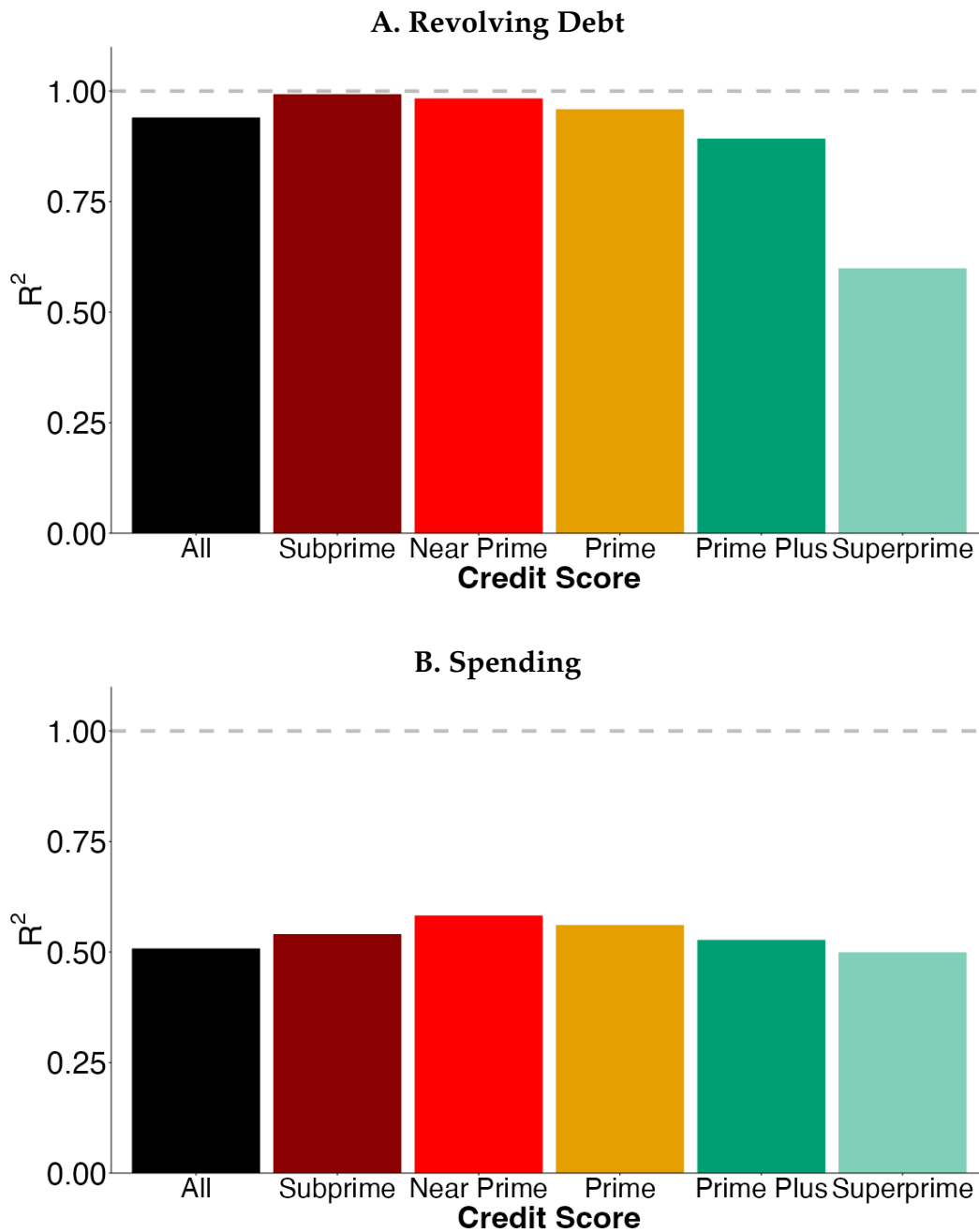
B. Spending

Notes: BTCCP data. R^2 from Equation 6 explaining credit card behaviors(Revolving Debt in Panel A and Spending in Panel B) at the account-level in December 2013. Regression includes 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 and each credit score segments subprime (the lowest credit scores), near prime, prime, prime plus, and superprime (the highest credit scores).

Figure 3: Estimated Financing Charges

## A. Financing Charges (2012) By Credit Card Behaviors
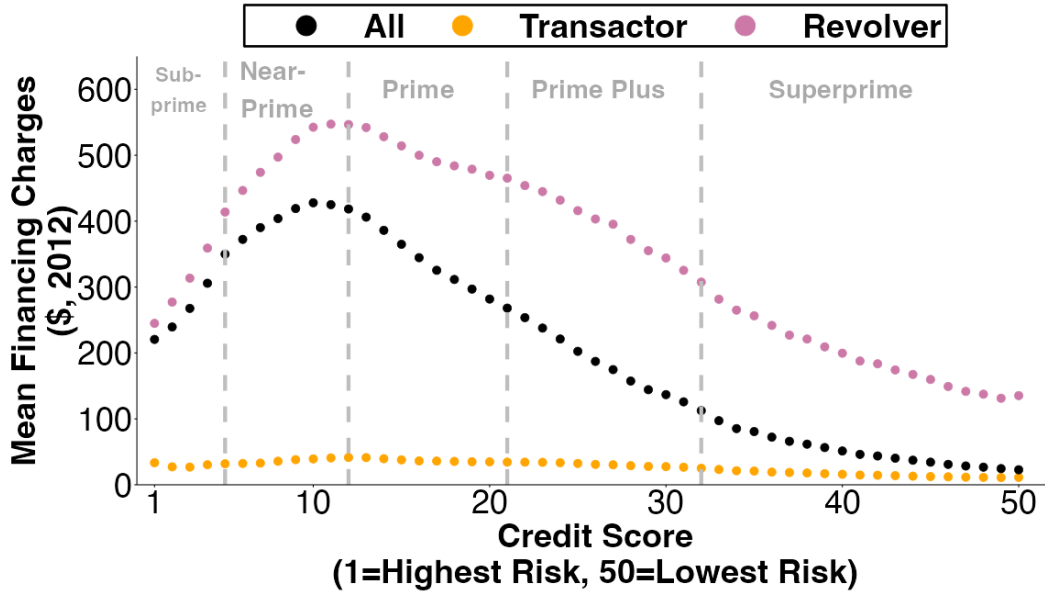
B. Financing Charges Net of Charge-Offs (2013 - 2022) By Lenders' Actual Payments Information Sharing Decisions
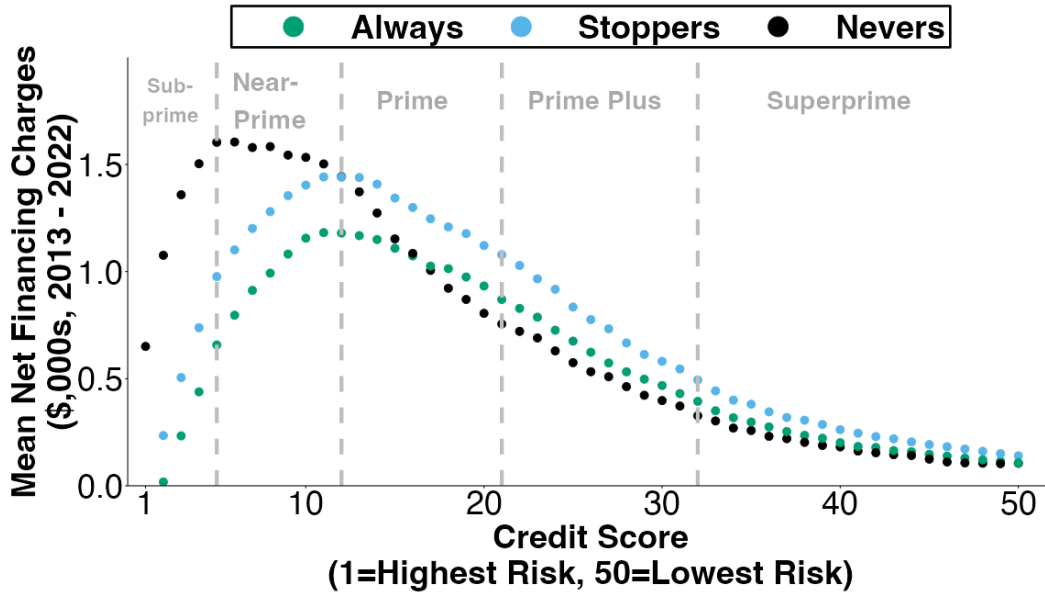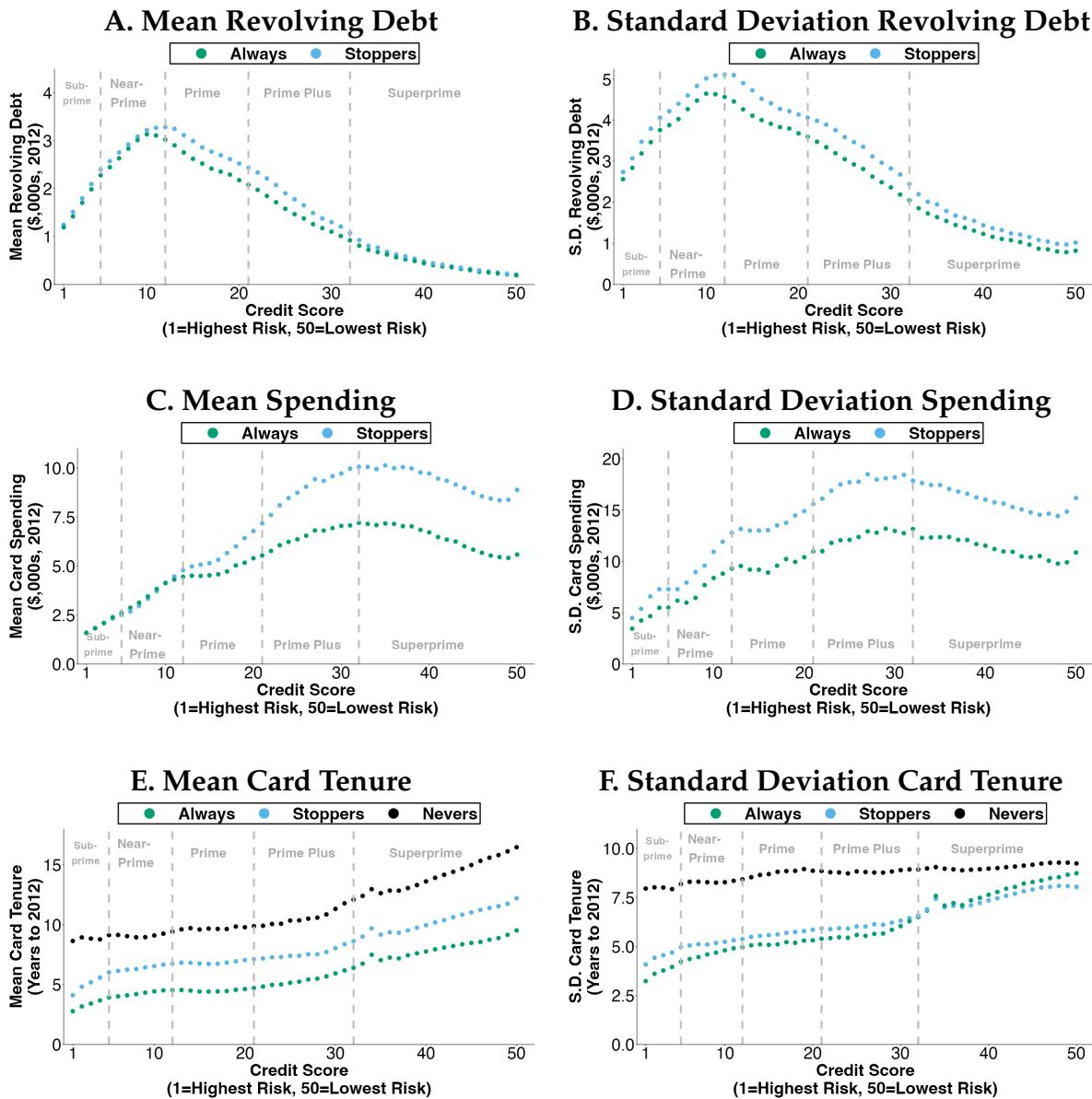

Notes: BTCCP data. Figures shows mean estimates conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Financing charges are estimated as described in section G.1. Panel A shows 2012 financing charges splitting by their 2012 card behaviors. Panel B shows financing charges accumulated across 2012 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 3 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 4: Marginal Value of Actual Payments (AP) Information for Predicting (A) Interchange Net of Rewards, (B) Financing Charges Net of Charge-Offs, (C) Lifetime Profits
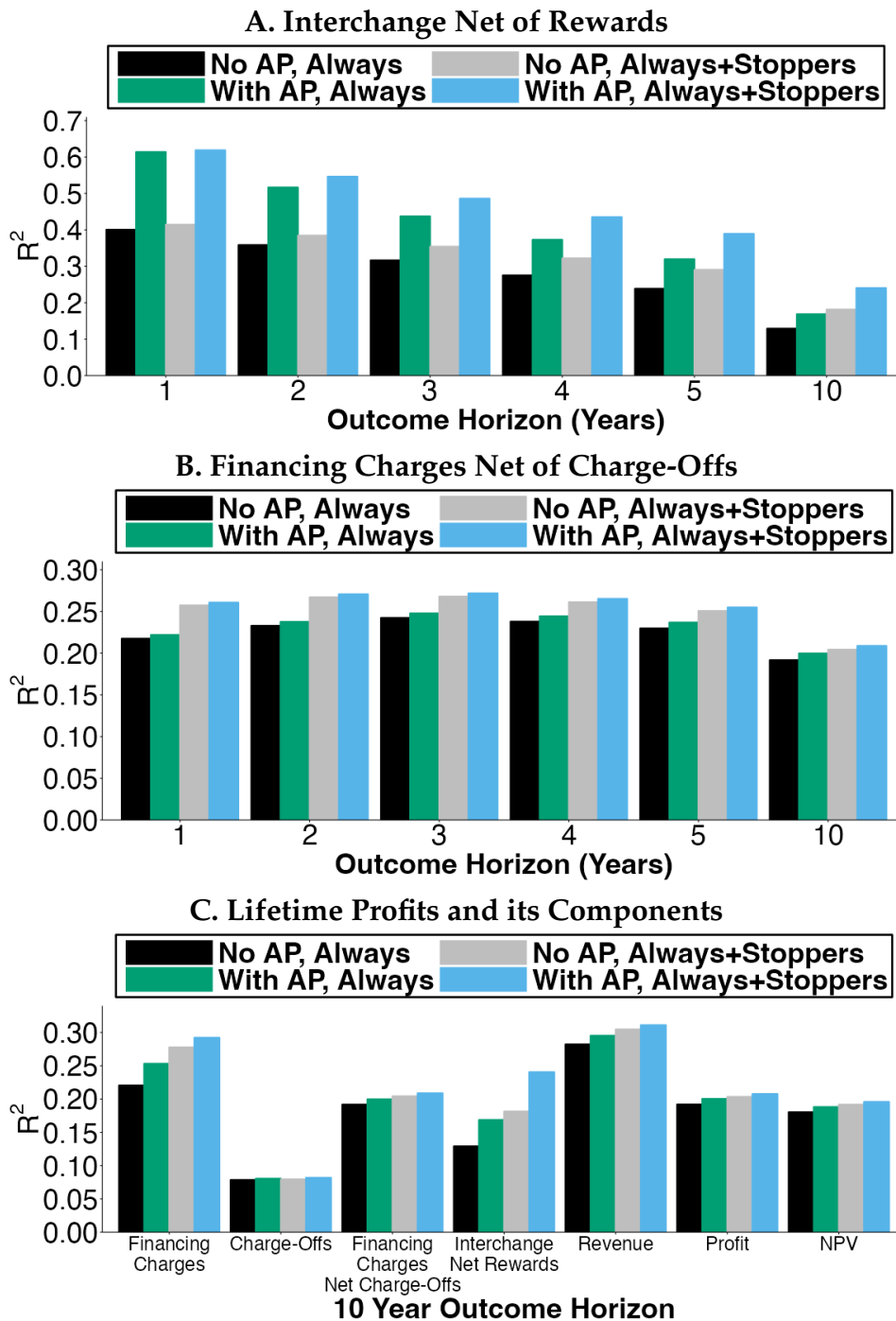
Notes: BTCCP data. Figures use data to December 2012 to predict account-level credit card profitability where predictive performance is measured by out-of-sample R^2. Results are shown without (black, gray) and with (green, blue) actual payments information. Performance is shown for two samples: "Always" (black, green) and "Always+Stoppers" (gray, blue) as described in paper section 2.2 and Table 3 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.

Figure 5: 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 3 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. 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 6: Effects of Trended Data on Any New Credit Card Account Opening

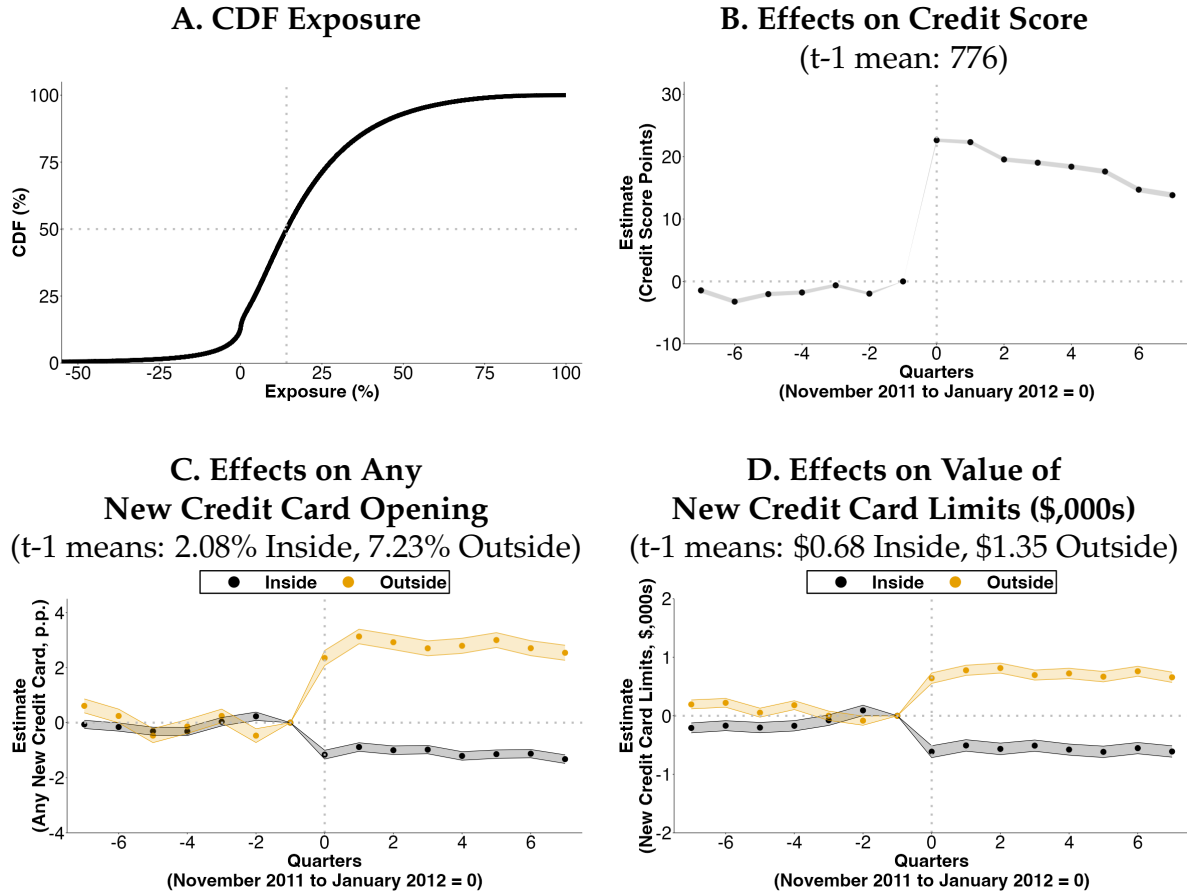**A. CDF Exposure to Trended Data**
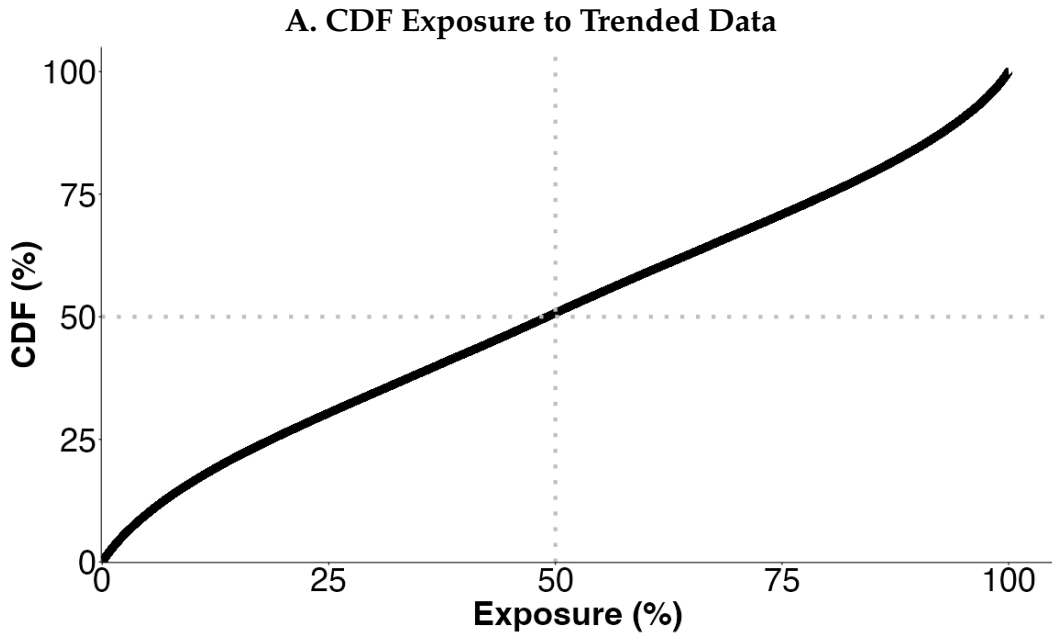
B. Estimates of Effects of Trended Data on Any New Credit Card Opening
(t-1 mean: 3.22%)
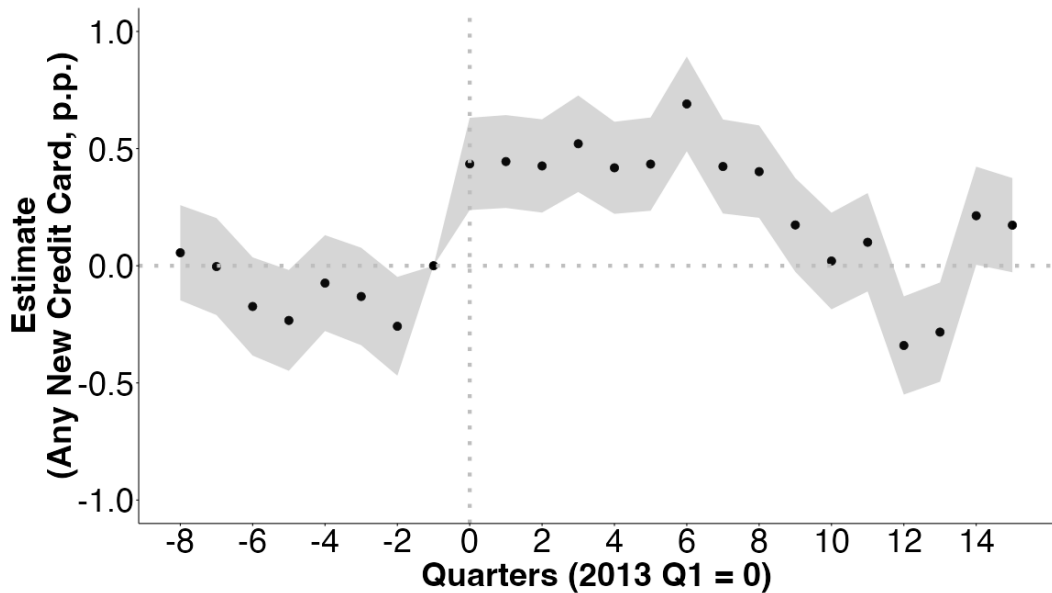
Notes: BTCCP data. Panel A shows CDF of exposure. Exposure is (pre-Trended Data) share of 2012 credit card balances held with furnishers who share actual payments information. Panel B shows difference-in-differences with varying intensity estimates in percentage points (p.p.) where the outcome is any new credit card account openings in a quarter. Difference-in-differences estimates are from balanced panel of consumers 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 12 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 7: Effects of Mandating Sharing of Credit Card Limit Information

A. CDF Exposure

B. Effects on Credit Score
(t-1 mean: 776)

C. Effects on Any
New Credit Card Opening
(t-1 means: 2.08% Inside, 7.23% Outside)

D. Effects on Value of
New Credit Card Limits ($,000s)
(t-1 means: $0.68 Inside, $1.35 Outside)

Notes: BTCCP data. Panel A shows CDF of exposure. Exposure is $EXPL_i = \frac{r_i - h_i}{r_i}$ the percentage difference between a consumers' observed credit limit and imputed credit limit. Panel B, C, D show difference-in-differences with varying intensity estimates in percentage points (p.p.) where the outcome is credit score, any new credit card account openings in a quarter, total value of of new credit card limits opened. Data is a balanced panel of consumers. Results are estimating OLS regression specified in Equation 13 with consumer and calendar year-quarter fixed effects and interaction term between exposure and calendar year-quarter 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: Marginal Value of Actual Payments Information for Predicting Lifetime Profitability on Credit Cards and Installment Loans (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

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.

Table 2: Marginal Value of Actual Payments Information for Predicting Credit Card Profitability as Measured by Top-Ranked Predicted Portfolio Values

Sample	A. Interchange Net of Rewards (1 Year)	
	Baseline	Change With Actual Payments (%)
Always	$171	+24%
Always & Stoppers	$319	+25%

Sample	B. Interchange Net of Rewards (10 Years)	
	Baseline	Change With Actual Payments (%)
Always	$473	+13%
Always & Stoppers	$531	+18%

Sample	C. Financing Charges Net of Charge-Offs (1 Year)	
	Baseline	Change With Actual Payments (%)
Always	$1,391	+1%
Always & Stoppers	$2,600	+0%

Sample	D. Financing Charges Net of Charge-Offs (10 Years)	
	Baseline	Change With Actual Payments (%)
Always	$4,959	+3%
Always & Stoppers	$7,954	+1%

Sample	E. NPV (10 Years)	
	Baseline	Change With Actual Payments (%)
Always	$4,772	+2.7%
Always & Stoppers	$7,424	+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 change in portfolio value relative to this baseline when instead ranking by predictions using actual payments information as predictors.

Table 3: Summarizing Selection (Residual of Credit Score) in Credit Card Portfolios By Lenders' Actual Payments Information Sharing Decisions

	Always	Stoppers	Nevers
Residual Tenure	71.0	97.6	136.5
(S.D.)	(73.8)	(75.5)	(106.0)
Residual Credit Limit	8,902.2	9,793.4	9,757.4
(S.D.)	(6,687.7)	(8,484.3)	(9,238.6)
Residual Statement Balance	2,004.3	2,294.8	2,576.5
(S.D.)	(3,405.9)	(3,842.4)	(4,130.1)
Residual Proxy Spending	2,486.2	2,800.2	3,286.2
(S.D.)	(4,036.2)	(4,987.6)	(6,998.7)
Residual Financing Charges	130.1	235.0	156.5
(S.D.)	(351.3)	(534.5)	(440.8)
Residual Revolving Debt	1,538.1	1,707.6	N/A
(S.D.)	(3,047.7)	(3,413.6)	
Residual 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 G.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.

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9 Online Appendix

Contents:

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B. Consumer Credit Markets

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H. Credit Card Selection

I. Mandating Sharing Credit Card Limit Information

A   Credit Reporting Legal Requirements

This appendix shows credit reporting legal requirements based on relevant 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 Consumer Credit Markets

Figure B1: Consumer Credit Market Sizes

A. Open Accounts (millions)

B. Outstanding Balances ($ trillions)
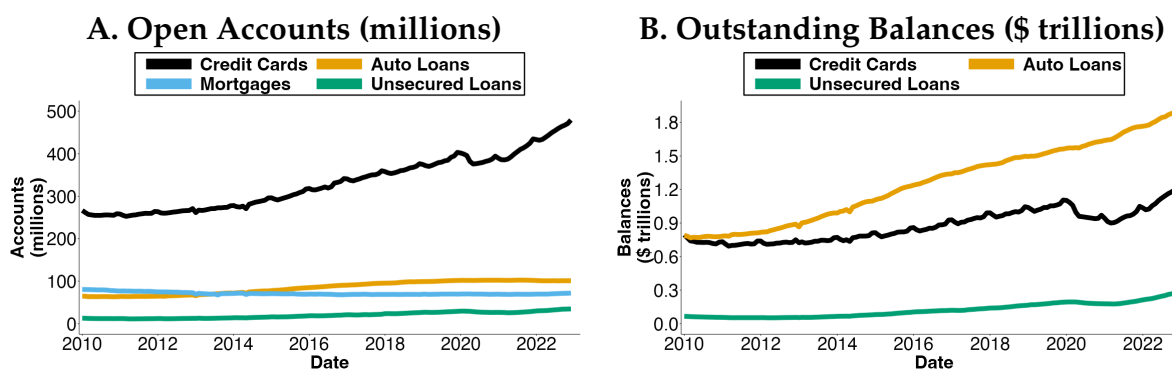
Notes: BTCCP data. Both panels restrict to open accounts with non-zero balances and which have been updated in the last year. Mortgage balances are excluded from Panel B due to their substantially larger balances.

## Table B1: Consumer Credit Product Comparison

	Auto Loans	Unsecured Loans	Credit Cards
Duration	Fixed-Term		Open-Ended
Revenue Streams	Financing Charges (Interest, Fees)		Financing Charges (Interest, Fees), Interchange
Uncertain Behaviors	Delinquency, Prepayment		Delinquency, Revolving Amount & Duration, Spending
Collateral	Secured		Unsecured

Notes: Financing charges is the sum of interest and consumer fees. The most common consumer fees are late fees. Other consumer fees include annual card fees, over credit limit, and foreign exchange fees. Interchange income is the amount of transaction fees credit card lenders receive from merchants when a consumer spends on their credit card.
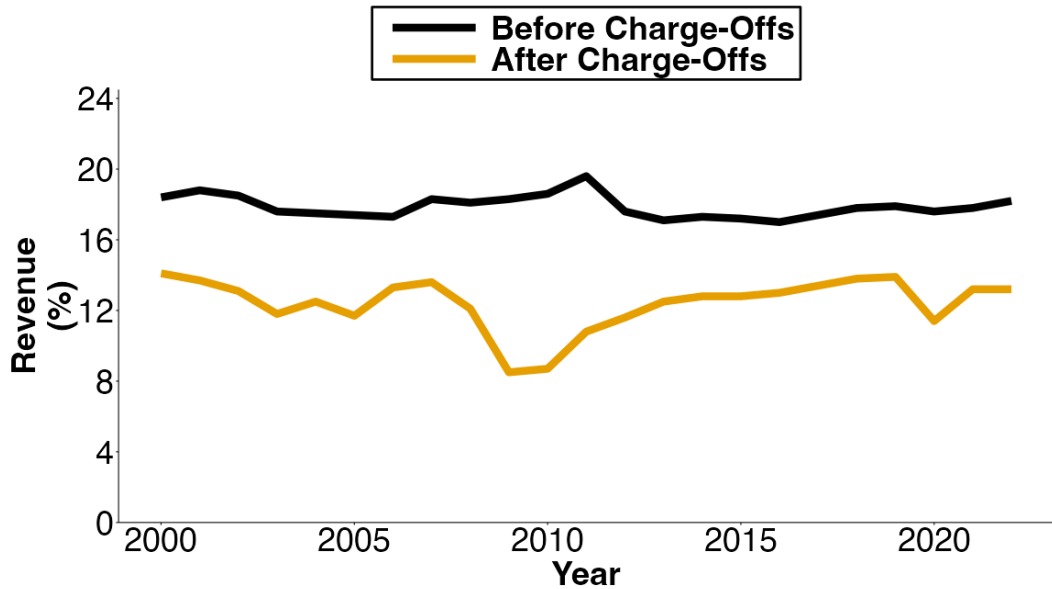
C   Credit Card Industry Statistics

Figure C1: Credit Card Profitability

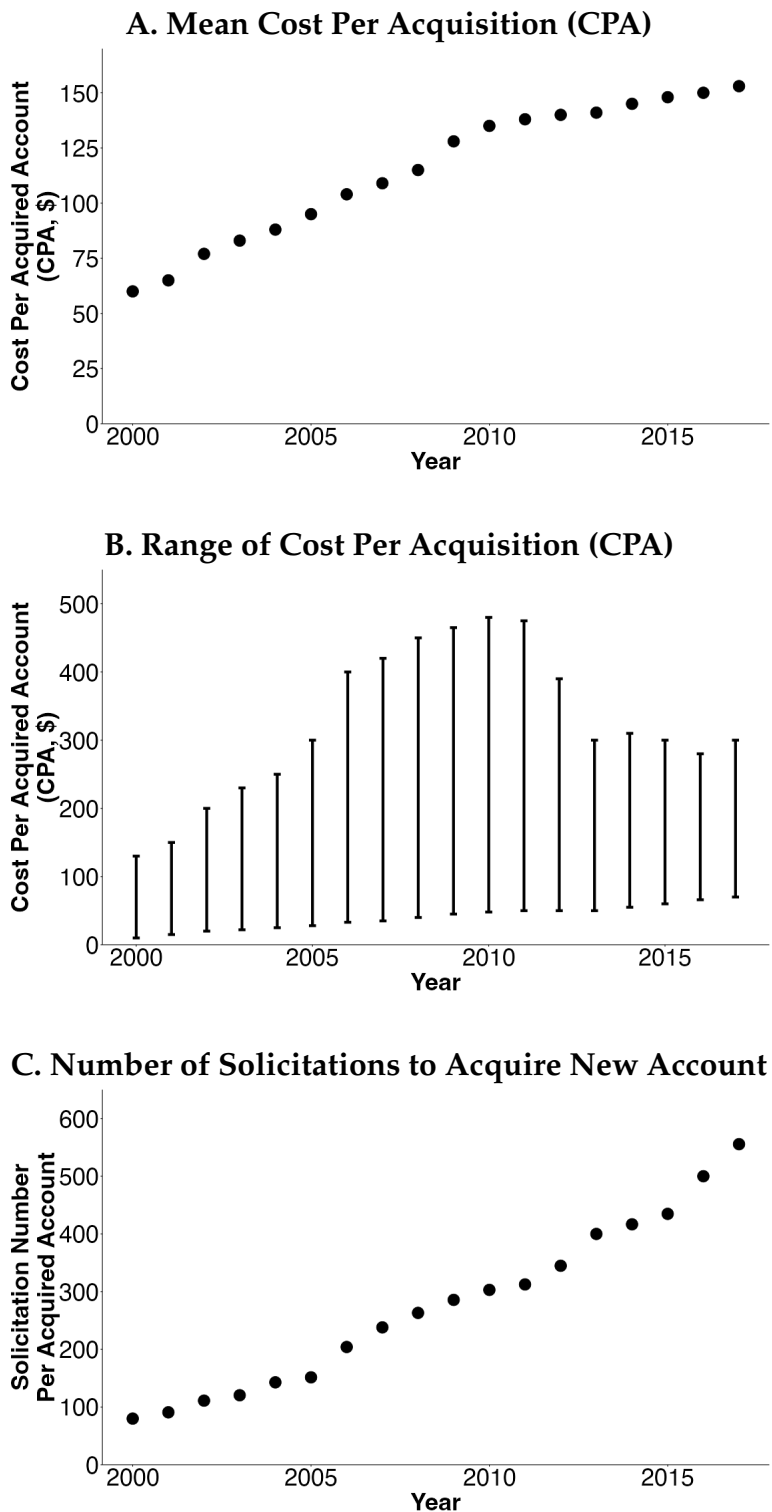### A. Return on Assets (ROA) and its Components (1983 - 2022)
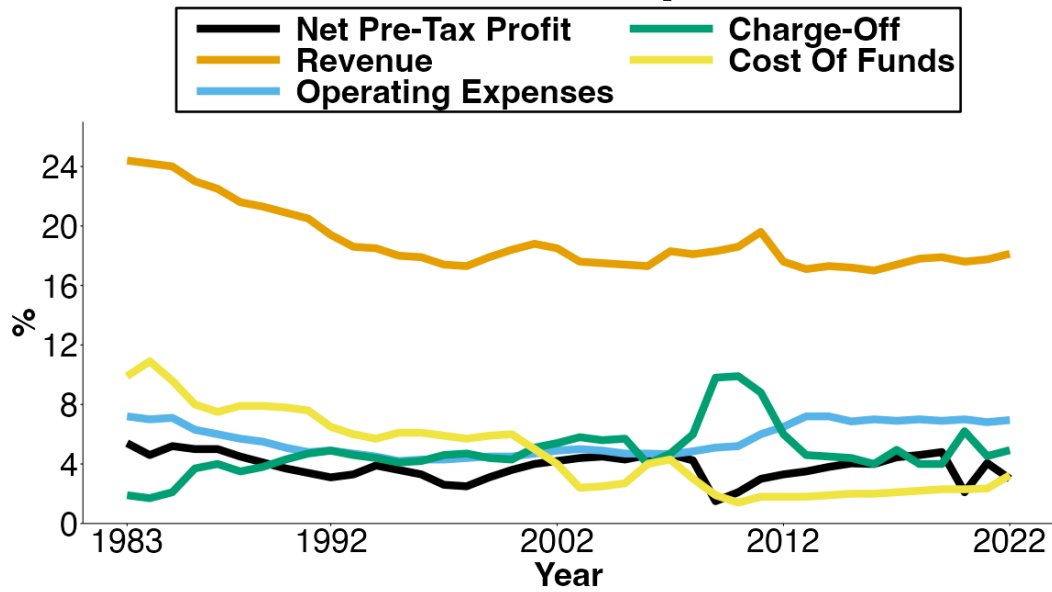
B. Revenue before and after Charge-Offs (2000 - 2022)

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 C2: 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 New Account

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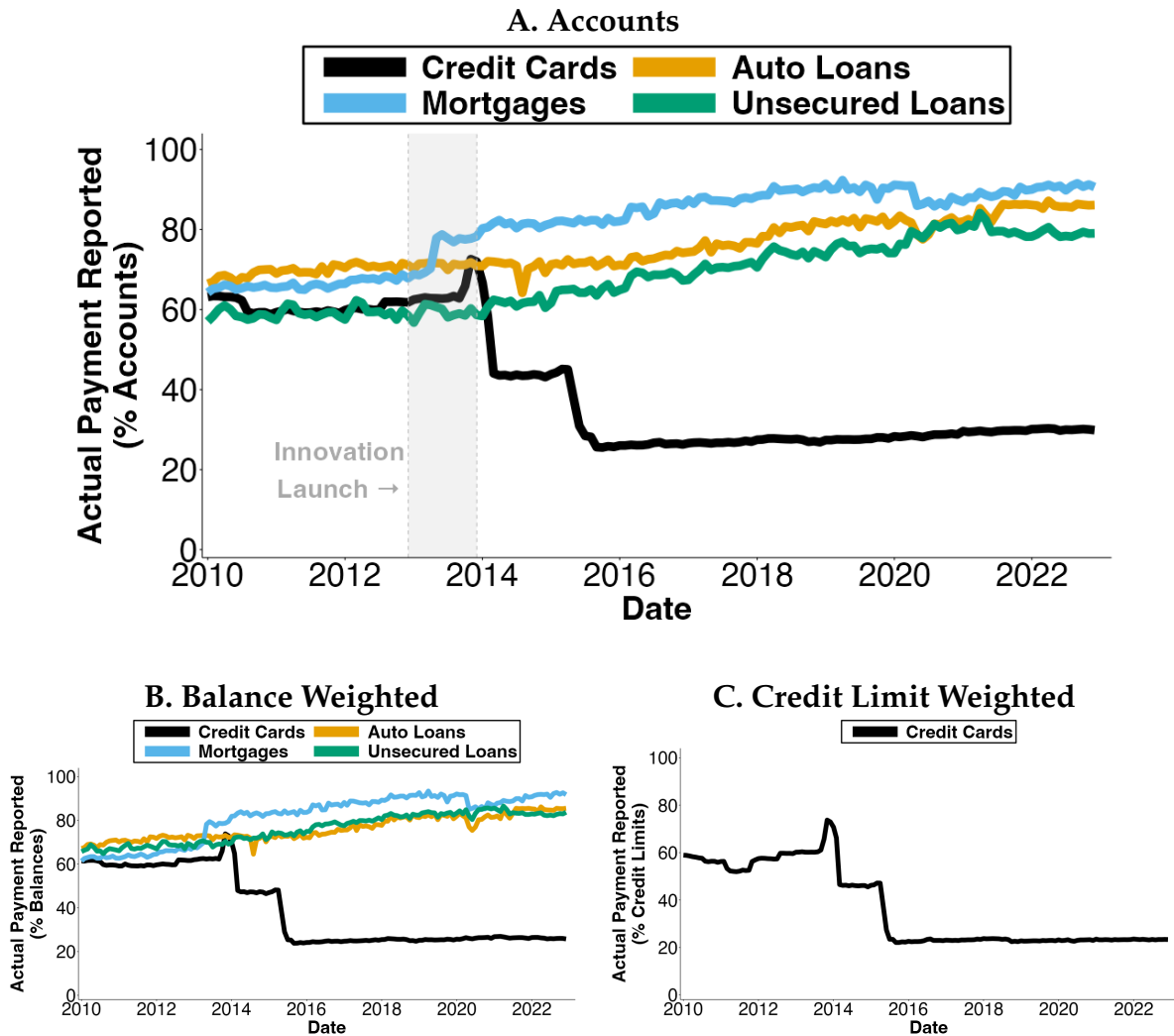
D   Actual Payments Information

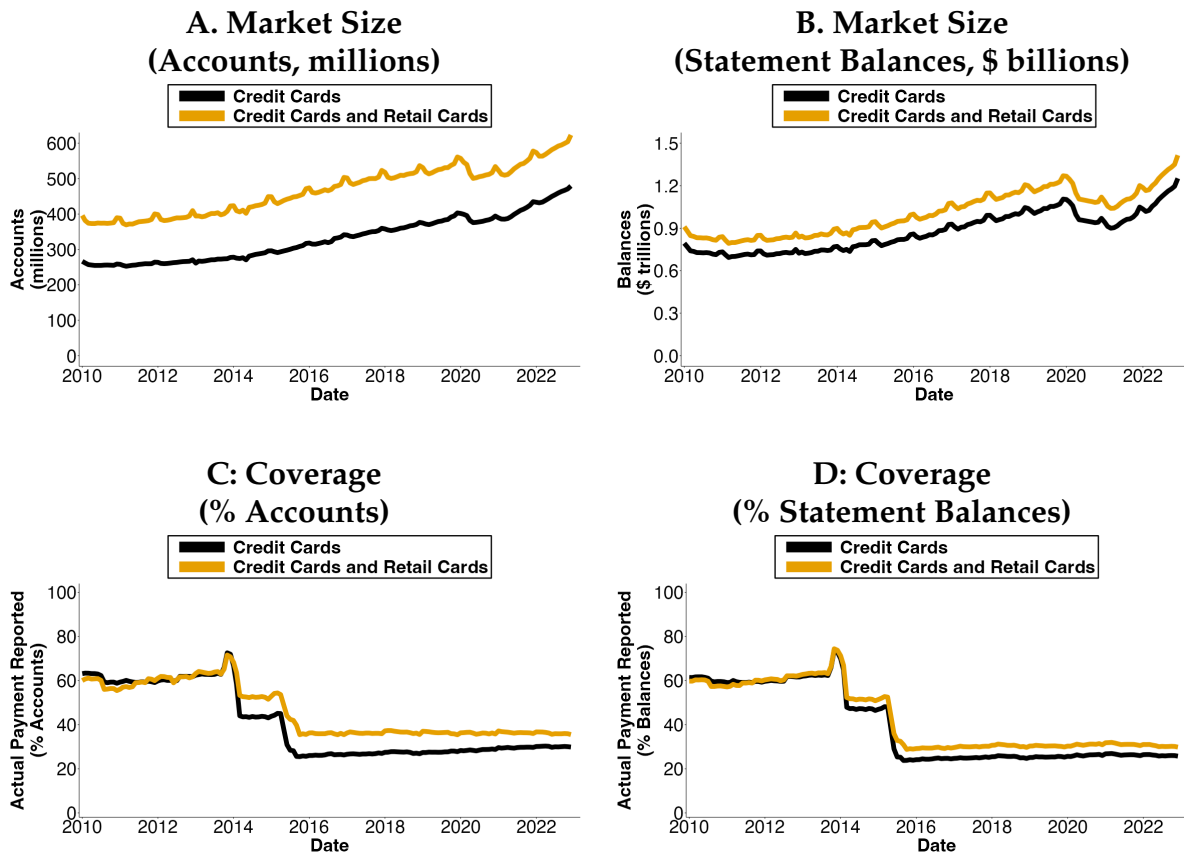**Figure D1: CDF of Excess Payment: Actual Payments Relative to Scheduled Payments**
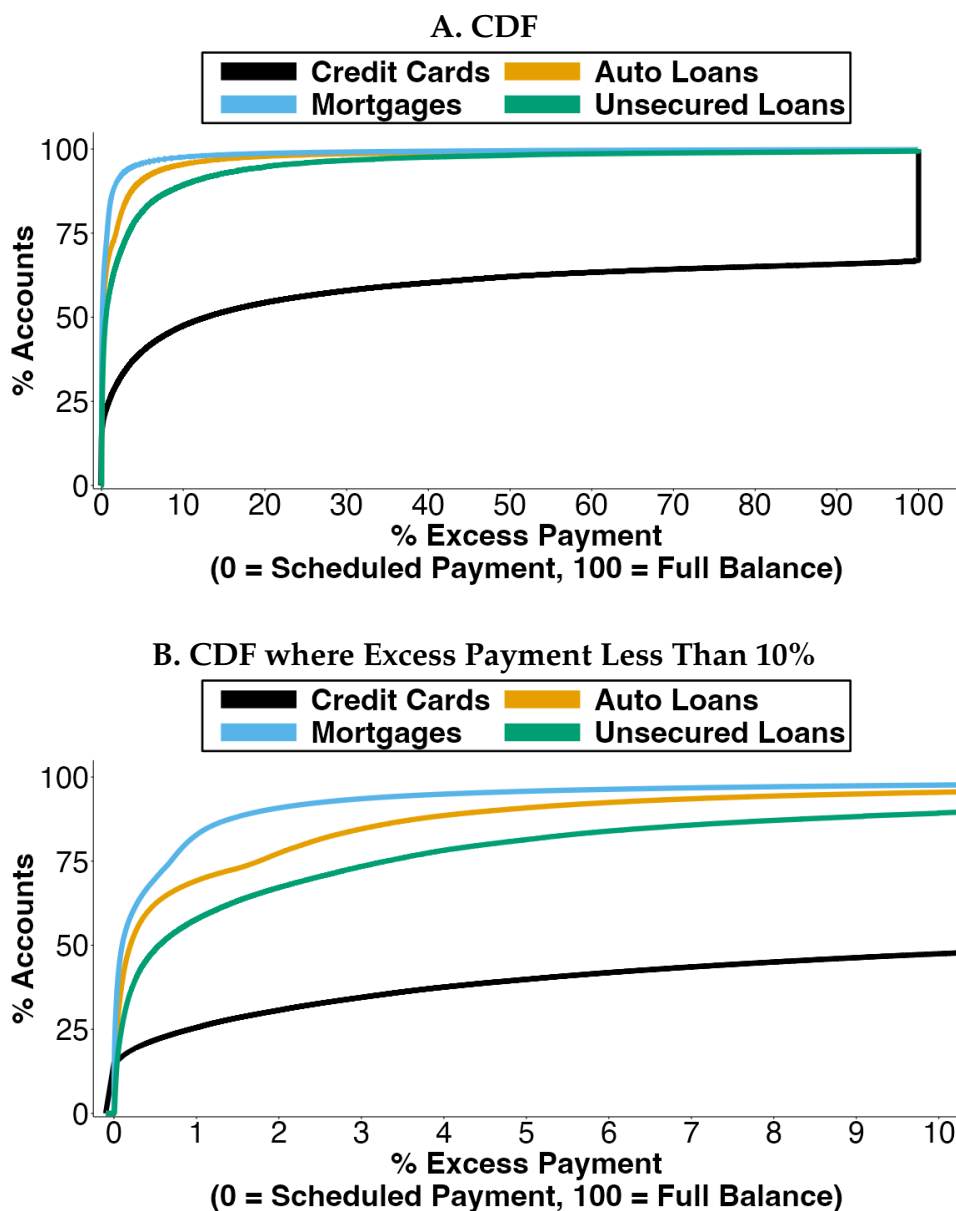
Notes: BTCCP data, December 2012. CDF of non-zero and non-missing actual payments by credit product for accounts with non-zero balances, non-zero scheduled payment amounts, and balances greater than scheduled payment amounts. X-axis shows excess payment calculated as actual payments less scheduled payment amount as a percentage of outstanding balance less scheduled payment amount. In this calculation where payments are equal to or in excess of the full outstanding balance they are assigned a value of 100%. For credit cards, scheduled payment amount is the minimum amount due. For installment loans, scheduled payment amount is the regular payment due (and for mortgages can include taxes and other fees such as to homeowner associations). Panel A shows CDF, Panel B focuses on the CDF where excess payment is less than 10%.

Figure D2: 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 D3: Robustness of Coverage of Actual Payments Information in Consumer Credit Reports to Inclusion of Retail Cards

A. Market Size (Accounts, millions)

B. Market Size (Statement Balances, $ billions)

C: Coverage (% Accounts)

### D: Coverage (% Statement Balances)

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 D4: Coverage of Scheduled Payment Amounts in Consumer Credit Reports
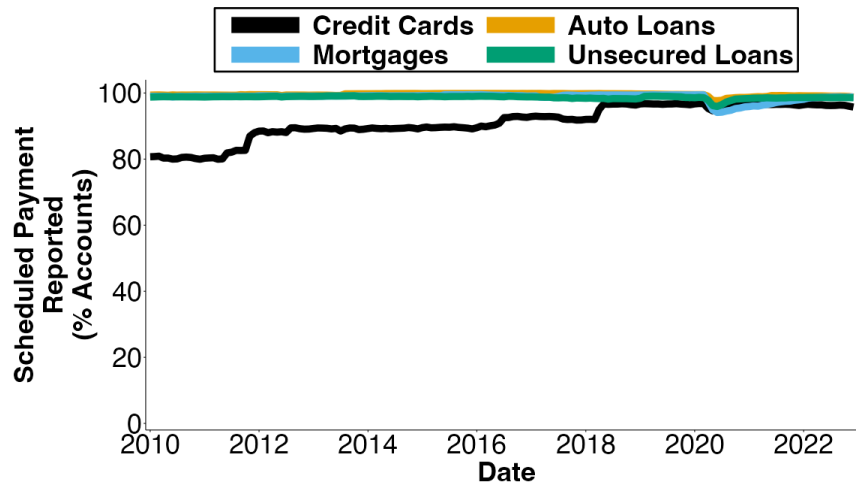

Notes: BTCCP data. Figure shows, for each consumer credit product, the fraction of accounts in consumer credit reports reporting non-zero and non-missing credit card scheduled payment amounts. These calculations restrict to open accounts with non-zero balances and which have been updated in the last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

Figure D5: 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)
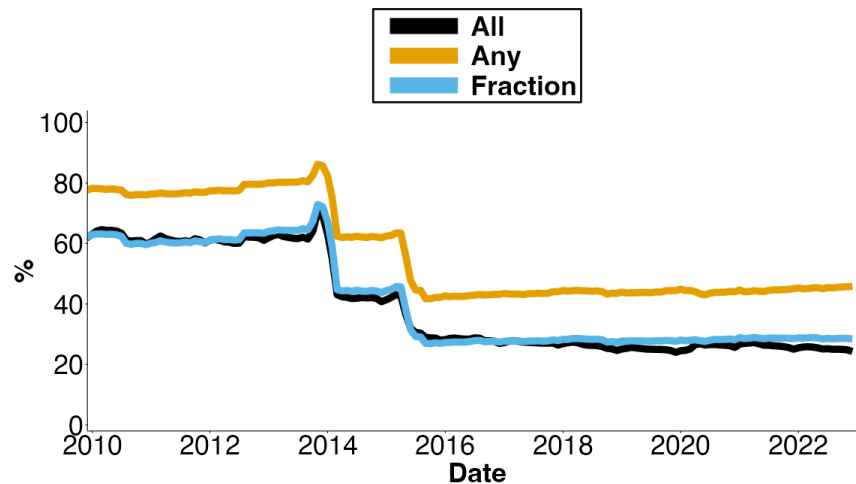
Notes: BTCCP data. The orange line shows the fraction of credit cardholders in consumer credit reports where credit card actual payments are zero or missing on at least one credit card account. The black line shows the fraction of credit cardholders in consumer credit reports where credit card actual 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.
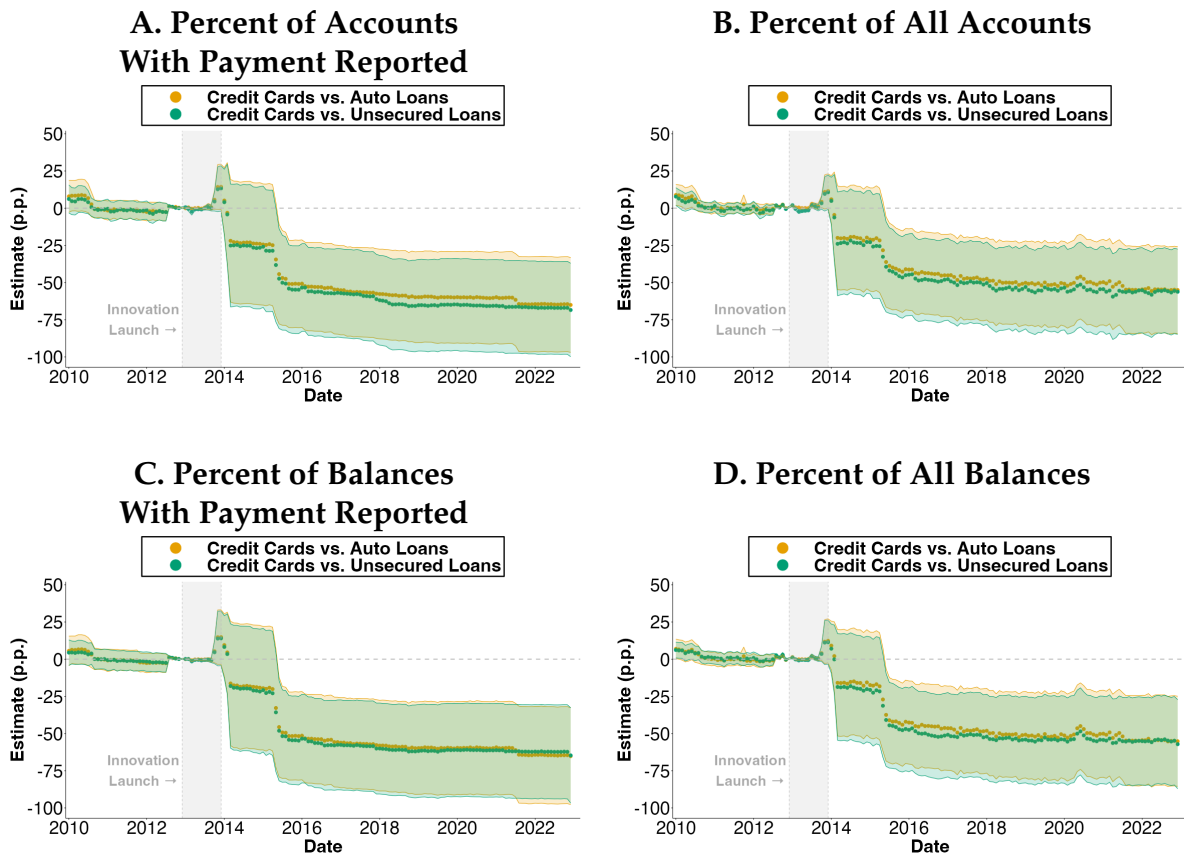
68

Figure D6: Consumers without Credit Card Actual Payments Information in Consumer Credit Reports

A: Number of Consumers

B: Percentage of Consumers
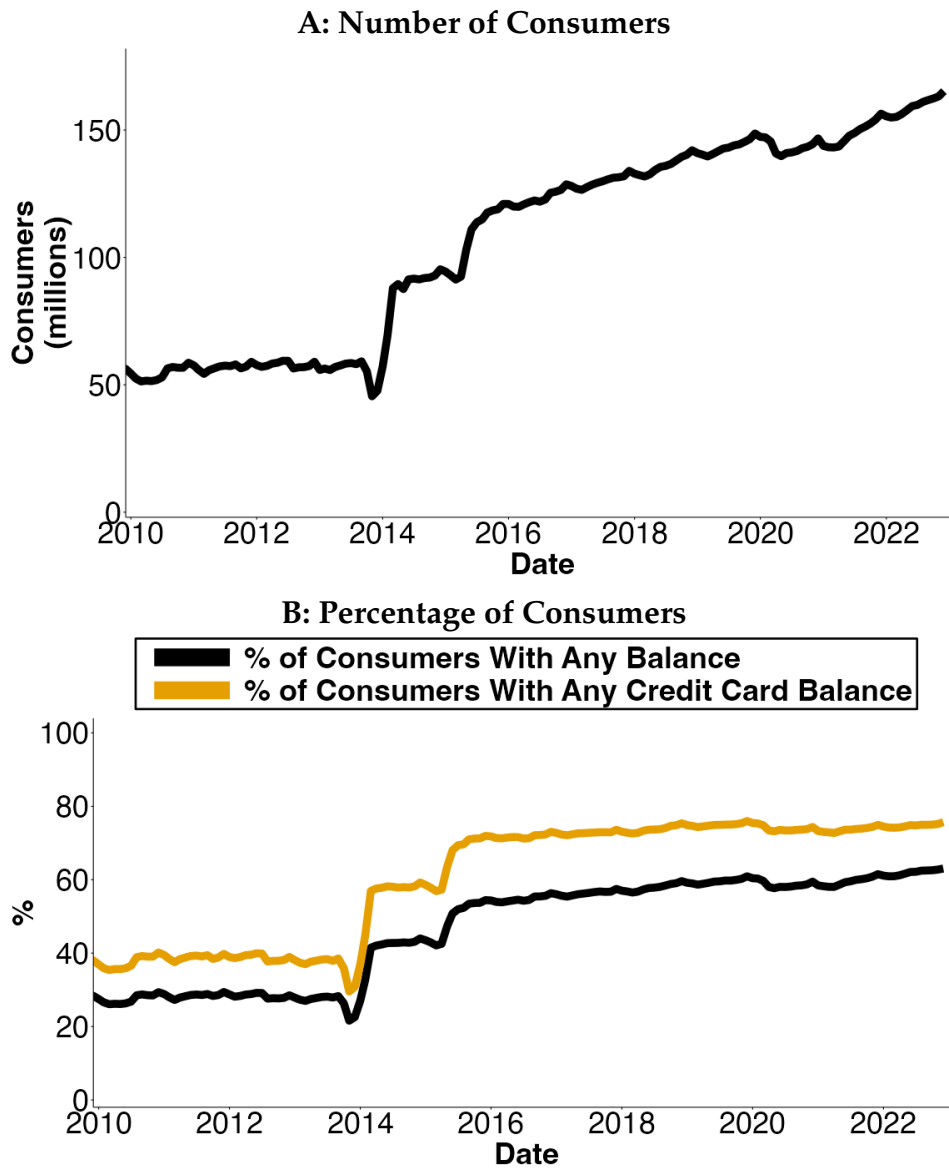
Notes: BTCCP data. Panel A shows the number of consumers in consumer credit reports where credit card actual payments are zero or missing on at least one credit card account. Panel B shows the fraction of consumers in consumer credit reports where credit card actual payments are zero or missing on at 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 D7: Difference-in-Differences Estimates of Actual Payments Information Sharing in Consumer Credit Reports for Credit Cards Relative to Auto Loans and Unsecured Loans

A. Percent of Accounts
With Payment Reported

B. Percent of All Accounts

C. Percent of Balances
With Payment Reported

D. Percent of All Balances

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.

Table D1: Difference-in-Differences Estimates of Actual Payments Information Sharing for Credit Cards Relative to Auto Loans (Column 1) and Unsecured Loans (Column 2)

	(1)	(2)
$D_{Dec\ 2015} \times CRED$	-0.5093^{***}	-0.5483^{***}
	(0.1501)	(0.1504)
$D_{Dec\ 2022} \times CRED$	-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 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. *** denotes statistical significance at the 1% level.

Table D2: Robustness of Difference-in-Differences Estimates of Actual Payments Information Sharing for Credit Cards Relative to Auto Loans (Column 1) and Unsecured Loans (Column 2)

	(1)	(2)
$D_{Dec\ 2015} \times CRED$	-0.4233^{***}	-0.4687^{***}
	(0.1436)	(0.1438)
$D_{Dec\ 2022} \times CRED$	-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. *** denotes statistical significance at the 1% level.

E   Consumer Credit Scores

We evaluate how incorporating credit card actual payments information affects the performance of consumer credit scores. We do so using data to December 2012 and estimate logistic regressions predicting outcomes over the next 24 months. We are only able to do this counterfactual exercise for consumers who only hold credit cards where actual payments information was shared in 2012. Broadly we would expect this sample restriction to make our results a lower bound on the uplift in predictive performance one might expect if the portfolio of credit card actual payments were observed. We evaluate predictive performance using out-of-sample AUROC and out-of-sample accuracy. As a baseline we use the performance of a credit score that is constructed without using actual payments information and without Trended Data.

Table E1 shows the uplift in credit scoring performance from incorporating one and three years of credit card actual payments (AP) information. Table E2 varies the outcome and also varies the inclusion of installment loan actual payments information as predictors.

Table E1: Consumer Credit Score Performance With Actual Payments (AP) Information

Outcome: Any 90+ Days Past Due (DPD)		
Model	**AUROC**	**Accuracy**
1. Credit Score	0.93419	0.88398
2. Credit Score + 1 Year AP Credit Cards	0.94108	0.89108
3. Credit Score + 3 Year AP Credit Cards	0.94540	0.89726

Notes: BTCCP data. Models are logistic regressions using data to December 2012 to predict any 90+ days past due (DPD) in the next 24 months (2013 to 2014). AUROC and accuracy are measures of out-of-sample performance. Model 1. uses credit score as predictors. Model 2. uses as predictors credit score and one year of credit card actual payments information. Model 3 uses as predictors credit score and three years of credit card actual payments information.

**Table E2: Consumer Credit Score Performance With Actual Payments (AP) Information**

A. Outcome: Any 90+ Days Past Due (DPD)

Model	AUROC	Accuracy
1. Credit Score	0.93419	0.88398
2. Credit Score + AP Installment	0.93438	0.88420
3. Credit Score + AP Credit Cards	0.94049	0.89187
4. Credit Score + AP Credit Cards + AP Installment	0.94052	0.89202

B. Outcome: Any Credit Card 90+ Days Past Due (DPD)

Model	AUROC	Accuracy
1. Credit Score	0.93348	0.88799
2. Credit Score + AP Installment	0.93418	0.88858
3. Credit Score + AP Credit Cards	0.94206	0.89823
4. Credit Score + AP Credit Cards + AP Installment	0.94228	0.89811

C. Outcome: Any Installment Loan 90+ Days Past Due (DPD)

Model	AUROC	Accuracy
1. Credit Score	0.88950	0.86356
2. Credit Score + AP Installment	0.89144	0.86627
3. Credit Score + AP Credit Cards	0.89119	0.86341
4. Credit Score + AP Credit Cards + AP Installment	0.89364	0.86686

Notes: BTCCP data. Models are logistic regressions using data to December 2012 to predict outcomes in the next 24 months (2013 to 2014). Outcome in Panel A. is any 90+ days past due (DPD). Outcome in Panel B. is any credit card 90+ DPD. Outcome in Panel C. is any installment loan 90+ DPD. AUROC and accuracy are measures of out-of-sample performance. Model 1. uses credit score as predictors. Model 2. uses as predictors credit score and installment loan actual payments information. Model 3 uses as predictors credit score and credit card actual payments information. Model 3 uses as predictors credit score, credit card actual payments information, and installment loan actual payments information.
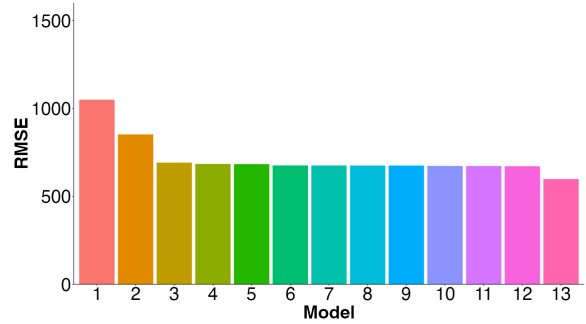
F Measurement Error in Credit Card Behaviors

Figure F1: R^2 **and Root Mean Squared Error (RMSE) Measurement Error in Estimating Contemporaneous Account-Level Credit Card Behaviors in December 2013**
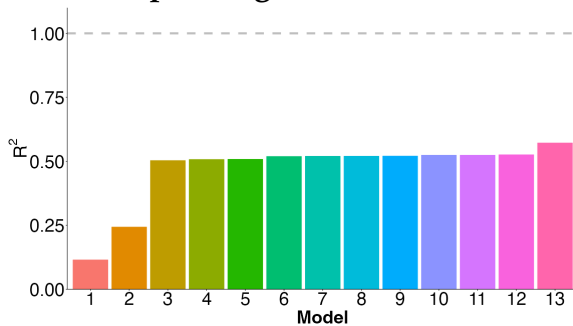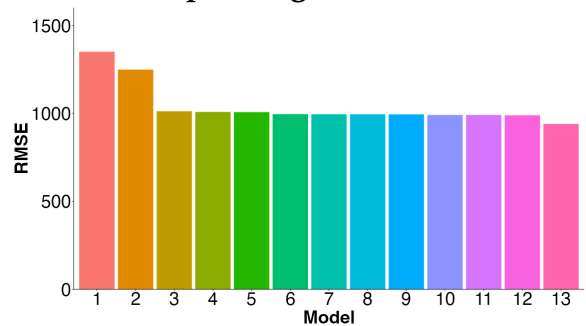
A. R^2 Revolving Debt in December 2013
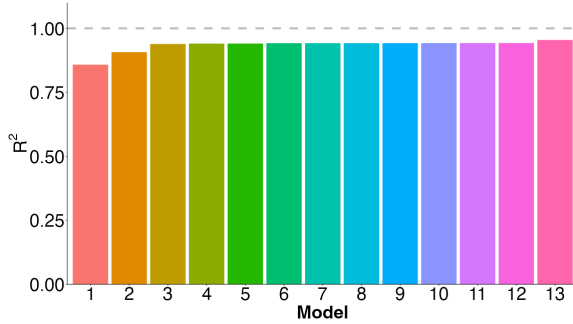
B. RMSE Revolving Debt in December 2013

C. R^2 Spending in December 2013

D. RMSE Spending 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 add in additional account-level variables. Model 12 adds in balance variables from other credit cards held by the consumer. 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. See Table F1 for more details of predictors in models.

Table F1: Predictors in Models 1 to 13 for Estimating Contemporaneous Account-Level Credit Card Behaviors

Model	Predictors
1	Statement Balance
2	1 + Lag Statement Balance
3	2 + Change in Statement Balance (zero if negative) + Non-Zero Dummies
4	3 + Credit Score
5	4 + Payment Due
6	5 + Utilization + Credit Limit
7	6 + Card Tenure
8	7 + IRS Zipcode Income
9	8 + Birth Year
10	9 + State
11	10 + Furnisher ID
12	11 + Rest of Credit Card Wallet Behaviors
	(Statement Balances, Changes in Statement Balances)
	Number, Limits, Utilizations)
13	12 + Three Years of Trends in Statement Balances

G   Estimating Profitability

G.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.

Credit card financing charges are \$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 (CFPB, 2021, 2022). Agarwal et al. (2023b) 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 14. This is the maximum of two components. The first component is a floor dollar amount \$$\mu$.[74] 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.

$$m_t = \max \left\{ \$\mu, \ \theta\% \, B_t + r_t + f_t \right\} \tag{14}$$

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 (2023) 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 set of the observed combinations of m_t and b_t. If we find the correct solution, transacting

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[74]If balances are below this floor amount then balance rather than the floor is owed. This is not an economically important case given how low the floor amounts are.

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. 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.

Given μ^* and θ^*, this produces a predicted minimum payment amount $\hat{m}_t^{interim}$ that would be due before financing charges.

$$\hat{m}_t^{interim} \equiv \max\left\{\$\mu^*, \; \theta^*\% \, b_t\right\} \tag{15}$$

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 16 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 17 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.[75]

$$\widehat{(r_t + f_t)}^{interim} \equiv m_t - \hat{m}_t^{interim} \tag{16}$$

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

$$(\widehat{r_t + f_t}) \equiv m_t - \hat{m}_t^* \quad , \text{where } \hat{m}_t^* \equiv \max \left\{ \$\mu^*, \ \theta^*\% \left(b_t - (\widehat{r_t + f_t})^{interim} \right) \right\} \qquad (17)$$

As these are estimated measures they are subject to measurement error. Our data only contains non-negative integers and therefore some error comes from 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 this matters for high balance account months. 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. We may evaluate these in the future.

G.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.[76] We discount this balance to allow for some delinquent debt being cured or later recovered in the collections process. 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 (2023) and our discussions with industry participants. Agarwal et al. (2015b) shows a dip in the middle of the distribution which we attribute to the particularly unusual time period their sample covering the great recession and their income their measures are point-in-time whereas ours cover most of a card's lifetime.

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[76]Many severely delinquent accounts become impossible to follow as the debt may be consolidated, transferred to a different furnisher, or moved into collections. Such cases can mean the anonymized trade identifier no longer applies to the account.

G.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.

We assume 0.5% spending is interchange net of rewards. 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. (2015b, 2018) who use a 2 percent interchange revenue and 1.4 percent rewards and fraud expense and Wang (2023) who assess merchant fees at 2.25 (MasterCard and VISA interchange revenue of 1.75) and rewards expense of 1.30. This is because mark-ups are higher on reward cards that are concentrated among high credit score consumers (Agarwal et al., 2023b) note interchange revenue in 2009 ranges from 1 to 3 percent and assume it is 1.5 for standard cards and for 2.5 for reward cards. Agarwal et al. (2023a) 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 (2019)'s estimates of $167 in annual rewards per rewards account in 2019 up from $139 in 2015. 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 also have annual fees (CFPB, 2019). Interchange fees in 2019 are approximately $50 bn – doubling since 2012 (WSJ 2020; The Ascent / Motley Fool 2021). Agarwal et al. (2023b) 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. One 2017 estimate 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.

Figure G1: Actual Payments Information Sharing in Consumer Credit Reports by Furnishers from 2012 to 2015
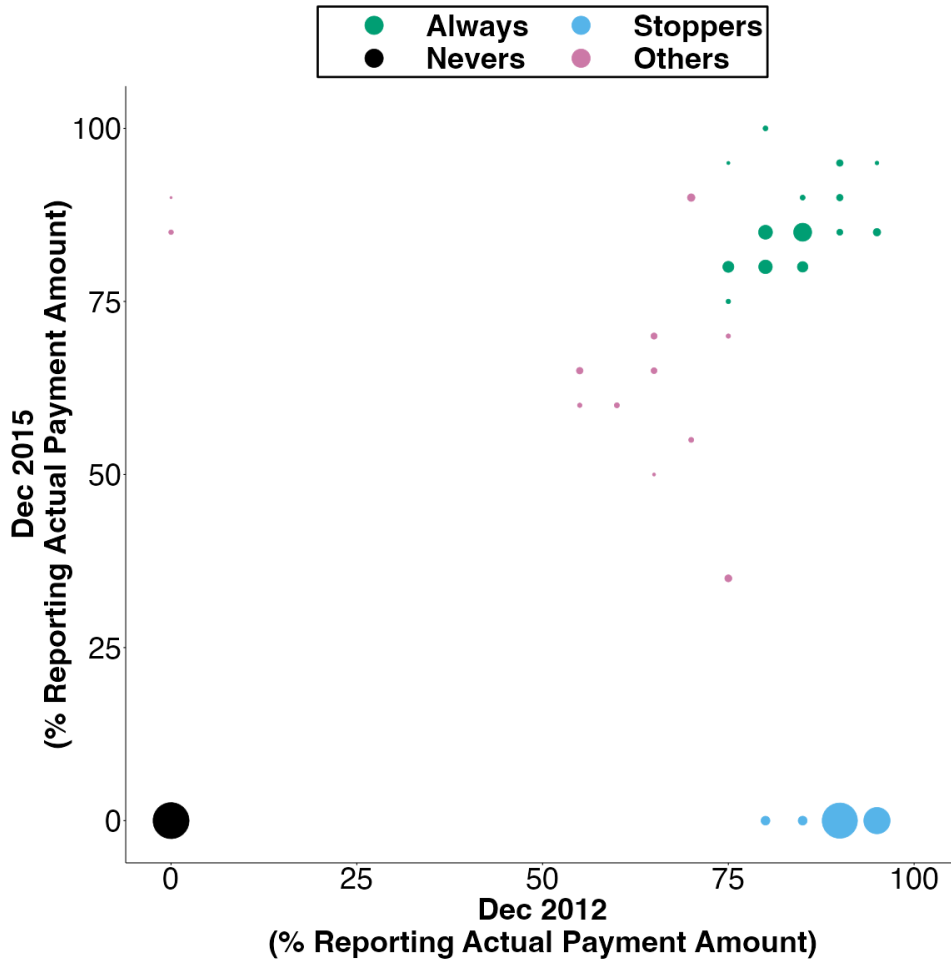

Notes: BTCCP data. This excludes furnishers who have fewer than 10,000 active credit cards (i.e. their portfolio is representative of fewer than 100,000 cards) in both December 2012 and in December 2015. This figure shows, for each consumer credit product, the fraction of accounts in consumer credit 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 3 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.

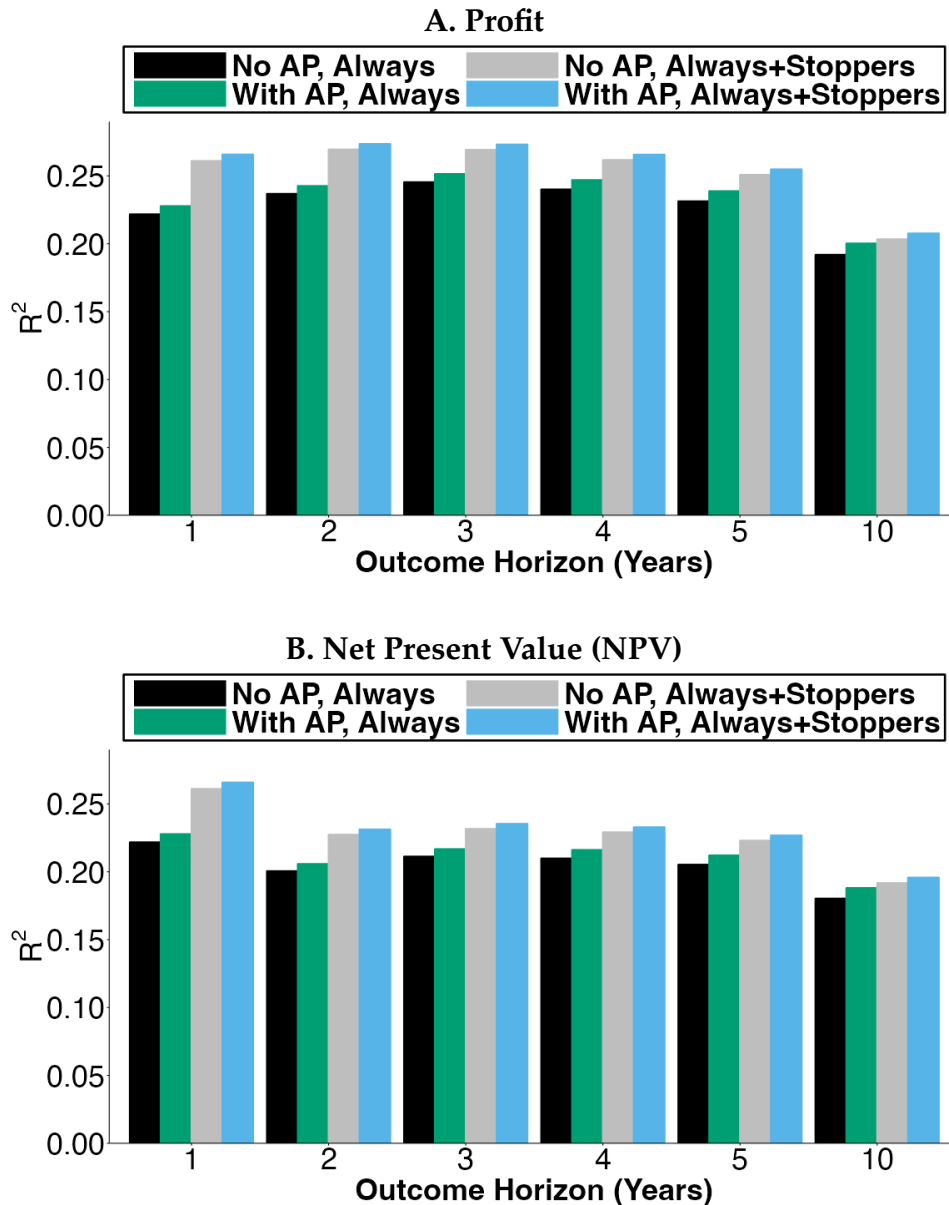**Figure G2: 2012 to 2022 Financing Charges Net of Charge-Offs**
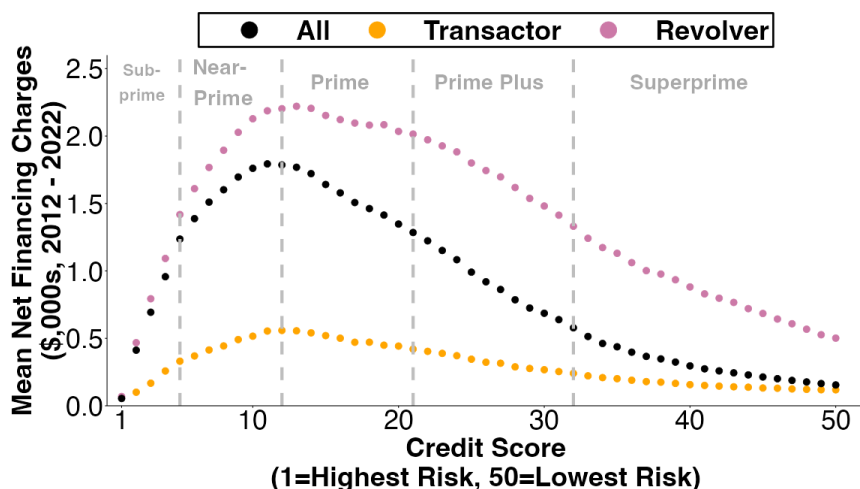
Notes: BTCCP data. Figure shows mean estimates conditional on 50 quantiles of credit score (x-axis) for credit cards in December 2012. Financing charges are estimated as described in section G.1. Figure shows financing charges accumulated across 2012 to 2022 net of charge-offs with results split by classifying 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 G3: Predicting Finance Charges Net of Charge-Offs Without Actual Payments Information
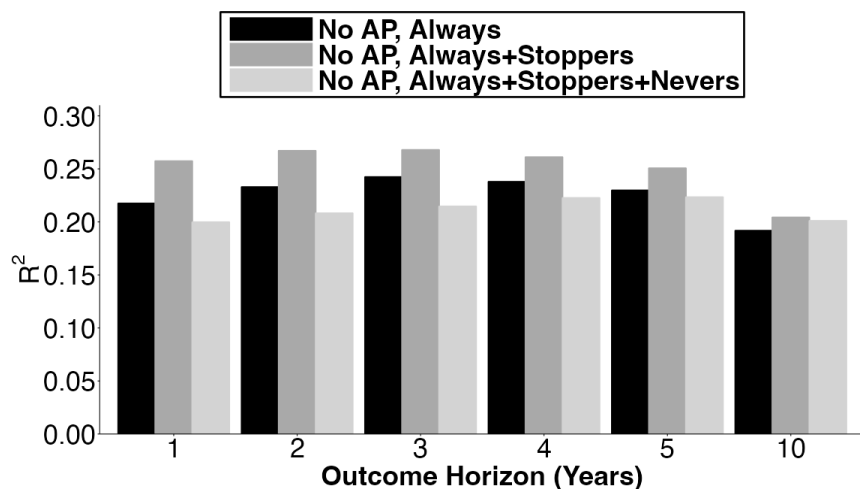
Notes: BTCCP data. Figures use data to December 2012 to predict credit card financing charges net of charge-offs at the account-level over one to ten year horizons. Predictive performance is measured by out-of-sample R^2. Predictive performance is shown without actual payments information. Performance is shown for three samples: "Always", "Always+Stoppers", "Always+Stoppers+Nevers" as described in paper section 2.2 and Table 3 notes.

Figure G4: Marginal Value of Actual Payments (AP) Information for Predicting Credit Card Profits over 1 to 10 Year Time Horizons

A. Profit

Legend:
- No AP, Always
- With AP, Always
- No AP, Always+Stoppers
- With AP, Always+Stoppers

R² vs Outcome Horizon (Years)

B. Net Present Value (NPV)

Legend:
- No AP, Always
- With AP, Always
- No AP, Always+Stoppers
- With AP, Always+Stoppers

R² vs Outcome Horizon (Years)

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 3 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.

H   Credit Card Selection

Table H1: 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)

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 G.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 H1: CDF of Credit Score

A. Mean

B. Standard Deviation
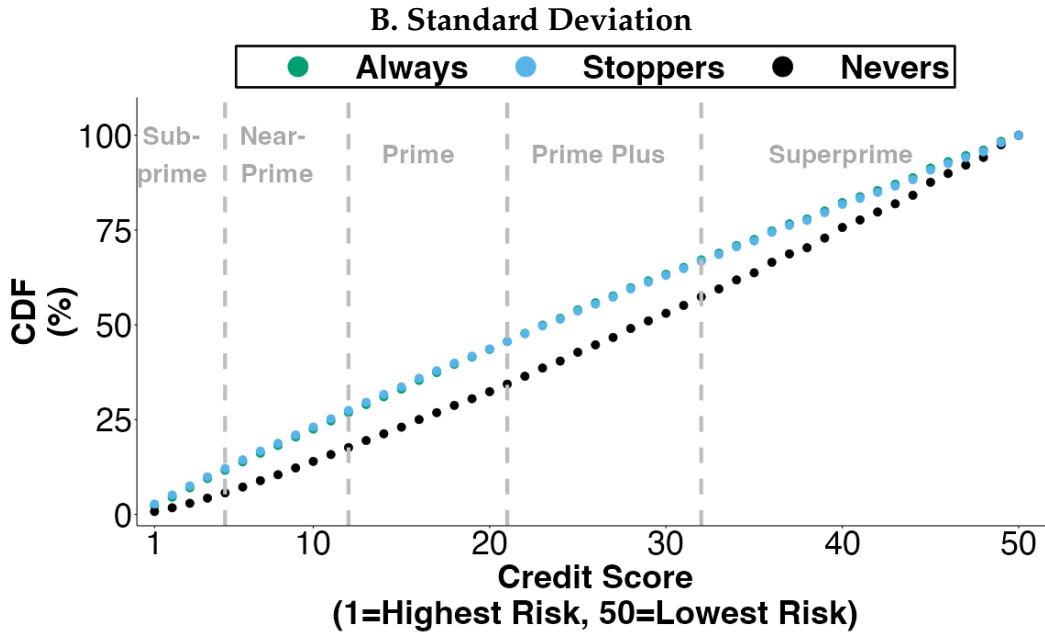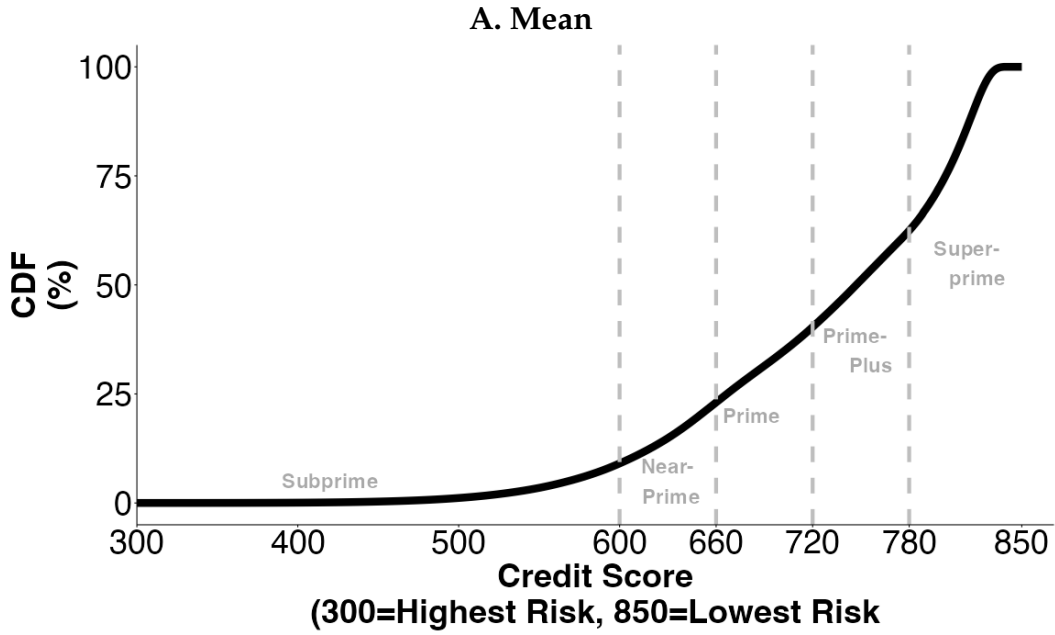
Notes: BTCCP data. Panel A shows CDF and Panel B shows CDF by 50 quantiles where thresholds are defined globally and fixed across classifications. Results in Panel B are split by classifying credit card furnishers by their sharing of actual payments information as described in paper section 2.2 or Table 3 notes. Gray dotted lines divide credit score into standard segments for subprime (lowest scores), near-prime, prime, prime-plus, and superprime (highest scores).
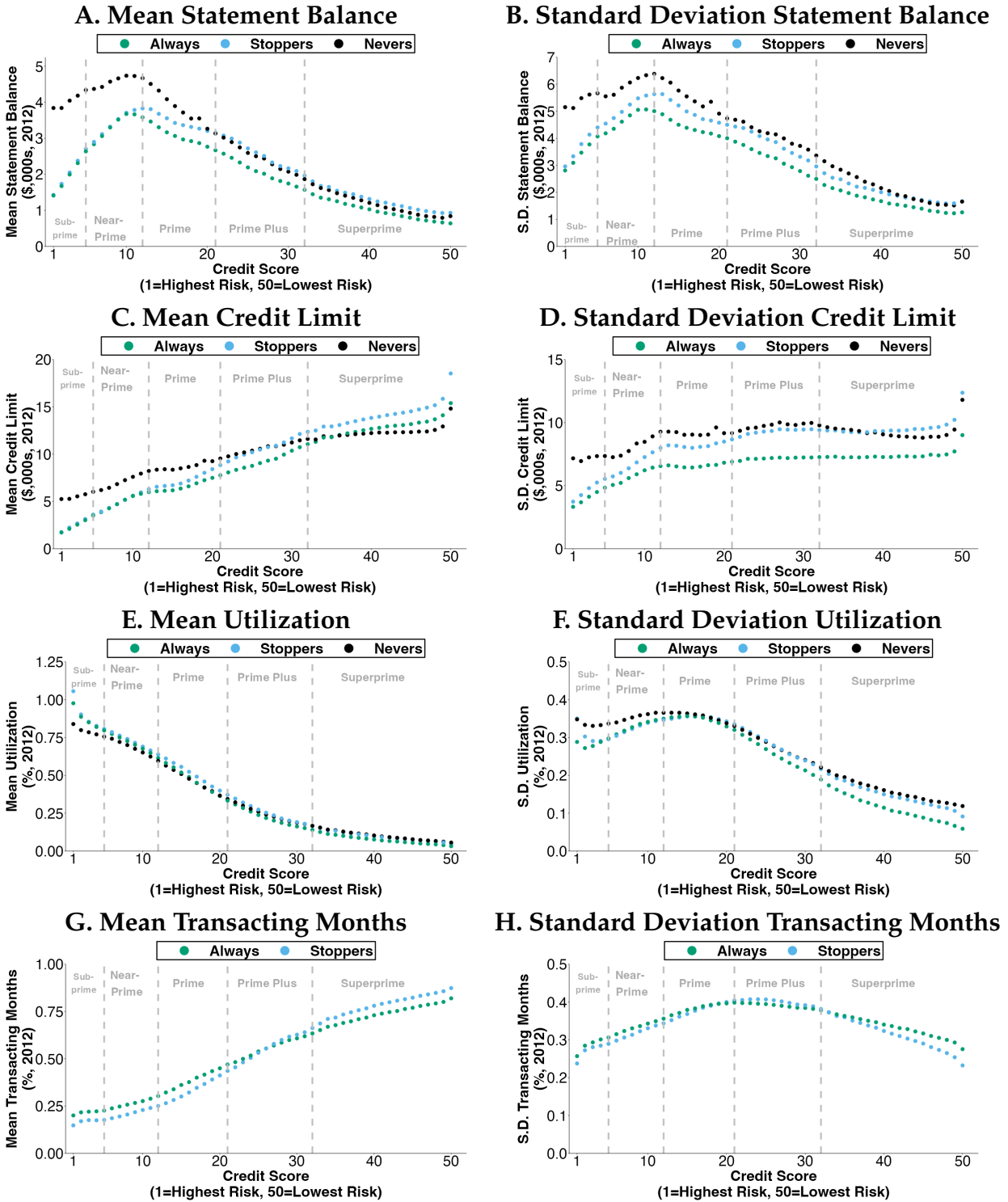
Figure H2: Credit Card Default Rates Conditional on Credit Score
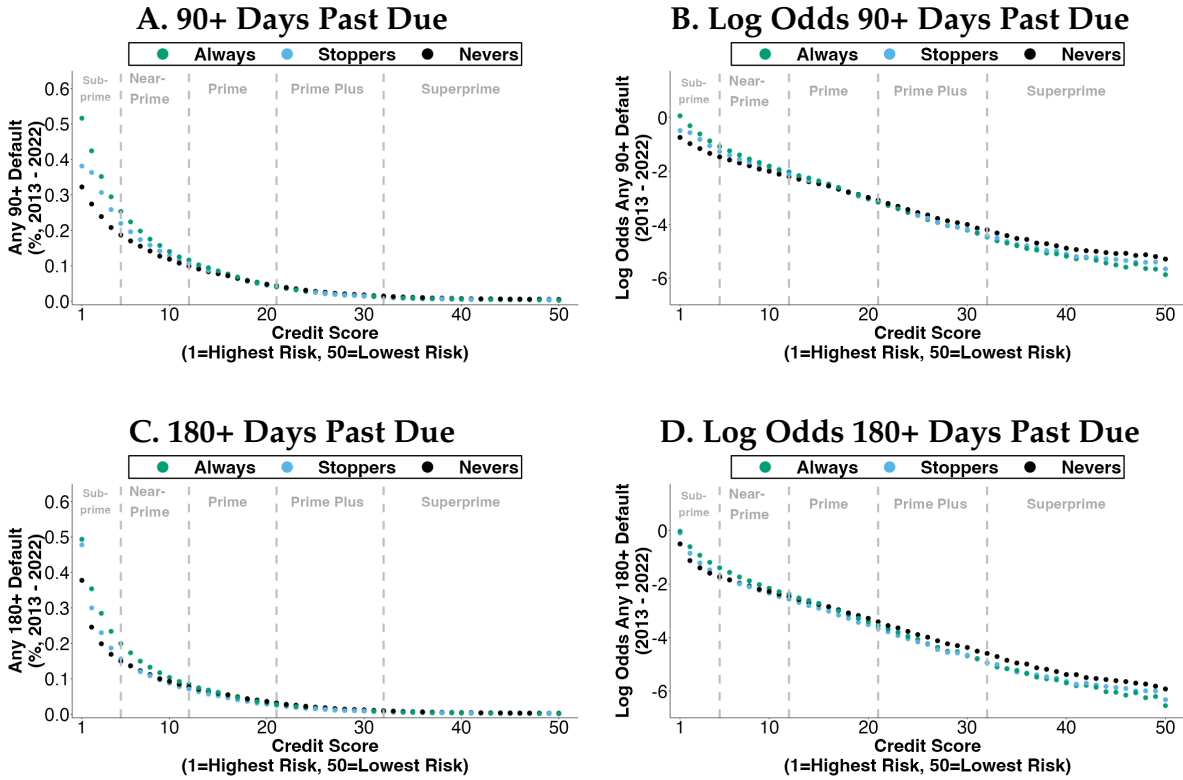
Notes: BTCCP data. Figure shows fraction of credit cards in December 2012 that become delinquent at any point 2013 to 2022 (y-axis) conditional on 50 quantiles of credit score (x-axis). Panel A shows delinquency defined as any 90 or more days past due (DPD) and Panel B shows this in log odds. Panel C 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 3 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.
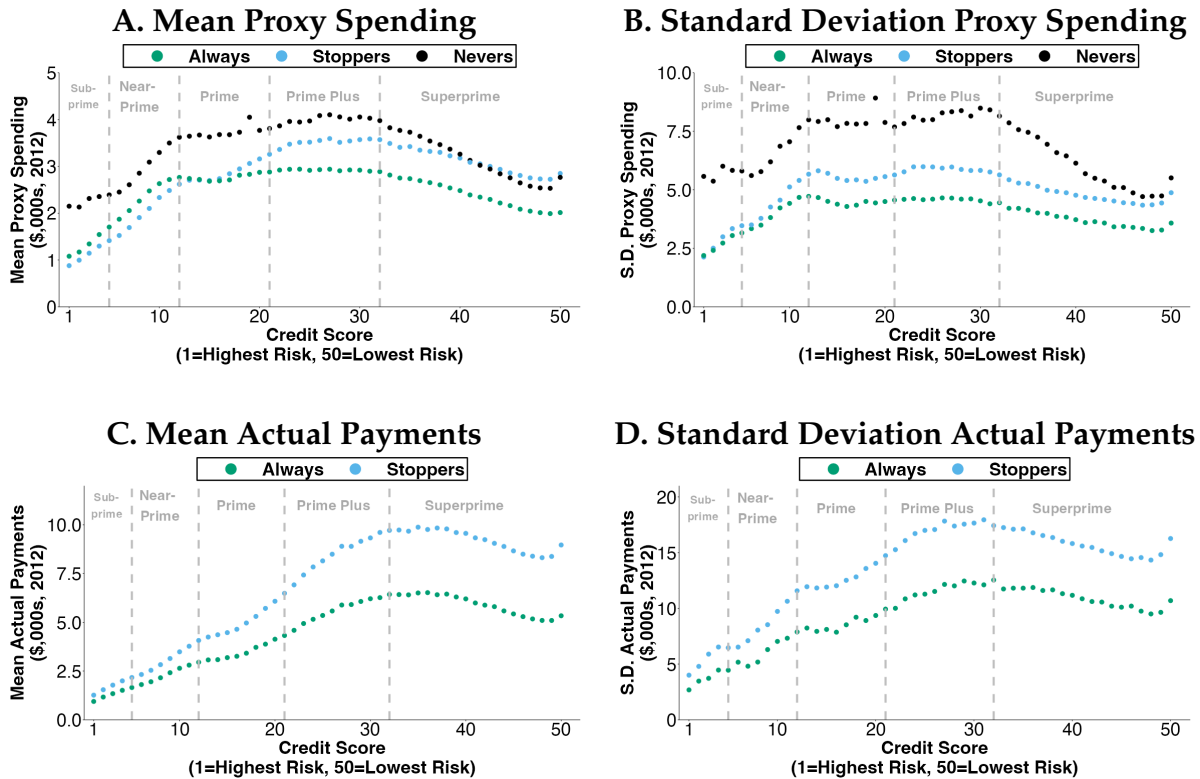
Figure H3: Credit Card Behaviors Conditional on Credit Score

A. Mean Statement Balance

B. Standard Deviation Statement Balance

C. Mean Credit Limit

D. Standard Deviation Credit Limit

E. Mean Utilization

F. Standard Deviation Utilization

G. Mean Transacting Months

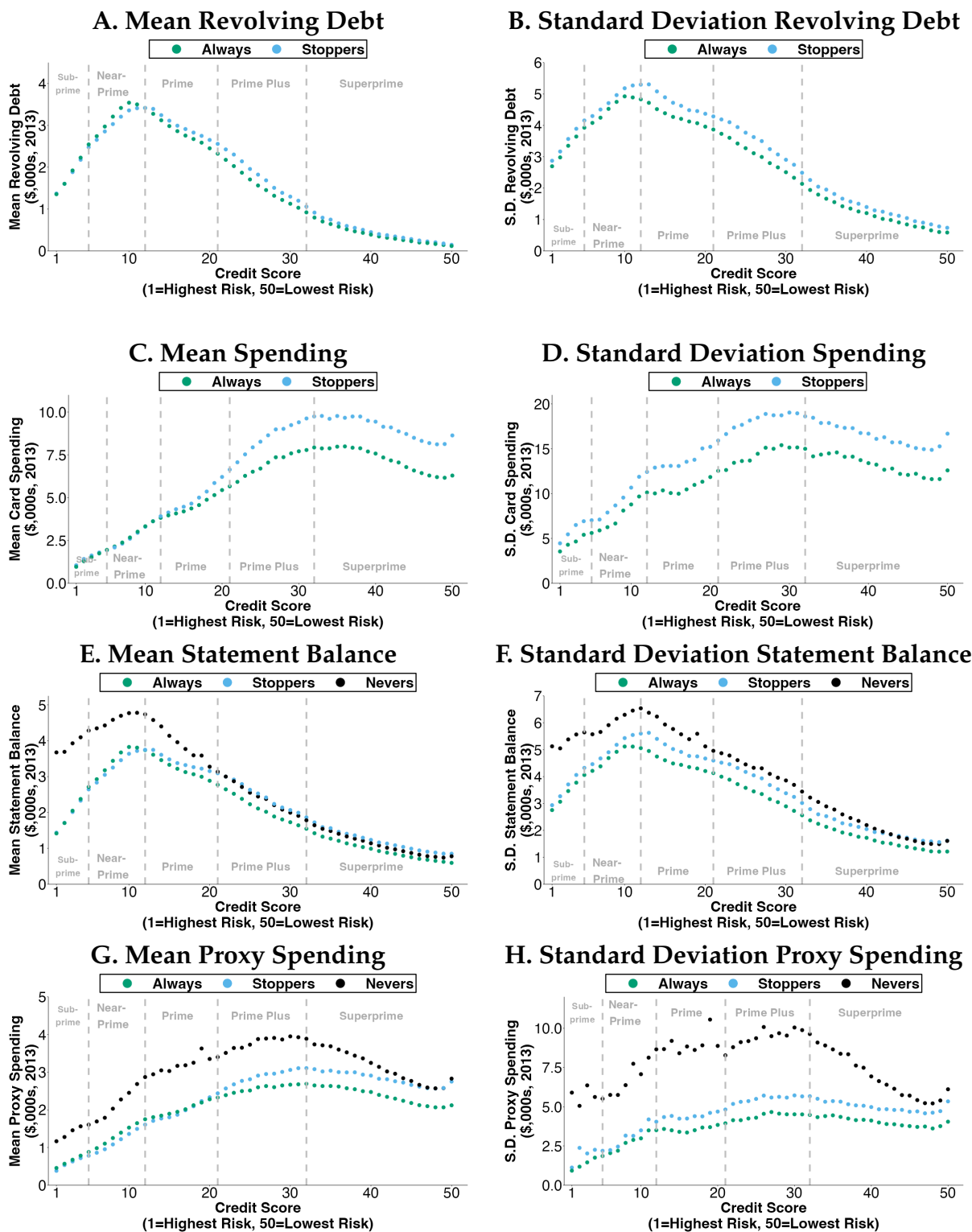## H. Standard Deviation Transacting Months

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 repayment amounts as described in paper section 2.2 or Table 3 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 H4: Credit Card Spending Behaviors Conditional on Credit Score

A. Mean Proxy Spending

B. Standard Deviation Proxy Spending

C. Mean Actual Payments
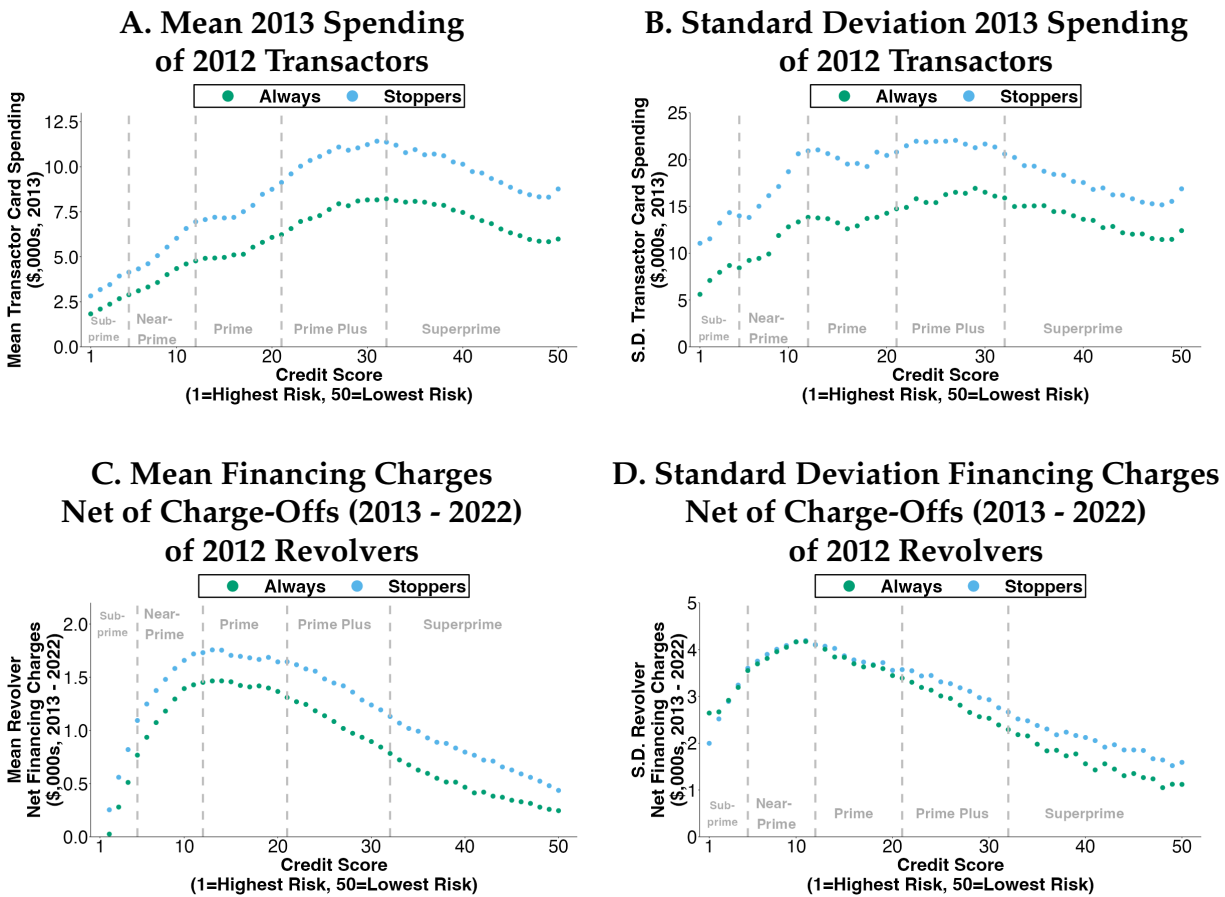
D. Standard Deviation Actual Payments

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 repayment amounts as described in paper section 2.2 or Table 3 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 H5: 2013 Credit Card Behaviors Conditional on Credit Score

A. Mean Revolving Debt

B. Standard Deviation Revolving Debt

C. Mean Spending

D. Standard Deviation Spending

E. Mean Statement Balance

F. Standard Deviation Statement Balance

G. Mean Proxy Spending

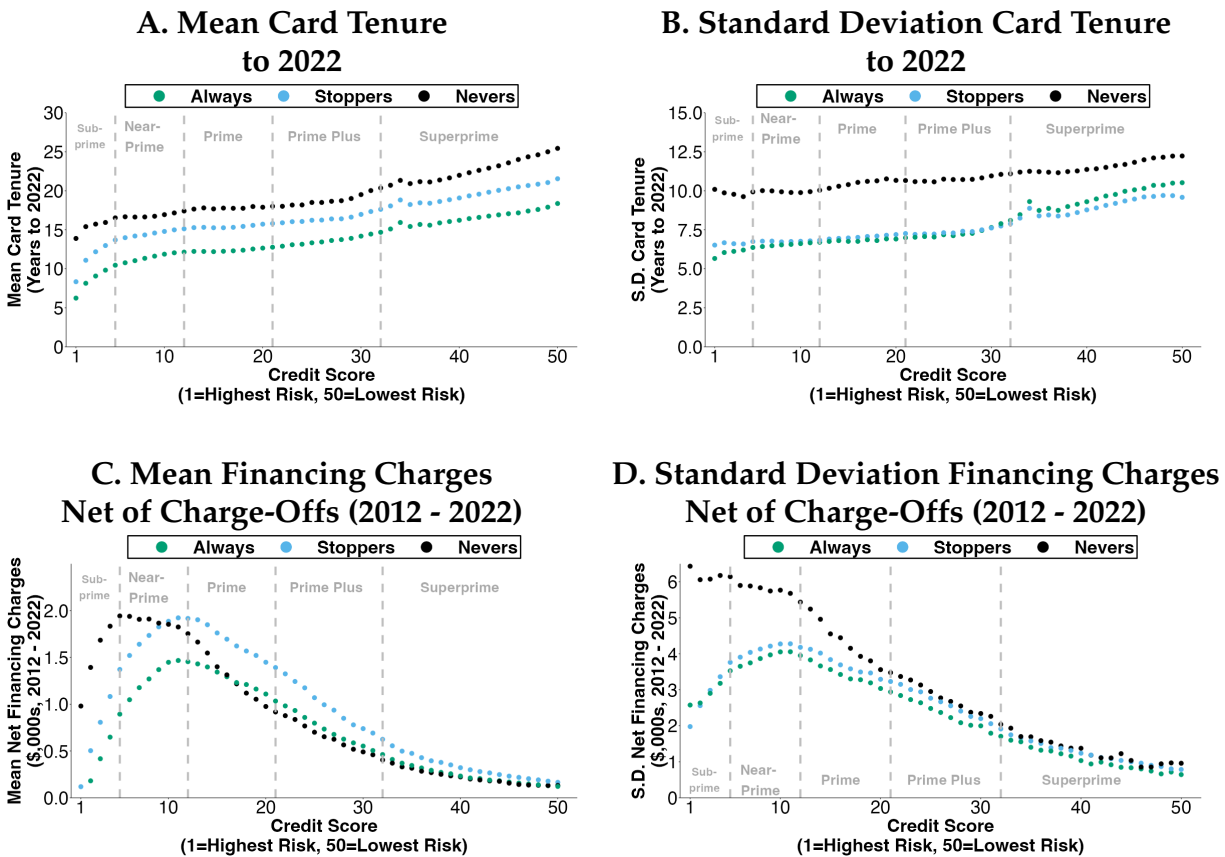### H. Standard Deviation Proxy Spending

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 3 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 H6: Credit Card Behaviors of Transactors and Revolvers Conditional on Credit Score

A. Mean 2013 Spending of 2012 Transactors

B. Standard Deviation 2013 Spending of 2012 Transactors

C. Mean Financing Charges Net of Charge-Offs (2013 - 2022) of 2012 Revolvers

D. Standard Deviation Financing Charges Net of Charge-Offs (2013 - 2022) of 2012 Revolvers

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 repayment amounts as described in paper section 2.2 or Table 3 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 H7: Credit Card Activity Rates Conditional on Credit Score**
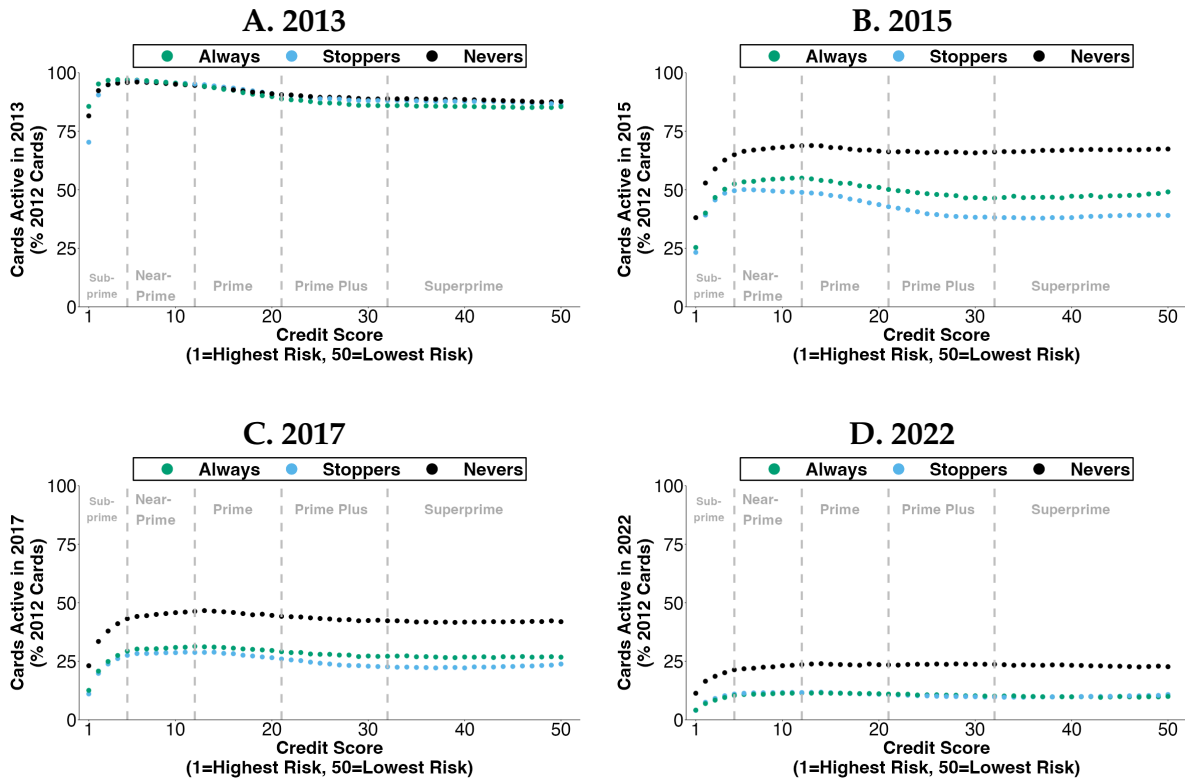
Notes: BTCCP data. Figure panels shows fraction of credit cards in December 2012 that remain active over different horizons. Panel A by 2013, B by 2015, C by 2017, and D by 2022. These are presented conditional on 50 quantiles of credit score (x-axis). A card is active if it remains open with a non-zero 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 3 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 H8: 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 3 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 H9: Mean Lifetime Credit Card Interchange Net of Rewards by Card Tenure, Split by Credit Score
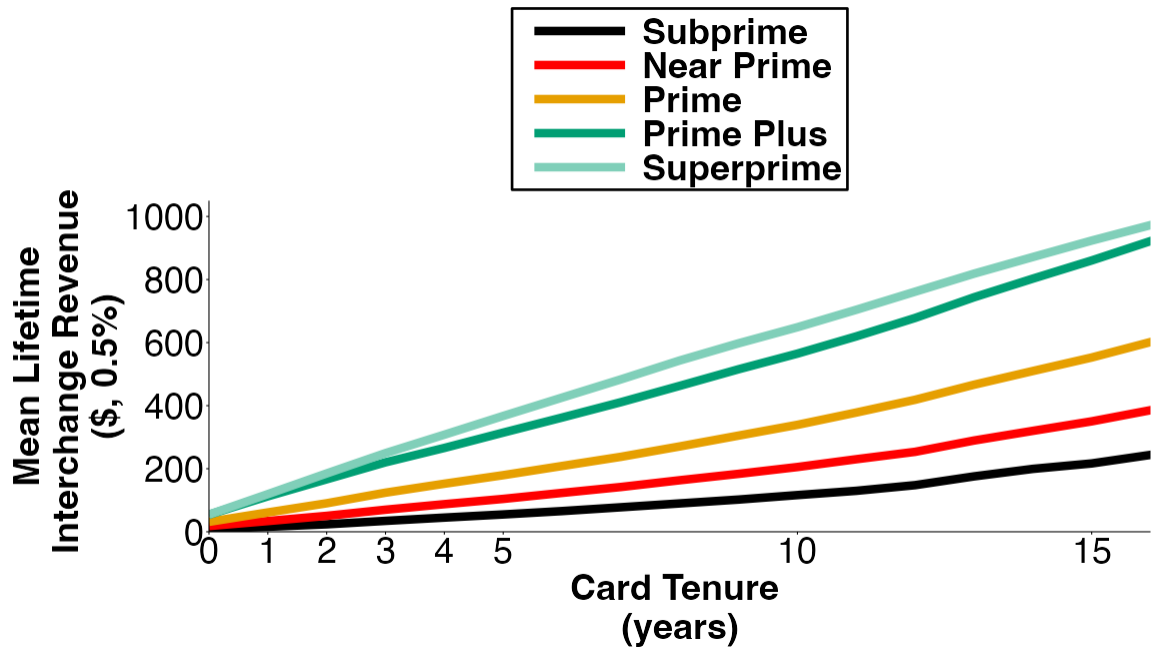

Notes: BTCCP data. Uses cross-sectional data on spending by tenure and credit score for accounts where actual payments information is shared during 2012 to 2013 to estimate lifetime interchange. Assumes constant 0.5% interchange income net of rewards expense. Interchange income is the amount of transaction fees credit card lenders receive from merchants when a consumer spends on their credit card.

Figure H10: Effects of Trended Data on Competition for 2 and 3 Card Samples

A. CDF Exposure to Trended Data
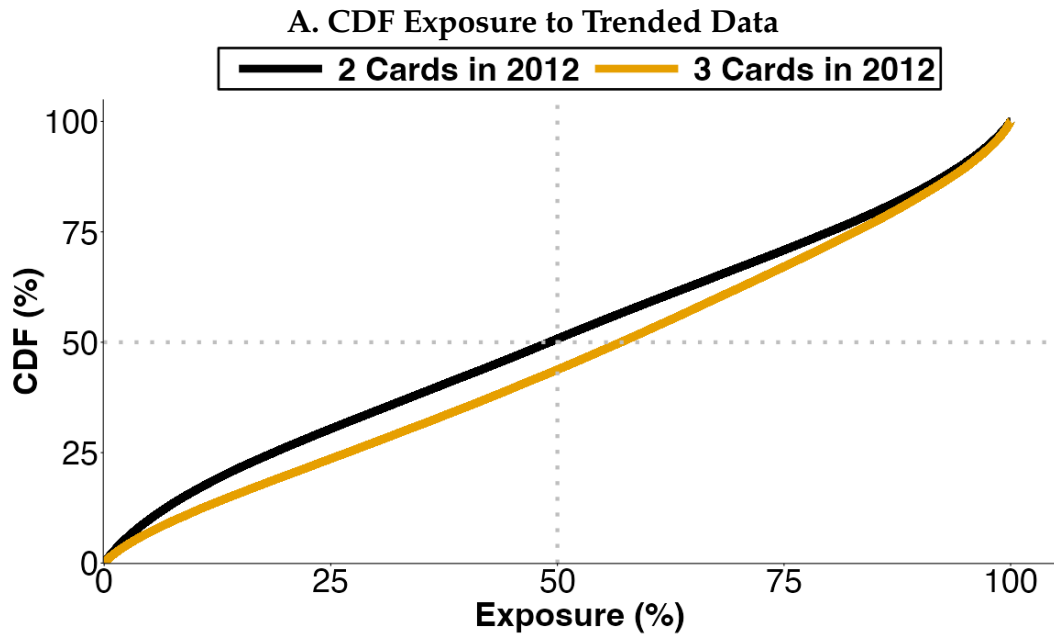
B. Estimates of Effects of Trended Data on Any New Credit Card Opening
(t-1 means: 3.22% for 2 card sample), 4.23% for 3 card sample)
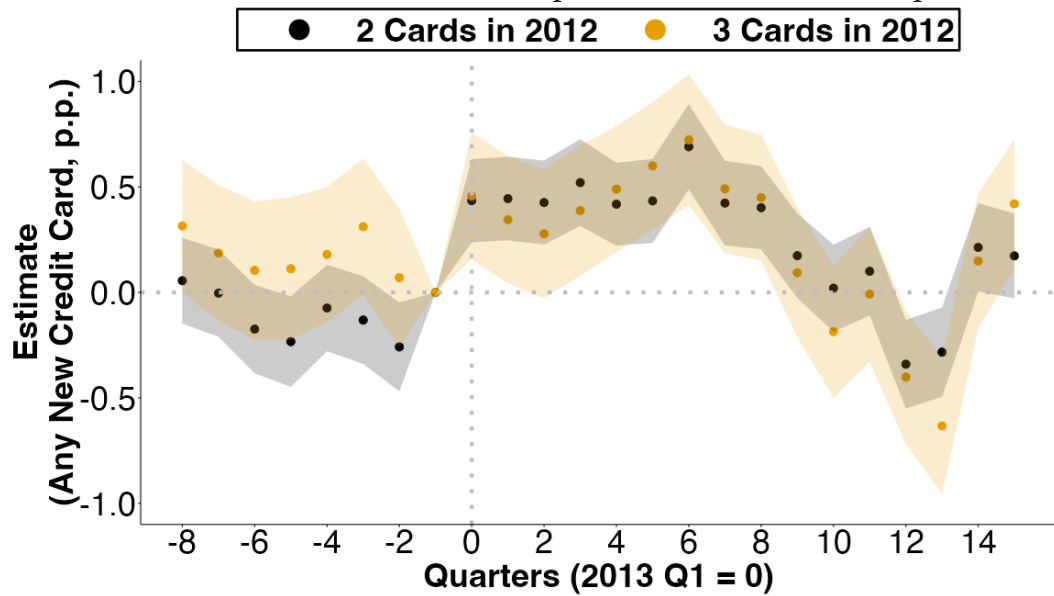
Notes: BTCCP data. Panel A shows CDF of exposure. Exposure is (pre-trended data) share of 2012 credit card balances held with furnishers who share actual payments information. Panel B shows our difference-in-differences with varying intensity estimates in percentage points (p.p.) where the outcome is 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. 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.

I Mandating Sharing Credit Card Limit Information

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 trade-lines 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 I1: Coverage of Credit Card Limits in Consumer Credit Reports
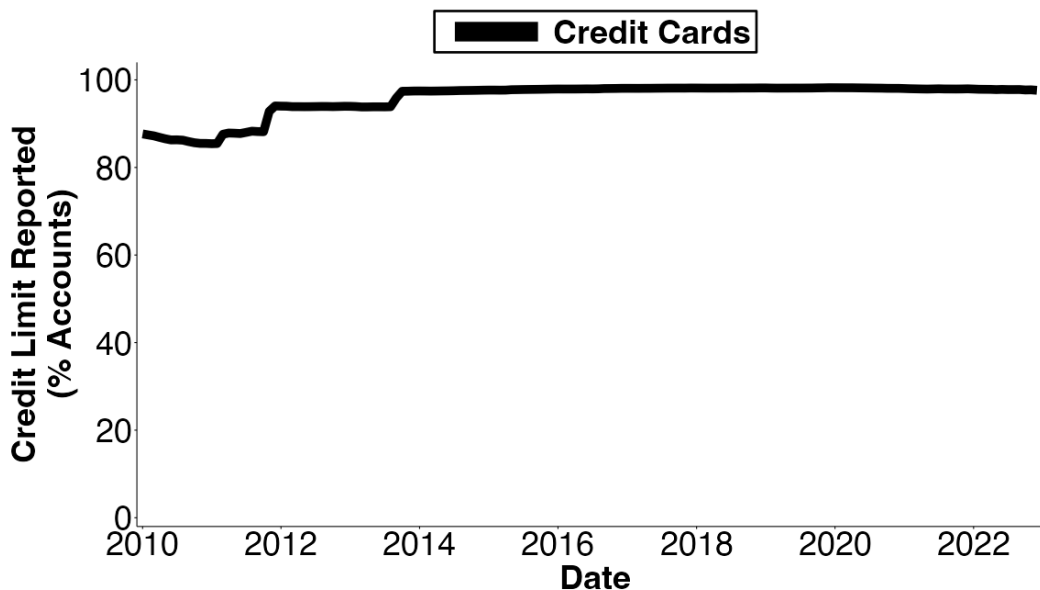
Notes: BTCCP data. Figure shows the fraction of credit card accounts in consumer credit reports with non-zero and non-missing credit card limits.These calculations restrict to open accounts with non-zero balances and which have been updated in the last year.