Rewards, Credit Access, and Inequality in the Credit Card Market

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Abstract

This paper examines the distributional consequences of credit cards by quantifying how unevenly welfare gains from these products are distributed across consumers. Whereas existing literature models credit cards as either payment methods or sources of liquidity; I model demand for both functions and quantify their value to consumers. I first show that cardholders who borrow from their credit cards (i.e., Revolvers), do so to fund their consumption. Because nominal reward-based metrics (i.e., rewards minus fees) omit this consumption utility, they understate the benefits of credit cards to these consumers. This omission is consequential: accounting for both functions reveals that credit cards generate CAD 9.1 billion in annual welfare gains to consumers, far exceeding the CAD 0.825 billion implied by reward-based metrics. Because revolving cardholders often receive negative net monetary transfers and earn lower incomes than their non-revolving counterparts, reward-based metrics also overstate the Gini coefficient of welfare gains by 44%. Finally, eliminating the credit function increases the Gini coefficient of card-derived welfare gains by 7%. This result indicates that access to revolving credit can be progressive and challenges the view of credit card borrowing as inherently exploitative.

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1 Introduction And Related Literature

1.1 Introduction

As credit cards have become increasingly widespread, so too have concerns about their effects on inequality. The existing literature typically frames this issue around the distribution of net rewards, defined as total rewards earned net of interest charges and fees. This metric captures the benefits of credit cards as a payment method (i.e., the payment function), but it omits the value of access to revolving credit (i.e., the credit function). Viewed through this lens, cardholders who carry outstanding balances (i.e., Revolvers) appear substantially worse off than Convenience users, who repay their balances in full and avoid interest charges. Because Revolvers are disproportionately lower-income cardholders, this disparity is widely cited as evidence that credit cards are regressive (Felt et al., 2023; Agarwal et al., 2023; Egan et al., 2026).

This paper evaluates the distributional effects of credit cards using consumer surplus. In particular, I calculate consumer surplus from credit cards as the monetary equivalent of the utility differences between the observed equilibrium with credit cards and a counterfactual world without credit cards (Small and Rosen, 1981). Because different consumer types derive utility from the payment function, the credit function, or both, this utility difference captures the welfare gains from both functions across different groups of cardholders.

The paper's primary contribution is to show that access to unsecured credit accounts for a significant share of the surplus generated by credit cards for Revolvers. Because net rewards fail to reflect this value, this metric understates the benefits of credit cards to Revolvers and overstates their regressive effects. The empirical analysis draws on the Bank of Canada's Digital Wallet and Payment Trends Survey (DWPT) for cross-sectional microdata on consumer payment behavior, revolving status, and expenditures. Using information from official issuing-bank and consumer review sites, I matched the respondents' exact credit card names (e.g., TD First Class Visa Travel Infinite) with various card characteristics, most notably reward earn rates. I then estimate a logit demand system for payment choices to measure individual-level consumer surplus and compare

the Gini coefficient of its distribution with that of net rewards.

Capturing the value of credit cards as a source of liquidity would ideally require high-frequency panel data linking transactions, payment choices, balances and repayments. Because no single dataset captures all of these dimensions, the DWPT offers a useful, albeit imperfect, alternative.[1] To resolve the DWPT's lack of time variation, I exploit the conditional separability between consumption and payment choices: holding consumption level fixed, individuals can reallocate consumption across payment methods without affecting future debt, rendering the payment-choice problem static. Because observed consumption reflects the equilibrium outcome of consumers' intertemporal choices, surplus estimated from the static payment-demand model also reflects the value of the credit function.

More broadly, the approach can be applied to other settings in which a within-period decision problem is conditionally separable from the evolution of dynamic state variables. In this respect, the paper makes a methodological contribution by establishing that consumer surplus derived from a static model can serve as a sufficient statistic for consumer welfare in dynamic environments. This result substantially reduces the data requirements relative to estimating a fully dynamic model.

Overall, the results indicate that credit cards generate sizable but unequally distributed welfare gains. Extrapolating to the aggregate market suggests that credit cards yield over CAD 9.1 billion annually in consumer surplus. These gains concentrate among high-income Convenience users, resulting in a Gini coefficient of 0.55. By contrast, a similar calculation based on net rewards implies an aggregate annual value of only about CAD 825 million. The distribution of net rewards is also extremely unequal, with a Gini coefficient of 0.79. Thus, although substantial, allocative inequality in consumer surplus remains significantly lower than that implied by net rewards.

The divergence between consumer surplus and net rewards arises primarily as the latter does not reflect the consumption value generated by credit-financed expenditure. Revolvers, who account for 21% of the sample, rely on revolving credit to finance between 7% and 14% of their monthly expenditure (Table 5), with greater reliance among lower-income cardholders. Regardless

[1] Section 2.2 discusses the limitations of the DWPT and their implications in greater detail.

of whether such borrowing is intentional, access to revolving credit generates substantial value for revolving cardholders that is not reflected in net rewards.

A secondary reason is preference heterogeneity. Consistent with prior work for the U.S. market (Agarwal et al., 2023), I find that Convenience users receive positive net rewards averaging CAD 204 per year, whereas Revolvers incur average annual losses of CAD 720.[2] However, the demand estimates show that Revolvers place less value on reward features than Convenience users. This difference reflects a mismatch between Revolvers' needs for liquidity (Zhou, 2022; Dao, 2025) and the lumpy nature of credit card rewards.[3] Consumers' valuation (i.e., preferences) of credit card rewards also varies by income and the type of reward collected (i.e., cashback or points). Because cashback operates as a direct price discount, preferences for this feature declines monotonically with income due to diminishing marginal utility of money.[4] By contrast, point programs allow high-income cardholders to extract greater monetary value per point through high-value reward categories (e.g., flight discounts). This flexibility offsets the diminishing marginal utility of money and keeps preferences for reward points constant across the income distribution.

Since net rewards ignore such heterogeneities , analyses based on this metric distort the distributional effects of credit cards by overstating the benefits to high-income cardholders while understating those to low-income cardholders. To the best of my knowledge, this paper is the first to document this preference heterogeneity and quantify its distributional implications.

The paper also explores the effects of the payment and credit functions on inequality in consumer surplus. Specifically, I benchmark the baseline Gini coefficient against two counterfactuals. The first eliminates reward programs, removing a central component of the payment function. The second eliminates the credit function by requiring cardholders to repay their balances in full at all times.

The Gini coefficient decreases by 10% under the no-reward counterfactual, confirming that rebate programs are regressive (Felt et al., 2023; Egan et al., 2026). While eliminating rewards

[2]Strictly speaking, Agarwal et al., 2023 compares net rewards across cardholders with different credit scores. Since utilization rates (i.e., outstanding balance relative to credit limit) are an important component of credit ratings, Revolvers typically have lower credit scores than Convenience users.

[3]Banks typically distribute credit card rewards once a year or after a redemption threshold is reached.

[4]2% cashback is equivalent to a 2-cent discount per dollar spent.

improves allocative equality, such an improvement comes at the cost of substantially lower surplus for Convenience users, whose surplus declines by up to 30% in the highest income decile.

By contrast, the Gini coefficient rises by 7% under the no-borrowing counterfactual. Removing the credit function reduces the surplus of middle-income Revolvers by up to 37%. Because these cardholders rely on revolving credit to finance their spending, eliminating the credit function reduces their overall expenditure, thereby worsening inequality. This finding challenges the conventional view that credit card borrowing is inherently regressive (Heidhues and Kőszegi, 2010; Agarwal et al., 2023).

1.2 Related Literature

This paper is closely related to a growing literature on credit cards and inequality. Prior studies emphasize how credit card charges, such as interchange and interest fees, together with rewards programs, generate cross-subsidization across different groups of cardholders. One important channel operates through interchange fees: although they are nominally charged to merchants, these fees are often passed through to consumers through higher retail prices. Because merchants generally do not price discriminate by payment method, these costs are borne by all consumers (Edelman and Wright, 2015), though not necessarily equally (Egan et al., 2026). This generates transfers from cash and debit card users to credit card users (Schuh, 2010; Felt et al., 2023). Alternatively, studies focusing on revolving credit often frame the primary margin of transfer as occurring from Revolvers to Convenience users (Agarwal et al., 2023).

Whereas prior studies use net rewards to quantify transfers across cardholder groups, I use consumer surplus to capture welfare gains from credit cards (Small and Rosen, 1981). This measure captures not only the value of credit cards as a source of unsecured credit but also heterogeneity in consumers' valuations of reward features. Thus, I contribute to the literature by providing a more comprehensive account of allocative inequality in welfare gains across cardholders. While the effects of interchange fees are implicitly reflected in welfare estimates through observed spending, I do not quantify the underlying transfers across consumers due to

this mechanism.

This paper also bridges the payments literature (Koulayev et al., 2016; Wang, 2023), which primarily treats credit cards as payment instruments, and the household-finance literature (Telyukova, 2013; Greene and Stavins, 2023), which emphasizes their liquidity value. My contribution is to demonstrate that the payment and credit functions have countervailing effects on inequality. While the payment function reinforces baseline inequality in consumption, the credit function mitigates it by allowing cash-strapped consumers to sustain higher levels of consumption.

This result also speaks to the debate over the optimal level of credit card use. When merchants cannot fully pass interchange fees through to consumers, these fees can be used to subsidize reward programs, which leads to inefficiently high levels of credit card usage (Wang, 2023). By decomposing credit card usage into demand for the payment and credit functions, I find that roughly 2.5% of consumers' expenditure is financed by credit card debt.[5] To the extent that some of these purchases would not occur without the liquidity provided by credit cards, observed card usage reflects demand for the credit function rather than excessive use of the payment function. Consequently, concerns that observed credit card use exceeds the socially optimal level may be overstated (Huynh, Nicholls, and Shcherbakov, 2022).

In a companion paper, I show that the key distinction between Revolvers and Convenience users is that the former face tighter liquidity constraints and hence rely on revolving credit as a necessary, albeit expensive, financial stopgap (Dao, 2025). The present paper builds on this result by explicitly quantifying the value of the credit function and its implications for inequality. The consumption-payment framework developed in this paper is similar to that in Fulford and Schuh, 2024, which integrates payment choice models into dynamic consumption settings. Relative to their work, my paper places greater emphasis on payment demand by explicitly modeling consumers' preferences for different credit card features.

The conditional separability between the consumption and payment problems builds on recent work that exploits separability between dynamic state choices and within-period decisions to simplify dynamic models. In particular, Huynh, Shcherbakov, and Stenzel, 2025 separate

[5]This average includes Convenience users who do not borrow from their credit cards.

consumers' decisions regarding how much cash to hold from the allocation between cash and non-cash expenditure. While the authors use separability to reduce the dimensionality of the dynamic problem and facilitate numerical solutions, I exploit it to calculate consumer surplus without estimating the underlying dynamic problem.

My approach is also related in spirit to Kalouptsidi, Scott, and Souza-Rodrigues, 2021; Kalouptsidi et al., 2026, who show that particular counterfactuals and welfare objects may be identified without identifying all primitives of the underlying dynamic model. Rather than deriving conditions under which a particular dynamic counterfactual is identified, I exploit conditional separability between the dynamic borrowing decision and the within-period payment-allocation problem. This structure allows welfare to be recovered without requiring long panel data. A limitation of my approach is that it restricts the range of counterfactuals that can be evaluated. Since welfare is assessed conditional on observed expenditure, the framework is not well suited to counterfactuals that substantially alter demand for revolving credit.

2 The Digital Wallet And Payment Trends Survey

2.1 Overview

The main data source for this paper is the Digital Wallet and Payment Trends Survey (DWPT), a cross-sectional study commissioned by the Bank of Canada and conducted by IPSOS. The survey provides a comprehensive overview of the Canadian payment market, offering detailed insights into credit card ownership, payment patterns, and borrowing behaviors. The key variables for this analysis include individuals' use of different payment methods (e.g., cash, debit cards, credit cards). Although the DWPT tracks usage using both dollar spending and total expenditure shares (i.e., share of wallet), the demand estimation relies specifically on the latter.

Even though the DWPT does not directly report objective measures of credit card characteristics (e.g., reward earn rate, annual fees), the survey contains the exact names of the credit cards owned by each respondent (e.g., TD First Class Visa Travel Infinite). Using this information, I

manually match each reported card to its characteristics using the issuing bank's official website and recover objective measures of credit card features. When official information is unavailable, I supplement the dataset with information from third-party review sites (e.g., creditcardgenius.ca, ratehub.ca).[6,7] The final dataset contains information on 220 credit cards, detailing the type of rewards collected (i.e., cashback versus reward points), reward earn rates as a percentage of transaction value, the number of types of insurance coverage, interest rates, and annual fees.

My analysis is based on the 2021 and 2022 surveys. I restrict the sample to respondents with positive credit card usage to focus on the welfare of cardholders. Given that 90% of Canadians aged 18 and older own at least one credit card, the highest ownership rate worldwide (Demirguc-Kunt et al., 2022), this restriction is unlikely to materially affect the results. The final sample consists of 10,309 respondents equally distributed between the two sampling periods. Because outstanding credit card balances in Canada declined substantially during the COVID-19 pandemic (Ho et al., 2022), the estimates of consumers' reliance on revolving credit presented here are likely conservative.

2.2 Data Features

Card Characteristics: Because approximately 80% of credit card spending and borrowing occurs through a single credit card (Table 13), I focus on the characteristics of each respondent's primary credit card. To facilitate comparison between cashback and point-based reward programs, I convert the latter into cashback-equivalent rates by multiplying the average points earned per dollar by the average value per point.[8] Finally, since I consider only the primary card, a cardholder can only receive either cashback or points on their credit card, but not both at the same time.

Demographics: The DWPT also contains a rich set of demographic and financial variables, including income, revolving status, outstanding balances, and financial assets and liabilities.

Total Expenditure: Because the survey does not directly report total consumption, I construct

[6]This typically occurs when a credit card has been discontinued or renamed.

[7]Whenever possible, I use archived versions of these websites accessed through the Wayback Machine to recover the card characteristics applicable in the corresponding survey year.

[8]Further details on the construction of this variable are provided in Appendix 10.1.

a measure of monthly expenditure by scaling each respondent's reported personal credit card spending by their estimated credit card spending share.[9] Throughout the empirical analysis, I equate this expenditure with consumption. Although the resulting expenditure measure does not distinguish between durable and nondurable consumption, its estimates closely align with average aggregate expenditure in Canada, excluding housing costs (Statistics Canada, 2025).

Limitations: Despite its usefulness, the DWPT has two important limitations, namely the lack of transaction-level information and its cross-sectional nature.

First, because merchant pass-through of interchange fees depends heavily on context (e.g., transaction categories, merchant identity), omitting transaction context would be a major limitation for quantifying cross-subsidization across cardholder groups (Egan et al., 2026). This is, nevertheless, not the primary focus of the analysis.[10] Section 5 illustrates how consumer surplus can be recovered from individuals' average payment patterns. Although payment diaries and payment-settlement data provide substantially richer transaction-level information, they either do not contain detailed card characteristics (Felt et al., 2023), include only limited indicators of whether consumers receive rewards (Ching and Hayashi, 2010), or rely on subjective attitudinal measures that already incorporate consumer preferences (Koulayev et al., 2016). By contrast, the DWPT combines rich demographic information with granular, card-level product features, allowing me to estimate how preferences for rewards vary across income, revolving status, and reward type. Given the substantial heterogeneity documented in the data, accounting for these structural differences is essential for accurately measuring consumer surplus.

Second, the DWPT does not track credit card repayments or the evolution of outstanding balances over time. As a result, the underlying dynamic consumption problem cannot be directly estimated. This lack of a time dimension motivates the sufficient-statistics approach developed in this paper. By contrast, administrative credit reports (e.g., TransUnion and Equifax) provide detailed histories of credit card balances and repayments. However, these datasets generally capture only credit card transactions and do not observe consumers' use of alternative payment

[9] See Appendix 10.1 for full details on the construction.

[10] Since the distributional effects of interchange fees operate through prices, they are implicitly incorporated into the welfare estimates through observed spending.

methods. Because the value of the credit function must be measured relative to total consumption, these sources cannot, on their own, capture the value of access to credit.

Overall, while the DWPT is admittedly imperfect, the combination of detailed card characteristics, payment patterns, and household expenditure makes it particularly well suited to quantifying welfare gains from credit cards.

2.3 Definition of Revolvers

Following the literature, I define cardholders who report carrying positive outstanding balances as Revolvers (Grodzicki and Koulayev, 2019; Fulford and Schuh, 2023). Conversely, Convenience users are cardholders who do not carry any outstanding balances. Under this definition, 21% of cardholders are classified as Revolvers. The reported revolving rate is consistent with other survey evidence for the Canadian market (Henry, Shimoda, and Rusu, 2024) but is less than half the rate observed in administrative credit report data (Xiao, 2024; Allen, Boutros, and Guttman-Kenney, 2024). Such discrepancies are well documented in both Canada and the United States (Zinman, 2009; Brown et al., 2011). In a companion paper (Dao, 2025), I argue that surveys, including DWPT, primarily capture persistent Revolvers, whereas credit reports also capture short-term borrowing.[11]

2.4 Summary Statistics

Table 1 reports the main summary statistics. The top panel reports the characteristics of credit cards owned by Convenience users as well as these cardholders' demographic profiles. The bottom panel reports the corresponding statistics for Revolvers.

Despite earning roughly 10% less than their non-revolving counterparts in pretax income, Revolvers maintain an expenditure level approximately 14% higher. This gap persists after controlling for demographic and household characteristics, including income, age, household

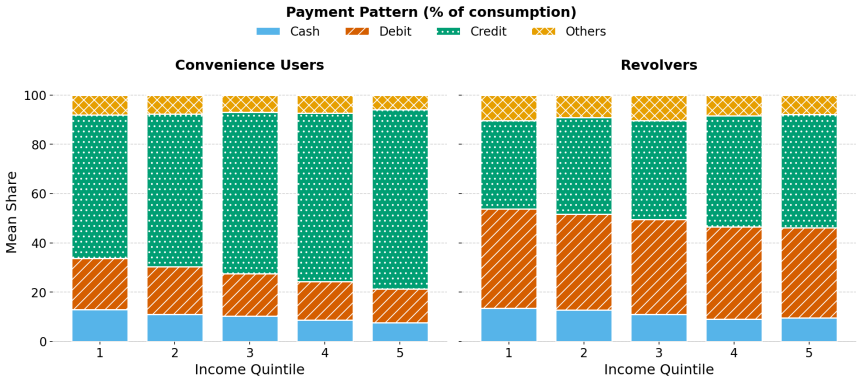
[11] Studies using administrative credit-report data often define cardholders as Revolvers if they carry an outstanding balance for at least two consecutive months (Grodzicki and Koulayev, 2019). Surveys, by contrast, often rely on self-reported revolving behavior, which are less likely to capture short-term borrowing.

size, and number of children (Dao, 2025). One possible explanation for this divergence is that Revolvers rely on revolving credit to bridge the income gap with Convenience users. Section 3 provides further descriptive evidence for this hypothesis.

In terms of credit card ownership, both groups appear similar: the median consumer in each group holds two credit cards. However, the characteristics of these cards differ considerably: Convenience users select into reward-intensive contracts with broad insurance coverage, while Revolvers prioritize cards with minimal annual fees. Figure 1 and the accompanying table illustrate how average payment patterns differ between Convenience users and Revolvers across the income distribution. Credit cards are the dominant payment method among Convenience users, accounting for 65% of total consumption for this group. By contrast, Revolvers allocate only 40% of their expenditure to credit cards. The gaps in credit card usage between revolving and non-revolving cardholders are also evident in absolute spending. On average, Revolvers spend roughly CAD 1,000 per month on credit cards, about 50% less than their non-revolving counterparts, despite having higher total expenditure. Overall, these payment patterns are consistent with Revolvers viewing credit cards as less attractive payment methods and using them primarily to obtain credit. Because Revolvers may incur interest on additional purchases, the high cost of revolving credit may limit how extensively they use credit cards.

Conditional on revolving, the average cardholder carries over CAD 4000 as an outstanding balance, resulting in an average debt-to-expenditure ratio of 2.7 (Figure 2). Because new credit card borrowing in a given month cannot exceed total card spending, these figures indicate that many Revolvers carry balances from previous months while accumulating new charges. At an annual interest rate of almost 21% (Table 1), these outstanding balances entail significant borrowing costs for revolving cardholders.

Figure 1: Variations in Payment Patterns

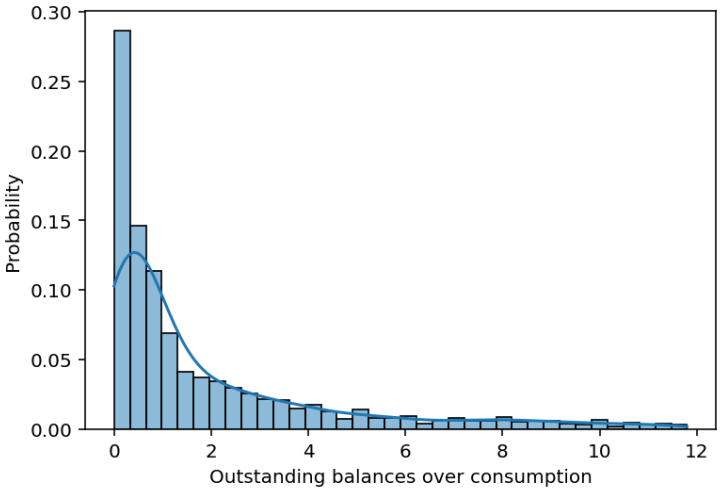


Notes: All values are expressed in CAD per month. Conv. = Convenience users; Rev. = Revolvers.

	Credit Card Spending		Cash Spending		Debit Card Spending	
Quintile	**Conv.**	**Rev.**	Conv.	Rev.	Conv.	Rev.
1st (Bottom 20%)	876	579	287	386	481	1,050
2nd Quintile	1,171	827	338	568	676	1,198
3rd Quintile	1,452	962	301	411	504	1,353
4th Quintile	1,732	1,455	254	416	554	1,467
5th (Top 20%)	2,476	1,634	318	694	1,275	1,545

Figure 2: Distribution of the Debt-to-Expenditure Ratio—Revolvers Only

Notes: Debt-to-expenditure = $\frac{\text{Outstanding balance}}{\text{Expenditure}}$. Convenience users are excluded from the figure and accompanying table.



	Mean	Stdev	p25	p50	p75
Outstanding balance (CAD)	4037	5851	500	1800	5000
Debt-to-expenditure ratio	2.7	5.17	0.28	0.88	2.85

Table 1: Summary statistics by revolving status

Notes: Point cards are credit cards that collect reward/loyalty points instead of cashback. Interest rate is based on the advertised purchase rate.
Credit cards charging an annual fee of CAD 120 or higher are classified as premium cards. Low-interest credit cards are those with an advertised annual rate of 15% or lower.
Pretax income is measured using the midpoints of the reported CAD 5,000 income brackets and treated as a continuous variable. After-tax income is approximated from reported pretax income using federal and provincial tax schedules. The calculation does not account for other tax credits.

Variable	Mean	Std. dev.	25th	Median	75th	Max
Panel A: Convenience Users						
Total monthly expenses (CAD)	2,360	2,144	1,000	1,750	3,000	10,714
Credit card characteristics						
No. of credit cards	1.81	0.77	1	2	2	3
Reward rate (%)	1.29	0.72	0.73	1.20	1.85	4.50
Interest rate (%)	20.96	2.4	9.99	20.99	20.99	20.99
Annual fee (CAD)	60	127	0	0	120	5,000
No. of insurance benefits	4.36	3.53	2	3	7	14
Share with points cards	0.60					
Share with premium cards	0.30					
Share with low-interest cards	0.036					
Demographics						
Pretax income (CAD/year)	86,816	50,435	50,000	80,000	100,000	250,000
After-tax income (CAD/year)	61,653	32,129	37,523	58,361	75,290	163,873
Household size	2.40	1.22	2	2	3	11
Age	51.6	16.6	38	53	65	95
Panel B: Revolvers						
Total monthly expenses (CAD)	2,706	2,607	1,000	1,857	3,333	10,714
Credit card characteristics						
No. of credit cards	1.84	0.78	1	2	2	3
Reward rate (%)	1.02	0.78	0.53	1.00	1.53	4.50
Interest rate (%)	20.75	3.897	9.99	20.9	20.99	20.99
Annual fee (CAD)	47	91	0	0	79	800
No. of insurance benefits	3.80	3.26	2	2	6	14
Share with points cards	0.54					
Share with premium cards	0.20					
Share with low-interest cards	0.112					
Demographics						
Pretax income (CAD/year)	76,081	45,510	40,000	70,000	100,000	250,000
After-tax income (CAD/year)	54,809	29,684	31,980	51,782	71,860	163,873
Household size	2.37	1.17	2	2	3	8
Age	45.9	14.6	34	45	57	86
Observations						10,309
Revolving rate						21%

3 Descriptive Facts

This section documents three empirical facts that motivate moving beyond net rewards as a measure of the redistributive effects of credit cards. Consistent with previous findings for the U.S. market (Agarwal et al., 2023), Fact 1 shows that Revolvers receive substantially lower and often negative net rewards than Convenience users. Fact 2 indicates that while Convenience users utilize credit cards strictly as payment instruments, Revolvers also utilize the credit function to obtain liquidity. Finally, Fact 3 suggests that by ignoring this credit function, net rewards severely understate the value of credit cards to Revolvers.

Fact 1: Revolvers Earn Negative Net Rewards.

Following the literature (Agarwal et al., 2023), I calculate the net monetary benefits of credit cards as:

$$\begin{aligned} \text{Net rewards}(\$/month) = {} & \text{Reward earn rate} \times \text{Credit Card spending} \\ & - \text{Monthly interest rate} \times \text{Revolving balance} \\ & - \frac{\text{Annual fee}}{12}. \end{aligned} \tag{1}$$

Here, the reward earn rate denotes the rebate earn rate as a percentage of spending, while the monthly interest rate is computed as

$$\text{Monthly interest rate} = \frac{\text{Advertised annual rate}}{365} \times 30.5.$$

Finally, credit card spending and revolving balance refer to average monthly card spending and the balance on which interest is incurred, respectively.[12] Because the DWPT reports both of these quantities on a monthly basis, I also divide annual fees by 12 to express them on a monthly basis.

Figure 3 plots the distribution of average monthly net rewards collected by Convenience users and Revolvers. On average, Convenience users gain roughly CAD 17/month from their card usage,

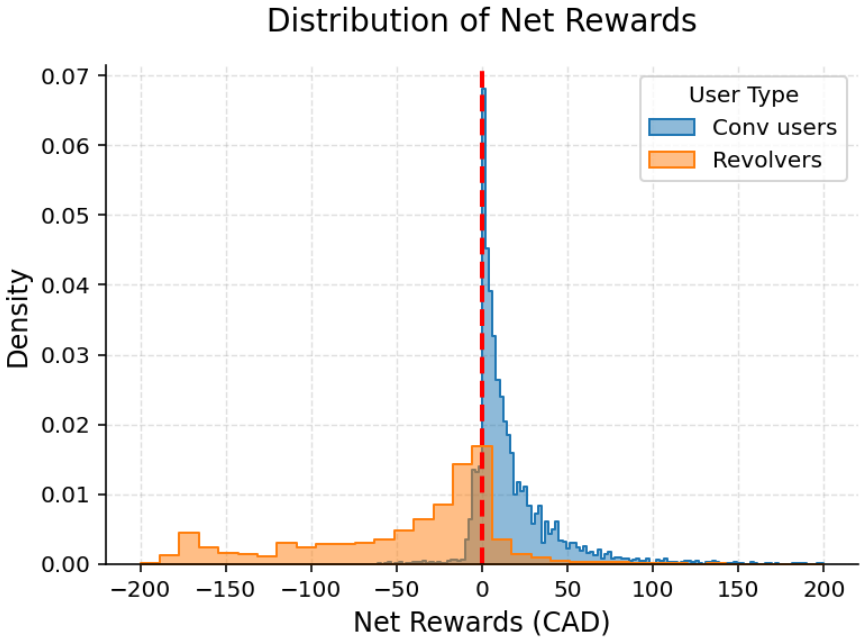
[12] Because credit limits change infrequently and utilization rates are highly persistent (Fulford and Schuh, 2024), I interpret the reported outstanding balance as the average revolving balance.

whereas Revolvers lose CAD 60/month. Only 15% of Revolvers in the sample earn positive net rewards versus 85% for Convenience users. This gap is largely mechanical due to the interest rate on credit cards.

Reward programs also heavily favor high-income Convenience users, who not only hold more reward-focused credit cards (Table 1) but also allocate a larger share of their spending to these cards (Figure 1). Non-revolving cardholders in the highest income decile earn nearly six times as much in net rewards as those in the lowest income decile (Table 2). The resulting distribution of net rewards is therefore highly unequal, with $Gini_{\text{Net Rewards}} = 0.79$. This pattern is consistent with evidence from the U.S. (Agarwal et al., 2023),[13] and has been interpreted as evidence that credit card reward programs generate regressive transfers from lower-income, less financially sophisticated consumers to their higher-income counterparts.

Figure 3: Distribution of net rewards by revolving status

Notes: Values are expressed in CAD per month. Net rewards = Reward earn rate - Interest charges - Annual fees. Rewards received =Reward earn rate $\times$ Credit Card spending; Interest charges = $\frac{\text{Advertised annual rate}}{365} \times 30.5 \times$ Revolving balance; Annual fees are divided by 12 to calculate the monthly cost.



[13] Agarwal et al., 2023 analyzes the distribution of net rewards by FICO score, which the authors use as a proxy for financial sophistication.

Table 2: Net Rewards by Income Decile

Notes: All values are expressed in CAD per month. Conv. denotes Convenience users, and Rev. denotes Revolvers. Rewards received =Reward earn rate × Credit Card spending; Interest charges = $\frac{\text{Advertised annual rate}}{365} \times 30.5 \times$ Revolving balance; Annual fees are divided by 12 to calculate the monthly cost. Net rewards = Reward earn rate - Interest charges - Annual fees.

		Income Decile									
Component	**Type**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Rewards received	Conv.	7.49	12.17	14.27	15.36	19.49	21.33	23.86	28.88	34.88	46.41
	Rev.	4.51	7.21	7.65	10.67	10.45	12.17	16.66	16.74	18.05	24.92
Annual fees	Conv.	2.26	3.30	3.29	4.36	5.11	4.81	5.28	6.26	7.51	10.67
	Rev.	2.01	2.88	4.20	3.31	3.79	5.69	4.85	5.14	4.65	6.85
Interest charges	Conv.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Rev.	38.85	52.12	56.96	52.15	56.64	53.04	63.70	61.54	62.07	54.24
Net rewards	Conv.	5.23	8.87	10.98	11.00	14.38	16.52	18.57	22.62	27.37	35.73
	Rev.	-36.35	-47.79	-53.49	-44.79	-49.98	-46.55	-51.89	-49.93	-48.66	-36.13

Fact 2: Revolvers Use Revolving Debt To Finance Expenses

To verify whether the additional expenditure among Revolvers is funded by credit card debt, I estimate the following model:

$$\log \text{Expenditure}_i = \beta_0 + \beta_1 \log \text{Balance}_i + \beta_2 \log \text{Income}_i + \beta_3 \text{r}_i + \epsilon_i \tag{2}$$

where $Balance_i$ denotes respondents' self-reported outstanding revolving balance, and r_i represents the advertised annual interest rate.[14]

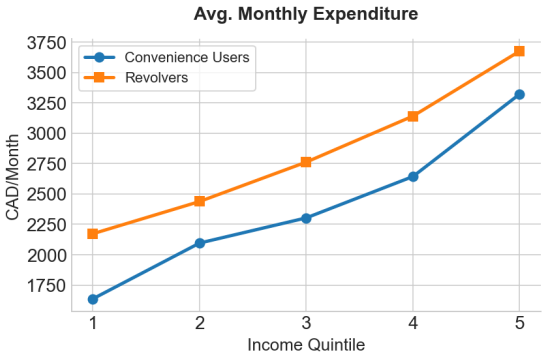
Figure 4b depicts the estimated relationship between consumption and outstanding balances. The data indicate a statistically and economically significant relationship between spending and revolving debt among revolving cardholders. In particular, a 1% increase in outstanding balances is associated with a 0.11% increase in expenditure. While comovement between total spending and credit card debt should by no means be interpreted as causal evidence, the observed pattern is consistent with Revolvers relying on credit cards to finance their expenditure.

[14]Since $\log \text{Balance}_i$ is undefined for Convenience users, who by definition do not carry outstanding balances, I estimate Equation (2) only on the Revolver subsample. The key parameter of interest is β_1, which captures the elasticity of expenditure with respect to outstanding revolving balances.

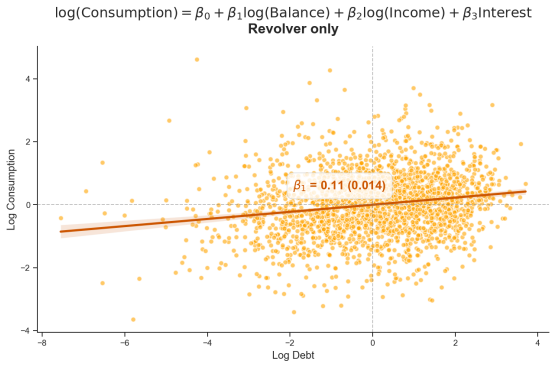
Figure 4: Consumption and Outstanding Balances

Left panel: income quintiles are defined based on the income distribution of the full sample.
Right panel: β_1 is the elasticity of consumption with respect to outstanding balance. $\beta_1 > 0$ is consistent with Revolvers using debt to finance expenditure.

(a) Average consumption by income quintile



(b) Debt and expenditure - Revolvers subsample



Fact 3: Revolvers Report Similar Satisfaction With Their Credit Cards As Convenience Users.

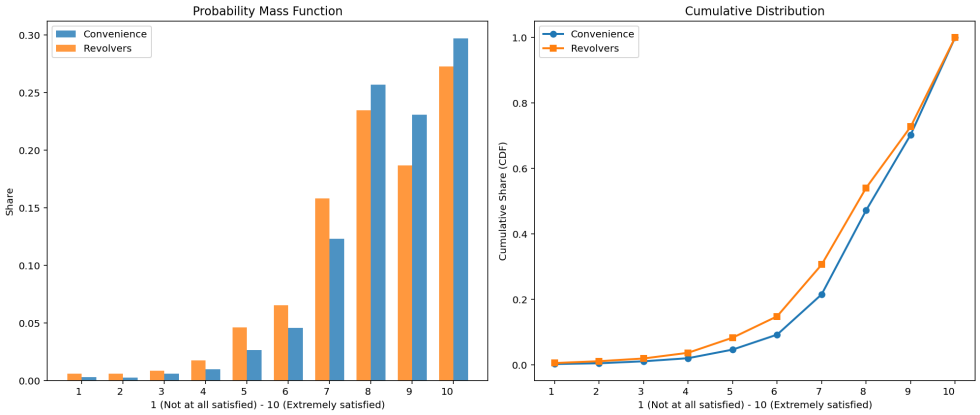
If net rewards fully capture the value of credit cards to consumers, Fact 1 implies that Revolvers should report significantly lower levels of card satisfaction. The empirical cumulative distribution of respondents' credit card satisfaction indicates otherwise (Figure 5).[15] Approximately 85% of Revolvers report being highly satisfied with their credit cards (i.e., a satisfaction score of 7 or higher). While this rate is slightly lower than the corresponding rate among Convenience users, the result of the Kolmogorov–Smirnov test suggests that this difference is statistically insignificant (p-value = 0.41). Moreover, satisfaction among Revolvers appears to be uncorrelated with the net rewards they receive. The Spearman rank correlation between net rewards and card satisfaction is 0.12 among Convenience users, compared with 0.04 among Revolvers.[16] These patterns suggest that net rewards may not fully capture the value of credit cards to Revolvers.

[15]Respondents select a satisfaction score on a scale from 1 (Not at all satisfied) to 10 (Extremely satisfied) in response to the question "Overall, how satisfied are you with your primary card?"

[16]The weak correlation between net rewards and card satisfaction among Convenience users may partly reflect the limited variation in reported satisfaction, as approximately 89% of non-revolving cardholders report a satisfaction score of seven or higher.

Figure 5: Satisfaction With Primary Card

Respondents are asked "Overall, how satisfied are you with your primary card?" on a scale from 1 (Not at all satisfied) to 10 (Extremely satisfied).



4 Theoretical Framework

This section proposes an alternative welfare measure based on consumer surplus from credit cards. Because credit card borrowing links current consumption to future repayment obligations, modeling Revolvers' demand for credit cards necessitates a dynamic framework. This creates an identification challenge, as the DWPT provides only cross-sectional variation. To resolve this, I establish the connection between the dynamic demand model of credit cards and the static discrete choice framework under standard assumptions (Anderson and De Palma, 1992; Ellickson, Grieco, and Khvastunov, 2020; Li, 2023). This result allows consumer surplus to be calculated using only cross-sectional variation between groups of cardholders.[17] The proposed approach is especially useful for settings where long panel data are unavailable.

I begin by introducing a partial-equilibrium model of credit card demand, taking the characteristics of adopted cards as given. The analysis therefore focuses on credit card usage conditional on card adoption and observed card characteristics, rather than modeling the upstream choice of which card to hold. The remainder of this section presents the general structure of the dynamic model of consumption and shows how consumer surplus can be calculated without estimating the

[17] Ellickson, Grieco, and Khvastunov, 2020 uses a discrete-choice framework to study competition among grocery retailers, whereas Li, 2023 applies a similar framework to predict consumer demand for central bank digital currency.

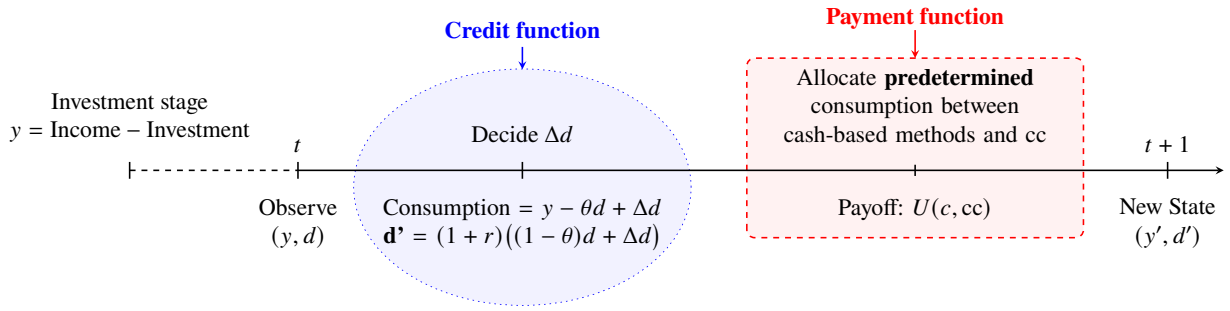
full dynamic model. A formal treatment of the model is provided in Appendix 9.

4.1 A Simple Model Of Consumption and Payment

The Rationality of Persistent Revolvers: Because the DWPT primarily captures persistent Revolvers, I model revolving behavior as a deliberate, forward-looking choice. The persistence of revolving behavior arises naturally in a rational framework in which income is deterministic or not explicitly modeled.[18] Because full repayment of existing outstanding balances entails substantial liquidity costs, liquidity-constrained cardholders who begin revolving are likely to continue doing so (see Table II, Nelson, 2025).

This is not to suggest that all credit card borrowing is necessarily both rational and persistent. In models with stochastic income, consumers may temporarily carry balances to smooth out unexpected shocks (Telyukova, 2013; Fulford and Schuh, 2024). Alternatively, short-term revolving behavior can reflect behavioral biases rather than deliberate choices (Han, 2023; Agarwal et al., 2026). Nevertheless, because such transitory Revolvers are largely absent from survey data (Dao, 2025), a rational framework remains well suited to this analysis.

Figure 6: Model Timeline



Consider a standard finite-horizon consumption-savings problem in discrete time (Figure 6).

State Variables: The model's state space consists of non-credit resources available for consumption, y, and the outstanding credit card balance at the start of the period, d. I interpret y as disposable income net of savings; that is, the model begins after consumers have determined

[18]The framework described below technically allows for income to be stochastic. However, since I only observe average household income, the empirical application treats this quantity as deterministic.

how much of their available income to save or invest. While this interpretation limits the model's capacity to explain why people revolve (Telyukova, 2013; Fulford and Schuh, 2024), it does not affect the quantification of welfare gains from credit access for Revolvers.[19]

Expenditure Choices: At the beginning of each period t, consumers observe their state variables (y, d). Before making any decisions, consumers must make the minimum required payment, θd, using their non-credit resources. They then choose net credit card borrowing (Δd), defined as the difference between new credit card spending and repayment within the period.

$$\Delta d = cc - R.$$

where R denotes repayment in excess of the minimum required payment, θd.

Because the model abstracts from additional saving within the period, net borrowing also uniquely determines the current period's expenditure level as well as next period's outstanding balances.

$$y - \theta d + \Delta d = c + cc, \tag{3}$$

$$d' = (1 + r)\Big((1 - \theta)d + \Delta d\Big). \tag{4}$$

where c and cc denote cash-based and credit card spending. Meanwhile, d' and r represent next period's starting balance and the interest rate on the outstanding balance, respectively.

Payment Allocations: Subject to the total expenditure implied by Equation (3), consumers determine how to allocate expenditure between cash-based methods and credit cards. This optimal allocation depends on the per-period utility function $U(c, cc)$, which incorporates credit card features and individual-specific preferences over those characteristics. Note that cash-based methods include all non-credit payment instruments such as currency and debit cards. Because the credit function was largely restricted to credit cards during the sample period, this grouping simplifies the analysis while preserving the paper's central mechanism.[20]

[19] For welfare assessment purposes, all that matters is how much consumption is financed by revolving credit.

[20] Although Buy-Now-Pay-Later (BNPL) mechanisms enable consumer borrowing via debit card networks, such

Discussion: In the absence of revolving credit (i.e., $d = \Delta d = 0$), $y = c + cc$ coincides with the expenditure level. Nevertheless, consumers retain the ability to transact with credit cards (i.e., choosing $cc > 0$). The framework therefore captures demand for both the payment and credit functions of credit cards.

While the framework can accommodate both persistent and transitory revolving behavior, the empirical implementation focuses on the former. This emphasis is data-driven as the DWPT dataset primarily captures persistent Revolvers. Accordingly, I assume Convenience users always repay their credit card balances in full and carry $d = 0$ in every period. By contrast, Revolvers always maintain a positive outstanding balance ($d > 0$). Importantly, $d > 0$ does not imply positive net borrowing in every period. Revolvers may incur more debt to finance current consumption ($\Delta d > 0$) or pay down existing balances ($\Delta d < 0$).

Finally, because default is costly, rational consumers who are at high risk of missing a payment may elect not to revolve to reduce the likelihood of default (Nelson, 2025). This consideration supports my decision not to model strategic default explicitly.

4.2 Conditional Separability Of Payment Allocation

Because the DWPT does not track balance and repayment histories, the dynamic model in Figure 6 cannot be directly estimated. Proposition 1 separates the dynamic consumption problem from the static payment allocation problem. Given that observed expenditure is an equilibrium outcome of the dynamic problem, this result also justifies using welfare gains from payment allocation as a sufficient statistic for consumer welfare in the underlying dynamic problem.

Proposition 1. *Conditional on net borrowing, the within-period payment-allocation problem can be represented as a static choice problem.*

Proof. See Appendix 9. □

To understand the intuition underlying this result, consider an example in which net borrowing is fixed at $\Delta d = 100$. For simplicity, assume further that $\theta = 0$ and $y = 900$. Equation (3) implies

services had minimal market penetration during the sample period.

that the within-period budget constraint is:

$$y + \Delta d = 900 + 100 = 1000 = c + cc$$

Given this budget, there are multiple ways to allocate consumption across payment methods while keeping the same net borrowing choice. Table 3 illustrates two possible allocations. Because Allocations A and B imply the same d' under Equation (4), they generate identical dynamic implications. Hence, conditional on predetermined expenditure, the allocation decision reduces to a static problem.[21]

Table 3: Examples Of Possible Allocations

Notes: c and cc denote spending using cash-based payment methods and credit cards, respectively. R denotes credit card repayment; Δd captures net credit card borrowing, defined as the difference between credit card spending and repayment. d' is the outstanding balance at the beginning of the next period.

	c	cc	R	$\Delta d = cc - R$	$d' = (1+r)(d+\Delta d)$
A	600	400	300	100	$(1+r)(d+100)$
B	300	700	600	100	$(1+r)(d+100)$

4.3 From Continuous To Discrete Choice

To link the continuous allocation problem to a discrete choice framework for empirical analysis, I assume that per-period utility follows a CES specification over cash-based and credit card expenditures (Anderson and De Palma, 1992). Following Ellickson, Grieco, and Khvastunov, 2020; Li, 2023, I impose the assumptions below, which allow expenditure shares to be interpreted as conditional choice probabilities under a discrete choice framework.

Assumption 1.

A*. *Exogenous consumption level: *An individual's total consumption is taken as given.*

B*. *Constant transaction value: *Each cardholder faces a sequence of homogeneous transactions of fixed value k.*

[21] Proposition 1 may not hold when consumers choose the corner solution $R = 0$, implying $cc = \Delta d$. Given that less than 4% of cardholders report paying only the minimum amount, such exceptions are not important empirically.

Assumption 1A allows payment allocations to be expressed as expenditure shares. For example, Allocation A can be written as 40% of consumption paid by credit card and 60% by cash-based methods. This framing presents a natural way to condition on the consumption level and connects the theoretical payment-allocation problem to the empirical demand specification.

Assumption 1B provides a convenient way to recast the continuous payment-allocation problem as a discrete choice over each k dollars of expenditure. Intuitively, if all transactions have the same value, choosing how much expenditure to allocate to each payment method is equivalent to choosing a payment method repeatedly across identical units of expenditure. Under this assumption, expenditure shares coincide with transaction shares and therefore with choice probabilities generated from a discrete choice model of payment.[22]

Furthermore, I normalize $k = 1$ and interpret the problem as one in which consumers discretely allocate each dollar of expenditure. This normalization is without loss of generality, except in cases where individual consumption consists of only a few high-value purchases. Such a scenario is unlikely to hold in practice as the DWPT reflects average consumer behavior. Appendix 10.3 provides further discussion of the implications of Assumption 1B and the normalization of k.

4.4 Demand Estimation

Indirect utility: For each individual, indirect utility is specified as:

$$U_{ijm} = \delta_{ij} + \epsilon_{ijm},$$

where U_{ijm} denotes the indirect utility that individual i receives from choosing payment method $j \in \mathbf{J} = \{c, cc\}$ for the m-th dollar. The term δ_{ij} captures the deterministic component of utility, while ϵ_{ijm} represents an idiosyncratic taste shock. Under Assumption 1B, the deterministic utility associated with each payment method is constant across dollars of expenditure; thus δ_{ij} does not carry an m subscript.

[22] Expenditure share $= M \frac{s_j \mathbb{E}[k_m | j \text{ is chosen}]}{\sum_1^T k_m} = M \frac{s_j \cdot k}{M \cdot k} = s_j$

Under Assumption 1, consumers select the payment method yielding the highest utility per dollar spent:

$$j^* = \arg\max_{j \in \mathbf{J}} U_{ijm}.$$

Denote by s_{ij} individual i's expenditure share for payment method j. Assuming that ϵ_{ijm} follows a Type-I extreme value distribution (McFadden, 1977), s_{ij} has the following closed-form expression:

$$s_{ij} = \frac{\exp(\delta_{ij})}{\sum_{\ell \in \mathbf{J}} \exp(\delta_{i\ell})}.$$

The deterministic utility depends on the features of the specific cards held by consumers, as well as cardholders' preferences for those features. Formally,

$$\delta_{ij} = \alpha_i \, \text{Cashback}_j + \beta_i \, \text{Points}_j + \gamma_i \, \text{Insurance}_j + \Xi_{ij}, \tag{5}$$

where Cashback and Points denote the cashback rate and cashback-equivalent rate of point-based cards, respectively. Insurance is the number of types of insurance coverage included with the credit card. Finally, Ξ_{icc} captures characteristics that are unobserved by the econometrician.

Because Cashback, Points, and Insurance are directly observable within the DWPT, cross-sectional variation across cards is sufficient for identification of the underlying preference parameters. Conversely, interest rates and credit limits affect the underlying dynamic problem, so variation in these characteristics violates Assumption 1A. Thus, preferences for interest rates and credit limits are not identifiable within the current framework. Appendix 10.3 discusses this point in detail (Table 10).

Estimating Equation: Following the literature, I decompose Ξ_{icc} into a component that is common across individuals and an individual-specific component (Berry, Levinsohn, and Pakes, 1993). That is,

$$\Xi_{ij} = \xi_j + \mathbf{1}_{Rev}\psi_j + \mathbf{1}_{Point}\Psi_j + \xi_{ij}. \tag{6}$$

Since cash-based methods do not offer any rebates or insurance coverage, I normalize $\xi_{ic} = \delta_c$ and estimate consumer preferences under the following specification (Berry, 1994):

$$\begin{aligned}\log \frac{s_{icc}}{s_{ic}} &= \delta_{icc} - \delta_{ic} \\ &= \xi_{cc} + \mathbf{1}_{Rev}\psi_{cc} + \mathbf{1}_{Point}\Psi_{cc} + \alpha_i \text{Cashback}_i + \beta_i \text{Points}_i + \gamma_i \text{Insurance}_i \\ &\quad + \tau \mathbf{Z}_i + \xi_{icc} - \xi_{ic}, \end{aligned} \tag{7}$$

where Cashback_i and Points_i denote the cashback and cashback-equivalent reward rates, respectively, and Insurance_i captures the number of types of insurance coverage included with the card.

The indicator function $\mathbf{1}_{Point}$ equals one for consumers holding a points-based credit card, while $\mathbf{1}_{Rev}$ equals one for Revolvers. Consumer preferences are modeled as:[23]

$$\begin{aligned}\alpha_i &= \alpha + \sigma_1 Income_i + \mathbf{1}_{Rev}\alpha_{Rev}, \\ \beta_i &= \beta + \sigma_2 Income_i + \mathbf{1}_{Rev}\beta_{Rev}, \\ \gamma_i &= \gamma + \mathbf{1}_{Rev}\gamma_{Rev}. \end{aligned}$$

Finally, the vector $\boldsymbol{Z}_i$ includes bank and income-group fixed effects, annual fees, and consumers' satisfaction with their primary card to mitigate potential endogeneity concerns due to selection (Ching and Hayashi, 2010).

Because cashback programs reduce the consumer's effective price by $k \cdot \text{Cashback}_i$, this characteristic enters the estimating equation as a price-like variable. For example, a 2% cashback rate on a \$100 purchase provides a \$2 rebate and is functionally identical to a 2% discount on the same purchase. The corresponding coefficient, α_i, therefore captures the marginal utility of income and is later used to convert consumer surplus into dollar terms. Note that transaction value will change the amount of rebates collected but not their marginal values. Thus, the interpretation

[23] Since both income and revolving status are directly observable, heterogeneity in consumer preferences can be captured directly through interaction terms.

of α_i and subsequent welfare calculations are invariant to Assumption 1B as well as the specific value of k.[24]

5 Measuring The Value Of Credit Cards

Because net rewards omit the liquidity value provided by credit cards, they understate the value Revolvers derive from card access. By contrast, this paper evaluates welfare through consumer surplus. Following the discrete-choice literature (Small and Rosen, 1981), I measure consumer surplus as the compensating variation associated with access to credit cards. Because the credit function is unique to credit cards, this framework incorporates both their payment and credit functions into the welfare calculation.

Since payment decisions are static, the resulting surplus estimates do not capture each individual's lifetime benefits from credit cards. Nevertheless, if the economy is in a steady state in which the joint distribution of consumer characteristics and card usage patterns remains stable, these estimates characterize the cross-sectional distribution of benefits at any point in time.[25]

5.1 Consumer Surplus

Let Expenditure_i denote individual i's observed monthly expenditure. Total indirect utility with credit cards is

$$V_i^{\text{with cc}} = \mathbf{v}_i^{\text{with cc}} \cdot \text{Expenditure}_i, \tag{8}$$

Because consumers choose the payment method that yields the highest utility, per-unit surplus with credit cards is given by the expected maximum utility across cash-based methods and credit

[24] Since Cashback_i is in percentage terms, I divide the resulting surplus measure by 100 when expressing it in monetary terms.

[25] All that required is for today's younger consumers to behave like today's older consumers, once the formers get older.

cards.

$$\mathbf{v}_i^{\text{with cc}} = \mathbb{E}\left[\max_{j\in\{c,cc\}} U_{ijm}\right] = \log \sum_{j\in\{c,cc\}} \exp(\delta_{ij}) + \gamma.$$

The Euler–Mascheroni constant $\gamma \approx 0.577$ arises from the assumption that shocks are drawn from a Type-I extreme-value distribution (McFadden, 1977).

Without credit cards, the consumer can use only cash-based methods. Per-unit surplus in this case is therefore

$$\mathbf{v}_i^{\text{without cc}} = \mathbb{E}[U_{icm}] = \delta_{ic} + \gamma.$$

Because cash-based methods do not have the credit function, cardholders can no longer sustain the debt-financed portion of expenditure. Hence, I calculate the counterfactual expenditure by scaling down observed expenditure by the estimated share financed through new credit card borrowing. Total indirect utility in the counterfactual without credit cards is therefore

$$\begin{aligned} V_i^{\text{without cc}} &= \mathbf{v}_i^{\text{without cc}} \text{Expenditure}_i^{\text{without cc}} \\ &= \mathbf{v}_i^{\text{without cc}} (1 - s_{id}) \text{Expenditure}_i, \end{aligned}$$

where s_{id} denotes the share of debt-financed expenditure. Section 5.2 defines this quantity in more detail.

Consumer surplus is the utility difference converted into monetary units, net of annual fees and borrowing costs:

$$CS_i = \frac{V_i^{\text{with cc}} - V_i^{\text{without cc}}}{\alpha_i} - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i.$$

Collecting the terms yields the final expression for consumer surplus:

$$\begin{aligned} CS_i = \frac{\left(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}\right) \cdot \text{Expenditure}_i}{\alpha_i} + \frac{\mathbf{v}_i^{\text{without cc}} \cdot s_{id} \cdot \text{Expenditure}_i}{\alpha_i} \\ - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i, \end{aligned} \tag{9}$$

where α_i denotes the preference for cashback, or equivalently, the marginal utility of income.[26, 27] Borrowing Costs$_i$ isolates the interest incurred specifically on new debt-financed expenditure (Δd_i). This differs from total interest charges, which reflect the cost of multiple instances of borrowing.

Equation (9) provides a sufficient statistic for the welfare gains from credit cards. Because its components are either directly observed (e.g., expenditure and annual fees) or estimable using cross-sectional variation (e.g., per-unit surplus, s_{id}), welfare can be measured without estimating the underlying dynamic consumption-saving model. Section 5.2 discusses the estimation of s_{id} and the associated Borrowing Costs$_i$.

Baseline Utility Without Credit Cards: Because the deterministic components of utility are identified only up to a constant (Train, 2009), most empirical applications normalize the utility of the baseline alternative to zero (i.e., $\delta_{ic} = 0$). Nevertheless, gross welfare gains from the credit function are

$$\mathbf{v}_i^{\text{without cc}} \cdot s_d \cdot \text{Expenditure}_i = (\delta_{ic} + \gamma) \cdot s_d \cdot \text{Expenditure}_i.$$

Because setting $\delta_{ic} = 0$ would mechanically reduce the estimated value of the credit function, I instead adopt a conservative calibration that bounds the utility of the outside option from below at zero (Babina et al., 2025).[28]

$$\delta_{ic} = \max\{0, \Xi_{ic} - \Xi_{icc}\}, \tag{10}$$

where $\Xi_{ic} - \Xi_{icc}$ captures the difference in the unobserved components between cash-based payment methods and credit cards for individual i.

This difference is estimated from Equation (7) as:

$$\Xi_{ic} - \Xi_{icc} = -(\Xi_{icc} - \Xi_{ic}) = -(\xi_{cc} + \mathbf{1}_{Rev}\psi_{cc} + \mathbf{1}_{Point}\Psi_{cc}).$$

[26] See the discussion of the estimating equation in the demand-estimation section.

[27] Because cashback enters the demand estimation in percentage terms, α_i is multiplied by 100 to convert surplus to dollar terms.

[28] Babina et al., 2025 calibrates the utility of the outside options to match moments from the data.

This calibration assumes that observed consumption generates weakly nonnegative surplus relative to forgoing consumption. Because individuals in the data chose to consume, revealed preference dictates that any chosen option $j \in \{c, cc\}$ must generate weakly nonnegative surplus.[29] Note that specific calibrations of δ_c have no impact on the improvement in per-unit surplus in the observed equilibrium with credit cards. Differences in per-unit surplus with and without credit cards can be calculated using the standard log-sum formula (Cardell, 1997):

$$\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}} = \log\left(1 + \exp(\delta_{icc})\right).$$

Table 12 presents robustness checks using the standard assumption of $\delta_{ic} = 0$. While such a normalization mechanically reduces the estimated value of the credit function for Revolvers, the central conclusion remains unchanged. That is, net rewards substantially overstate inequality in the benefits of credit cards.

5.2 Estimating The Value Of The Credit Function

Share Of Debt-Funded Expenditure: Because the DWPT reports average spending by payment method around the time of the survey, the quantities used in this section are best interpreted as short-term average monthly measures. Accordingly, s_{id} is best understood as the short-term average monthly share of expenditure financed by new borrowing around the survey window.

Define an individual's average share of debt-funded spending as:

$$s_{id} = \max\{0, \mathbb{E}\big[\frac{\Delta d_i}{\text{Expenditure}_i}\big]\},$$

where the max operator reflects that Revolvers who are actively paying down their balances (i.e., $\Delta d_i < 0$) do not rely on revolving credit to finance their expenditure.

Given this definition, reliance on debt depends only on the average flow of new borrowing and not the total stock of outstanding balances (i.e., d_i). Because the DWPT reports only the

[29] $\delta_{ic} = \Xi_{ic} - \Xi_{icc} > 0$ when cash-based methods have greater unobserved utility than credit cards, and $\delta_{ic} = 0$ otherwise.

latter, there is a fundamental mismatch between the required variable and the observed data. Furthermore, given that roughly 45% of Revolvers carry outstanding balances exceeding their total monthly expenditure (Figure 2), it is not possible to proxy s_{id} with the observed debt-to-consumption ratio. I resolve this issue by using the model from Section 4.1 to impute the average level of net borrowing, $\overline{\Delta d}_i$.

Consider the average within-period budget constraint as specified by Equation (3):

$$\bar{y}_i - \overline{\theta d}_i + \overline{\Delta d}_i = \bar{c}_i + \bar{cc}_i = \text{Expenditure}_i,$$

where $\bar{c}_i$ and $\bar{cc}_i$ denote the observed individual-level average monthly cash-based spending and credit card spending, respectively.[30] Similarly, $\bar{y}_i$ and $\overline{\theta d}_i$ represent average non-credit resources and the average minimum required payment.

Since Convenience users neither carry outstanding balances nor incur new revolving debt, their average expenditure is exactly equal to their total non-credit resources:

$$\bar{y}_i^{Conv} = Expenditure_i^{Conv}.$$

Revolvers' expenditure, on the other hand, is given by

$$\bar{y}_i^{Rev} - \overline{\theta d}_i + \overline{\Delta d}_i = Expenditure_i^{Rev}.$$

To calculate $\overline{\Delta d}_i$, we must first recover the minimum required payment and non-credit resources. While $\overline{\theta d}_i$ is easily calculable using available data, estimating $\bar{y}_i$ is more complicated.

Estimating Revolvers' Non-Credit Resources: $\bar{y}_i$ is perfectly observable for Convenience users but remains unobserved for Revolvers, whose spending also contains new borrowing. To solve this, I predict *Revolvers'* average non-credit resources using a Gradient Boosting Regressor trained on the conditional relationship between disposable resources and observed characteristics among Convenience users. This empirical strategy requires the following assumption.

[30] Recall that the DWPT reports respondents' average spending across different payment methods.

Assumption 2. *Convenience users and Revolvers have the same expected level of non-credit resources, conditional on gross income and other demographics. That is,*

$$\mathbb{E}[\bar{y}_i|Z_i, \mathbf{1}_{Rev} = 0] = \mathbb{E}[\bar{y}_i|Z_i, \mathbf{1}_{Rev} = 1],$$

where Z_i is a high-dimensional vector of demographic variables.

Recall that non-credit resources available for consumption equal income net of investment decisions; that is, $y_i = \text{Income}_i - \text{Investment}_i$. Hence, Assumption 2 requires the two groups to have the same expected level of net investment conditional on income and other demographic characteristics.[31] The plausibility of this assumption is supported by the similar asset and liability distributions of Revolvers and Convenience users (Figure 15). Appendix 10.5 provides additional robustness checks for Assumption 2 by allowing the relative magnitudes of $\bar{y}_i^{\text{Conv}}$ and $\bar{y}_i^{\text{Rev}}$ to vary by constant factors, à la Altonji, Elder, and Taber, 2005, thereby assessing the sensitivity of the results to selection on unobservables.[32]. The paper's central results are robust to these alternative specifications, with the corresponding sensitivity estimates reported alongside the main findings.

Using Revolvers' predicted non-credit resources, $\hat{y}_i$, I recover average net borrowing from the budget constraint:

$$\widehat{\Delta d}_i = \text{Expenditure}_i - (\hat{y}_i - \theta d_i). \tag{11}$$

Here, the hat notation indicates that the quantity is estimated rather than directly observed.

The corresponding estimate of the average share of debt-financed expenditure is:

$$\hat{s}_{id} = \min\{SoW_i, \max\{0, \frac{\widehat{\Delta d}_i}{\text{Expenditure}_i}\}\},$$

where SoW denotes credit card usage as a percentage of total spending. Since consumers must first pay with credit cards in order to borrow, the outer min operator ensures that $\hat{s}_{id}$ does not

[31] Here, "Investment" is a catch-all term for all non-consumption allocations, including asset accumulation and debt-servicing outflows.

[32] i.e., $\mathbb{E}[\bar{y}_i|Z_i, \mathbf{1}_{Rev} = 0] = a \cdot \mathbb{E}[\bar{y}_i|Z_i, \mathbf{1}_{Rev} = 1]$

exceed total card usage.[33]

Borrowing Costs: The cost of credit is calculated as the total interest charges generated by a particular instance of Δd. If an instance of Δd remains outstanding for $\tilde{T}$ periods, the total borrowing costs are calculated as

$$\text{Borrowing costs} = P_i(\tilde{T}_i + 1) - \Delta d_i, \tag{12}$$

where $P_i = \theta d_i + R_i$ denotes the fixed stream of payments.

$\tilde{T}_i$ is calculated by attributing the entire per-period stream of repayments to Δd_i. This aligns with regulatory requirements that permit lenders to credit payments toward the outstanding balance components carrying the highest interest rates.[34] The main results of the paper remain robust under an alternative allocation rule that distributes each payment proportionally across all outstanding borrowing increments, albeit with lower estimated surplus for Revolvers. Appendix 9.1 provides further details on the calculation of $\tilde{T}$.[35]

6 Results

6.1 Preferences For Credit Card Rewards Are Highly Heterogeneous

Table 4 reports the preference parameters estimated from Equation (7), while Figure 7 plots average preferences for cashback and points across income deciles. The estimates show substantial heterogeneity in preferences for credit card rewards. Valuations vary with both consumer characteristics and the type of reward earned.

On average, Revolvers place a lower value on both cashback and point-based rewards than Convenience users (Table 4, Figure 7). The estimated differences are economically substantial

[33] Such inconsistencies may emerge due to prediction and measurement errors in $\hat{y}_i$ and θd_i.

[34] Because $d_0 = 0$, the first positive balance consists entirely of new borrowing, Δd_i. The regulation then implies that all the subsequent repayment streams are attributed to this borrowing increment until full repayment.

[35] Both repayment allocation rules are permitted under the Canadian Bank Act (Government of Canada, 2026).

across both reward structures. These results are also consistent with the reduced-form evidence showing that revolving cardholders are 13 percentage points less responsive to changes in reward earn rates than their non-revolving counterparts (Appendix 10.2, Figure 12). Because most issuers distribute rebates annually or only after a threshold is reached, it is possible that the lumpiness of credit card rewards renders them less valuable to the liquidity-constrained Revolvers (Zhou, 2022; Dao, 2025).[36] Regardless of the reason, this heterogeneity means that inequality in net rewards may not reflect the true effects of credit cards on inequality.

Interestingly, conditional on revolving status, preferences for cashback decline with reported income, whereas preferences for points remain relatively stable (Figure 7). Specifically, cardholders in the highest income decile value cashback rebates approximately 29% less than those in the lowest decile (0.85 versus 1.2). Conversely, top-decile cardholders are willing to pay 52 cents on the dollar for points equivalent to a 1% cashback rate, compared with just 28 cents on the dollar among bottom-decile consumers, though this difference is not statistically significant (Figure 13). These point estimates suggest that consumers may value the two reward structures differently.

Because cashback programs provide rebates equal to a fixed percentage of the transaction value, they function as direct price discounts and are subject to the diminishing marginal utility of money. Point-based reward programs, on the other hand, do not have a fixed monetary value per point. Instead, redemption values vary across categories, with higher-income consumers better positioned to redeem points in high-yield categories such as flights and hotel stays (Table 8). This flexibility can offset the diminishing marginal utility of income.

The practical importance of these differences is reflected in the abundance of consumer guides devoted to maximizing the value of reward points. Yet academic research has largely overlooked systematic differences in preferences for cashback versus point-based reward schemes. The distinction matters for inequality. Specifically, because the marginal utility of cashback declines with income, net rewards overstate the welfare value of these rebates among high-income cardholders and, consequently, the extent of inequality in the welfare gains from credit cards.

[36]For example, BMO's cardholder terms and conditions state that cashback rewards may be redeemed only once annually in December. See BMO.

Conversely, the relative stability of preferences for point-based rewards implies that, as these programs become more prevalent, net rewards may become more reflective of welfare among Convenience users.[37]

Table 4: Estimates of preferences

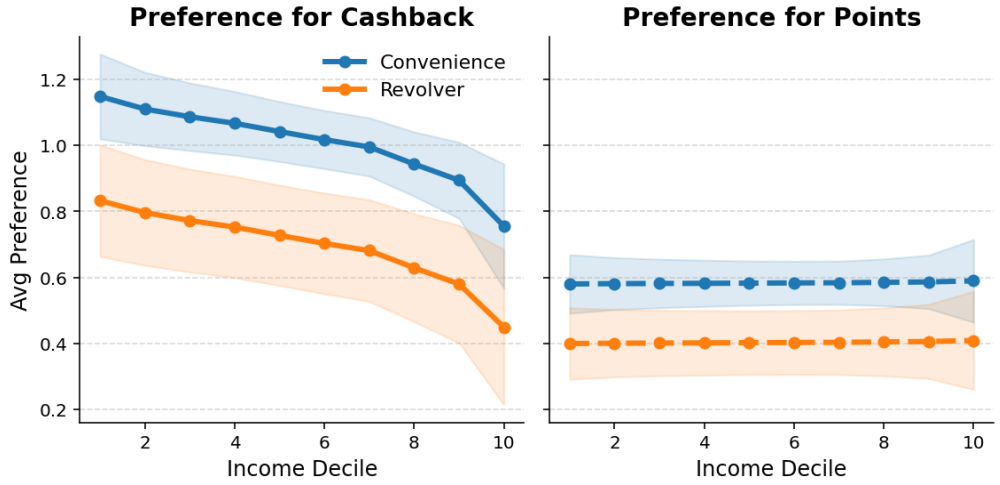
α, β, and γ denote the average preferences for cashback, reward points, and insurance coverage, respectively. The parameters σ_1 and σ_2 capture how preferences for cashback and reward points vary with pretax income. The parameters α_{Rev}, β_{Rev}, and γ_{Rev} measure Revolvers' preferences relative to those of Convenience users. $\Xi_{cc} - \Xi_c$ captures the utility derived from unobserved credit card characteristics, relative to cash-based payment methods. The parameter ξ_{cc} represents the component common to all cardholders, ψ_{cc} captures the difference between Revolvers and Convenience users, and Ψ_{cc} captures the additional unobserved utility associated with point cards relative to cashback cards. Standard errors are reported in parentheses.

Cashback	
α	1.4*** (.077)
σ_1	-.024*** (.0080)
α_{Rev}	-.36*** (.086)
Reward points	
β	.41*** (.059)
σ_2	.0039 (.0050)
β_{Rev}	-.24*** (.055)
Insurance	
γ	.0062 (.0060)
γ_{Rev}	.047*** (.012)
$\Xi_{cc} - \Xi_c = \xi_{cc} + \mathbf{1}_{\text{Rev}}\psi_{cc} + \mathbf{1}_{\text{Point}}\Psi_{cc}$	
Ψ_{cc}	.50*** (.077)
ψ_{cc}	-.98*** (.071)
ξ_{cc}	-2.2*** (.16)

[37] Roughly 60% of Convenience users and 54% of Revolvers collect point-based rewards in my sample.

Figure 7: Preferences for credit card rewards

While decile-specific cashback estimates are imprecise, the interaction with income is statistically significant. Preferences for cashback (α_i) and points (β_i) are calculated as: $\alpha_i = \alpha + \sigma_1 Income_i + \mathbf{1}_{Rev}\alpha_{Rev}$, and $\beta_i = \beta + \sigma_2 Income_i + \mathbf{1}_{Rev}\beta_{Rev}$.



6.2 Consumer Surplus

Welfare Gains From Credit Cards: Despite the high interest rates on outstanding balances, roughly 86% of Revolvers derive positive surplus from credit cards (Figure 8). This finding stands in stark contrast to the earlier result showing that fewer than 15% of Revolvers earn positive net rewards from their card usage (Figure 3). The difference between these measures arises because net rewards omit the value of the credit function. The omission is particularly consequential in the lower half of the income distribution, where Revolvers rely heavily on revolving debt to finance expenditure (Table 5, Figure 17). Because income and credit scores are positively correlated (Albanesi, DeGiorgi, and Nosal, 2022), the negative relationship between income and reliance on revolving credit is consistent with U.S. estimates showing that the utility from credit card borrowing declines with FICO score (Nelson, 2025).

Whereas net rewards are uncorrelated with card satisfaction among Revolvers (Spearman rank correlation = 0.04), the relationship between consumer surplus and satisfaction is substantially stronger (Spearman rank correlation = 0.14).[38] This provides further evidence that net rewards

[38]The rank correlations of card satisfaction with net rewards and consumer surplus are 0.14 and 0.15, respectively.

do not fully reflect the value Revolvers derive from credit cards.

Despite the welfare gains generated by the credit function, Revolvers' average surplus remains lower than that of Convenience users: CAD 17 per month, compared with CAD 23. This gap reflects differences in the value of the payment function. Revolvers not only hold fewer reward-focused credit cards than Convenience users but also place a lower value on those rewards (Table 1, Figure 7). Consequently, Revolvers derive 0.63 cents of surplus per dollar of expenditure from credit card access, approximately 44% less than the 1.12 cents derived by Convenience users (Figure 16, Table 5).

Figure 8: Distribution of Consumer Surplus

Consumer surplus is defined as: $CS_i = \frac{\left(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}\right) \cdot \text{Expenditure}_i}{\alpha_i} + \frac{\mathbf{v}_i^{\text{without cc}} \cdot s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i$, where $\mathbf{v}_i^{\text{with cc}}, \mathbf{v}_i^{\text{without cc}}$ are per-unit surplus with and without credit cards, respectively. $\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}} = \log(1 + \delta_{icc})$ is per-unit surplus expressed in cents per dollar of expenditure. Borrowing Costs_i is the average borrowing cost across all instances of net borrowing. Expenditure_i is the average expenditure level. Finally, α_i is the marginal utility of cashback.

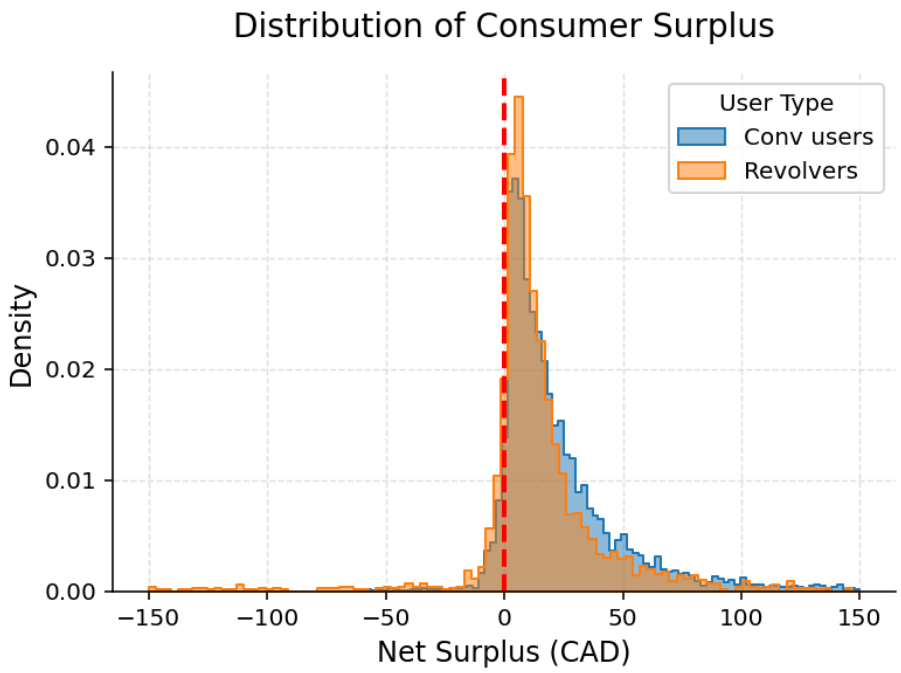


Table 5: Consumer Surplus and Net Rewards by Income Decile

Notes: Conv. denotes Convenience users, and Rev. denotes Revolvers. Net rewards and consumer surplus are expressed in CAD per month. All figures for consumer surplus are winsorized at the 2.5^{th} and 97.5^{th} percentiles. Net rewards are the nominal value of credit card rewards net of interest charges and annual fees. Consumer surplus is defined as:

$$CS_i = \frac{\left(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}\right) \cdot \text{Expenditure}_i}{\alpha_i} + \frac{\mathbf{v}_i^{\text{without cc}} \cdot s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i,$$

where $\mathbf{v}_i^{\text{with cc}}, \mathbf{v}_i^{\text{without cc}}$ are per-unit surplus with and without credit cards, respectively. $\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}} = \log(1 + \delta_{icc})$ is per-unit surplus expressed in cents per dollar of expenditure. Borrowing Costs_i is the average borrowing cost across all instances of net borrowing. Expenditure_i is the expenditure level inferred from average monthly credit card spending (CAD/month) and the credit card share of total expenditure. Finally, α_i is the marginal utility of cashback.

		Income Decile									
Metric	**Type**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Net rewards (CAD/month)	Conv	5.23	8.87	10.98	11.00	14.38	16.52	18.57	22.62	27.37	35.73
	Rev	-36.35	-47.79	-53.49	-44.79	-49.98	-46.55	-51.89	-49.93	-48.66	-36.13
	All	-6.81	-5.84	-5.68	-1.38	-0.35	4.62	4.14	8.41	14.32	25.52
Consumer surplus (CAD/month)	Conv	8.64	12.92	16.30	16.35	19.35	21.65	25.24	30.77	36.87	49.83
	Rev	4.14	9.73	10.46	12.12	17.13	14.00	24.82	28.15	36.00	48.47
	All	7.33	12.09	14.79	15.41	18.85	20.21	25.15	30.25	36.73	49.63
Per-unit surplus (cents/dollar)	Conv	0.73	0.88	0.94	0.98	1.05	1.10	1.21	1.29	1.51	1.78
	Rev	0.39	0.48	0.53	0.54	0.61	0.65	0.77	0.87	0.98	1.24
	All	0.64	0.78	0.84	0.88	0.95	1.02	1.12	1.20	1.42	1.70
Debt-Funded Expenditure (%)	Rev	14.2	12.6	12.3	10.9	10.4	11	10.2	9.1	9.6	7.04
	All	4.12	3.27	3.19	2.42	2.37	2.08	2.09	1.79	1.66	1

6.3 Measuring Inequality

Extrapolating estimates of consumer surplus to the Canadian market yields an annual gain of approximately CAD 9.12 billion. Given the magnitude of these gains, I next examine how they are distributed across cardholders.[39, 40]

Inequality in Consumer Surplus: At almost CAD 50 per month, cardholders in the highest income decile derive roughly 6.5 times as much surplus as those in the lowest income decile (Table 5). This concentration reflects their high credit card usage and tendency to own premium point-based cards (Table 15). The high reward earn rates and flexible redemption options of these cards help insulate high-income non-revolving cardholders from the declining valuation of cashback (Figure 7). Consequently, the distribution of consumer surplus is highly unequal, as

[39]The annual surplus is extrapolated assuming an average monthly surplus of CAD 22, a card ownership rate of 83%, and a total population of 41.4 million (i.e., CAD 9.12 billion = $22 \times 0.83 \times 41,400,000 \times 12$).

[40]In 2025, total transfers in social security benefits reached CAD 99.6 billion (Source: Statistics Canada).

indicated by $Gini_{CS} = 0.55$.[41,42]

The Gini coefficient for net rewards is 0.79 (Table 2), approximately 44% higher than the corresponding coefficient for consumer surplus. Thus, while welfare gains from credit cards are indeed unevenly distributed across cardholders, net rewards severely overstate the true extent of such inequality. The comparison between $Gini_{\text{CS}}$ and $Gini_{\text{Net Rewards}}$ reinforces the importance of incorporating the credit function into welfare assessment, especially as low-income Revolvers rely heavily on revolving credit to fund their spending (Figure 17).

The result is robust to violations of Assumption 2, which dictates the relationship between Convenience users' and Revolvers' non-credit resources, i.e., y. In particular, the Gini coefficients for consumer surplus and net rewards become similar only if Revolvers' non-credit resources are assumed to be 70% of those of otherwise comparable Convenience users (Appendix 10.5, Table 11). Since $y_i = \text{Income}_i - \text{Investment}_i$, this would imply that Revolvers invest more than Convenience users, an unlikely scenario given their similar asset and liability distributions (Figure 15) as well as experimental evidence that Revolvers are generally more impatient (Meier and Sprenger, 2010).

Assuming an alternative payment-allocation rule that attributes repayments to each borrowing increment proportionally does not change the core finding regarding inequality in net rewards versus consumer surplus (Appendix 9.1, Table 7). Even under this assumption, $Gini_{\text{Net Rewards}}$ remains approximately 20% larger than $Gini_{\text{CS}}$. Because this rule lengthens the implied repayment timeline for each Δd, it inflates borrowing costs and provides conservative estimates for the value of the credit function. That the main qualitative result holds under this specification further underscores the necessity of accounting for credit access in welfare assessments.

Mechanism: Figure 9 plots Lorenz curves for per-unit surplus, baseline expenditure, and the resulting consumer surplus. Because low-income consumers receive higher marginal utility from rewards (Figure 7), per-unit surplus varies only modestly across cardholders. Hence, the resulting

[41] For comparison, the Gini coefficient for adjusted after-tax income in Canada is approximately 0.30. See Statistics Canada.

[42] Gini coefficients are calculated following Raffinetti, Siletti, and Vernizzi, 2015 to accommodate negative observations.

distribution is fairly even, with $Gini_{\text{per-unit}} = 0.25$ (Figure 9a). Conversely, total expenditure is substantially more concentrated among high-income cardholders, yielding a moderately high level of inequality with $Gini_{\text{Expenditure}} = 0.45$ (Figure 9b).[43] Because total surplus scales with expenditure, spending inequality magnifies the smaller differences in per-unit surplus (Figure 9c). Consequently, heterogeneity in the value of the payment function plays a surprisingly limited role in determining allocative inequality in the welfare gains from credit cards.

[43] See the note accompanying Figure 1 in the World Bank blog post.

Figure 9: Lorenz curves

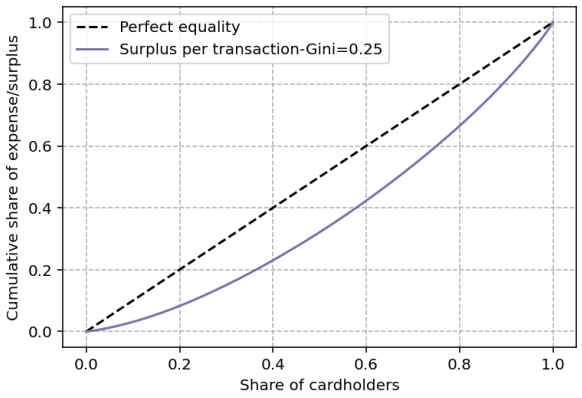
A point (x, y) indicates that the bottom x% of cardholders account for y% of the variable's aggregate value. The 45-degree line represents perfect equality, with larger deviations from this line indicating greater inequality.

Consumer surplus is calculated as:

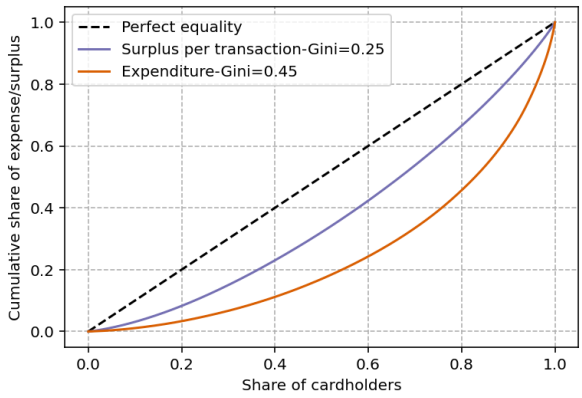
$$CS_i = \frac{\left(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}\right) \cdot \text{Expenditure}_i}{\alpha_i} + \frac{\mathbf{v}_i^{\text{without cc}} \cdot s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i,$$

where $\mathbf{v}_i^{\text{with cc}}, \mathbf{v}_i^{\text{without cc}}$ are per-unit surplus with and without credit cards, respectively. $\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}} = \log(1 + \delta_{icc})$ is surplus per transaction. Borrowing Costs$_i$ is the average borrowing cost across all instances of net borrowing. Expenditure$_i$ is the expenditure level inferred from average monthly credit card spending (CAD/month) and the credit card share of total expenditure. Finally, α_i is the marginal utility of cashback.

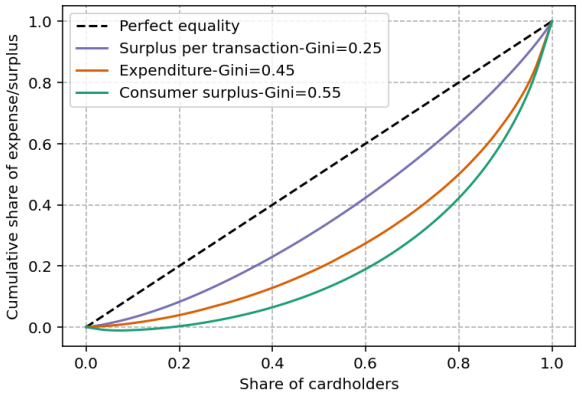
(a) Low inequality in per-unit surplus



(b) Moderate inequality in expenditure



(c) High inequality in consumer surplus



7 Counterfactuals

Because the payment function operates by increasing per-unit surplus, the resulting welfare gains are concentrated among higher-income cardholders, who generally hold credit cards with more generous features (Table 15). Consequently, the payment function drives inequality in welfare

gains from credit cards. By contrast, low-income cardholders rely more heavily on revolving credit (Figure 17) and therefore derive greater benefits from the liquidity it provides. By allowing them to spend beyond what current income alone would permit, the credit function reduces baseline expenditure inequality and partially offsets the regressive effect of the payment function.

These opposing forces create a tug-of-war between the payment and credit functions. To quantify their respective distributional effects, I simulate welfare under two counterfactuals and compare the resulting Gini coefficients with the baseline $Gini_{CS}$.

The first counterfactual removes credit card rewards, thereby eliminating the main distributional channel associated with the payment function. Since reward programs are the main justification for annual fees (Table 14), I also set this fee to zero for the no-reward counterfactual. Consumer surplus under the no-reward counterfactual is given by:

$$CS_i^{\text{no rewards}} = (\mathbf{v}_i^{\text{no rewards}} - \mathbf{v}_i^{\text{without cc}}) \cdot \frac{\text{Expenditure}_i}{\alpha_i} + \mathbf{v}_i^{\text{without cc}} \cdot \frac{s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \text{Borrowing Costs}_i, \tag{13}$$

where $\mathbf{v}_{\text{no rewards}}$ denotes the per-unit surplus when credit cards have no rewards.

The second counterfactual eliminates access to revolving credit while leaving reward programs intact. Since cardholders have to repay their balances in full at the end of the billing cycle, the expenditure level is reduced by the amount previously financed through the credit function (i.e., s_d). This counterfactual is equivalent to removing the credit function of credit cards. Since cardholders can only utilize the payment function, consumer surplus under the no-borrowing counterfactual is calculated as:

$$CS_i^{\text{no borrowing}} = (\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}) \cdot \frac{(1 - s_{id}) \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12}. \tag{14}$$

The no-borrowing counterfactual assumes Revolvers do not adjust their investment behavior in response to the removal of revolving credit. If Revolvers instead reduce investment to offset the loss of credit, their expenditure would fall by less than assumed here. The estimated effect

of removing the credit function therefore provides an upper bound on the impact of the credit function.[44] Figure 10 and Table 6 summarize the results of this exercise.

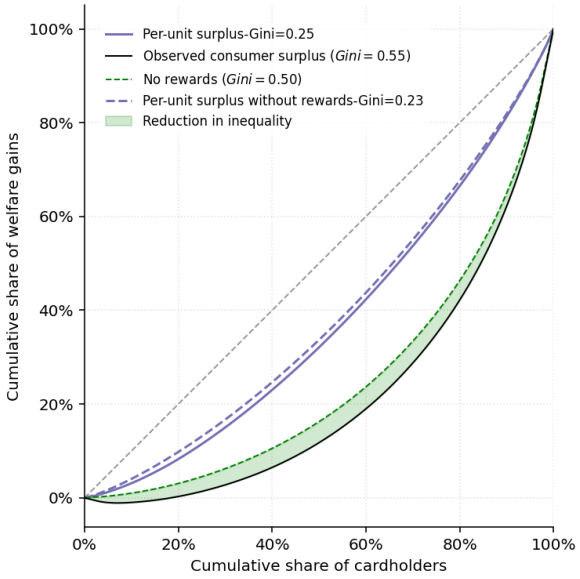
Figure 10: Counterfactual Lorenz Curves

$CS_i^{\text{no rewards}} = (\mathbf{v}_i^{\text{no rewards}} - \mathbf{v}_i^{\text{without cc}}) \cdot \frac{\text{Expenditure}_i}{\alpha_i} + \mathbf{v}_i^{\text{without cc}} \cdot \frac{s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \text{Borrowing Costs}_i$

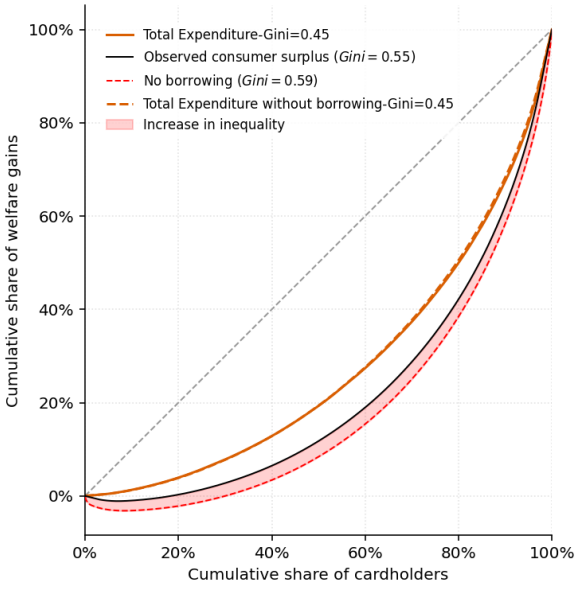
$CS_i^{\text{no borrowing}} = (\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}) \cdot \frac{(1 - s_{id}) \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12}$. where $\mathbf{v}_i^{\text{with cc}}, \mathbf{v}_i^{\text{without cc}}$ are per-unit surplus with and without credit cards, respectively. Borrowing Costs_i is the average borrowing cost across all instances of net borrowing. Expenditure_i is the observed level of expenditure. Finally, α_i is the marginal utility of cashback.

The no-reward counterfactual sets both the reward earn rate and annual fees to zero. The no-borrowing counterfactual forces all cardholders to always repay their balances in full and thus reduces Revolvers' expenditure by s_{id}.

(a) No-reward counterfactual



(b) No-borrowing counterfactual



Results

No-Rewards Counterfactual: Relative to the observed baseline, the Gini coefficient for consumer surplus declines by 10% in the no-rewards counterfactual, from 0.55 to 0.5. The reduction in inequality comes from a more equal distribution of per-unit surplus (Figure 10a). Because Revolvers do not value rebates as much as Convenience users, decreases in per-unit surplus are more severe for the latter than for the former, thereby narrowing the disparity between the two

[44] Recall $\bar{y}_i^{Rev} - \overline{\theta d}_i + \overline{\Delta d}_i = Expenditure_i^{Rev}$ where $\bar{y}^{Rev} = Income - Investment$.

groups. The reduction in inequality, unfortunately, comes at the cost of lower overall surplus. As rebate programs represent a major appeal of credit cards as a payment method (Ching and Hayashi, 2010; Wang, 2023), the elimination of these programs reduces the total surplus level by over 25%, with the reduction being particularly pronounced among high-income Convenience users (Table 6). Average surplus among the highest-income non-revolving users declines by over 30%, as opposed to only 19% among revolving users in the same income bracket. On the other hand, low-income Revolvers experience an increase in consumer surplus when reward programs are eliminated, as the reduction in annual fees more than offsets their loss of reward benefits (Table 6). Given the availability of credit cards with no annual fees, this result raises questions as to why these cardholders did not select cards that align better with their usage patterns.

One possible explanation is the presence of market frictions, such as search costs. When search is costly, issuers can offer both high-fee cards with generous rewards and cheaper no-fee cards with less generous rewards, while primarily advertising the former. This strategy can generate sorting whereby consumers with higher search costs are more likely to adopt more expensive cards. Because these consumers are less price-elastic, issuers could exercise greater market power over this segment and extract a larger share of their surplus. This mechanism could produce a distribution of consumer surplus with substantial mass near zero among high-search-cost consumers and a long right tail among consumers facing lower search costs, a pattern that closely resembles the distribution observed in the data (Figure 8). Because the current analysis does not model the supply side directly, however, this explanation remains speculative.

No-Borrowing Counterfactual: Conversely, eliminating access to revolving credit exacerbates inequality, increasing the Gini coefficient for consumer surplus by 7%, from 0.55 to 0.59 (Figure 10b). Because only 21% of cardholders are Revolvers, restricting access to revolving credit has little effect on the distribution of total expenditure. This modest aggregate effect, however, masks substantial losses among Revolvers. These users experience sizable declines in expenditure once the credit function is removed, with larger reductions among low- and middle-income cardholders than among their higher-income counterparts (Figure 17).

The effects of eliminating the credit function are both direct and indirect. Directly, lower

expenditure reduces the welfare Revolvers derive from consumption. Indirectly, because the credit function expands the expenditure base over which cardholders derive payment benefits, removing it also reduces the welfare Revolvers obtain from the payment function.[45] Together, these effects translate into substantially lower consumer surplus. In particular, revolving cardholders in the fourth through seventh income deciles experience reductions in consumer surplus of over 30% under the no-borrowing counterfactual (Table 6). Because Revolvers already derive less value from the payment function than Convenience users, these losses further compound existing disparities and widen the overall inequality gap between the two groups.

Table 6: Consumer Surplus Under Counterfactuals

Notes: Conv. denotes Convenience users, and Rev. denotes Revolvers. Net rewards and consumer surplus are expressed in CAD per month. All figures for consumer surplus are winsorized at the 2.5^{th} and 97.5^{th} percentiles. Net rewards are the nominal value of credit card rewards net of interest charges and annual fees. Consumer surplus is defined as:

$$CS_i = \frac{\left(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}\right) \cdot \text{Expenditure}_i}{\alpha_i} + \frac{\mathbf{v}_i^{\text{without cc}} \cdot s_{id} \cdot \text{Expenditure}_i}{\alpha_i} - \frac{\text{Annual fee}_i}{12} - \text{Borrowing Costs}_i,$$

where $\mathbf{v}_i^{\text{with cc}}, \mathbf{v}_i^{\text{without cc}}$ are per-unit surplus with and without credit cards, respectively. $\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}} = \log(1 + \delta_{icc})$ is per-unit surplus expressed in cents per dollar of expenditure. Borrowing Costs_i is the average borrowing cost across all instances of net borrowing. Expenditure_i is the expenditure level inferred from average monthly credit card spending (CAD/month) and the credit card share of total expenditure. Finally, α_i is the marginal utility of cashback.

		Income Decile									
Metric	**Type**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Consumer surplus											
No rewards – Level	Conv	6.46	9.38	11.81	12.00	13.96	14.95	17.68	21.67	26.12	34.84
	Rev	5.76	10.16	11.59	12.19	16.02	14.37	22.81	25.30	30.67	39.08
No rewards – Relative to baseline	Conv	-25.3%	-27.4%	-27.5%	-26.6%	-27.9%	-31.0%	-29.9%	-29.6%	-29.2%	-30.1%
	Rev	39.1%	4.4%	10.8%	0.6%	-6.5%	2.6%	-8.1%	-10.1%	-14.8%	-19.4%
No revolving credit – Level	Rev	4.85	7.48	7.17	8.40	11.48	8.79	17.31	20.47	26.55	41.33
No revolving credit – Relative to baseline	Rev	17.3%	-23.1%	-31.5%	-30.7%	-33.0%	-37.2%	-30.2%	-27.3%	-26.2%	-14.7%
Per-unit surplus											
No rewards – Level	Conv	0.44	0.52	0.57	0.57	0.61	0.63	0.71	0.75	0.89	1.05
	Rev	0.29	0.36	0.39	0.41	0.44	0.47	0.57	0.64	0.73	0.90
No rewards – Relative to baseline	Conv	-39.4%	-41.1%	-40.0%	-42.1%	-41.8%	-43.1%	-41.7%	-41.5%	-41.3%	-41.2%
	Rev	-26.5%	-25.8%	-25.9%	-24.9%	-27.6%	-28.2%	-25.8%	-26.1%	-25.5%	-27.8%

[45] The value of the payment function can be decomposed as

$$(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}) \cdot (1 - s_d) \cdot \text{Expenditure}_i + (\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}) \cdot s_d \cdot \text{Expenditure}_i.$$

Shutting off access to credit reduces Revolvers' surplus from the payment function to

$$(\mathbf{v}_i^{\text{with cc}} - \mathbf{v}_i^{\text{without cc}}) \cdot (1 - s_d) \cdot \text{Expenditure}_i$$

8 Conclusion

This paper revisits the distributional effects of credit cards by distinguishing between their roles as payment instruments and sources of unsecured credit. Instead of net rewards, I explore the benefits of credit cards through the lens of consumer surplus. Using data from the Bank of Canada's Digital Wallet and Payment Trends Survey, I estimate demand for credit card usage and recover the resulting welfare gains.

The results show that credit cards generate approximately CAD 9.1 billion in annual consumer surplus for most cardholders, including Revolvers. These gains are distributed unequally, resulting in a Gini coefficient of 0.55. Inequality in consumer surplus remains considerable, but substantially smaller than that implied by net rewards. The Gini coefficient for net rewards is 0.79, approximately 44% higher than the corresponding measure based on consumer surplus. There are two reasons for this difference.

First, net rewards deduct the costs of borrowing without accounting for the utility generated by the associated credit-financed expenditure. This omission is especially consequential for lower-income Revolvers, who finance a larger share of their expenditure through revolving debt. Second, revolving cardholders place less value on reward features than Convenience users, so nominal differences in rebates do not translate one-for-one into differences in welfare.

The counterfactual analysis reveals an unexpected "tug-of-war" between the payment and credit functions. Eliminating rewards reduces the Gini coefficient of consumer surplus by 10%, confirming that reward programs are regressive. By contrast, eliminating access to revolving credit increases the Gini coefficient by 7%. These findings qualify the conventional view that credit card borrowing is necessarily regressive. Instead, they suggest that policies aimed at reducing borrowing costs may have progressive distributional effects.

The finding that some lower-income Revolvers benefit when rewards are eliminated suggests that existing card offerings may be poorly aligned with the preferences and usage patterns of certain consumer segments. Combined with the substantial heterogeneity in consumer surplus, this pattern is consistent with differences in the degree of market power across consumer segments.

Extending the current framework to incorporate both consumers' card-adoption decisions and banks' product offerings therefore represents a promising direction for future research.

9 Theoretical Appendix

9.1 Calculation Of Borrowing Costs

Calculation Of The Revolving Spell

Suppose consumers make a fixed payment P in each period toward the new borrowing Δd, beginning in period $t+1$. The balance attributable to Δd immediately before the first payment is

$$b_0 = (1+r)\Delta d.$$

After making the first payment P, the remaining balance attributable to Δd in the next period, b_1, is [46]

$$b_1 = (1+r)\Delta d - P.$$

Carrying this balance into period $t+2$, applying interest, and making another payment P gives

$$b_2 = (1+r)^2\Delta d - P(1+r) - P.$$

More generally, the remaining balance of Δd after j payments evolves according to

$$b_j = (1+r)b_{j-1} - P,$$

and has the closed-form solution

$$b_j = (1+r)^j\Delta d - P\sum_{s=0}^{j-1}(1+r)^s.$$

Using the finite geometric sum,

$$b_j = (1+r)^j\Delta d - P\frac{(1+r)^j - 1}{r}.$$

[46] Note that this is the balance attributable to Δd, which is not the same as the total revolving balance d.

Suppose the debt is fully repaid after $T + 1$ payments. Imposing the terminal condition

$$b_{T+1} = 0$$

gives

$$(1 + r)^{T+1}\Delta d = P\frac{(1 + r)^{T+1} - 1}{r}.$$

Equivalently,

$$P = \frac{r\Delta d}{1 - (1 + r)^{-(T+1)}}.$$

Solving instead for the repayment horizon yields

$$\tilde{T} + 1 = \frac{\log\left(\frac{P}{P - r\Delta d}\right)}{\log(1 + r)}.$$

Because the consumer makes $\tilde{T} + 1$ payments of size P, the total payment obligation generated by Δd is

$$\text{Debt Service} = P(\tilde{T} + 1).$$

Total borrowing costs are defined as total debt service net of the original principal:

$$\begin{aligned}\text{Borrowing Costs} &= \text{Debt Service} - \Delta d \\ &= P(T + 1) - \Delta d. \end{aligned} \tag{15}$$

Substituting the expression for the repayment horizon gives

$$\text{Borrowing Costs} = P\frac{\log\left(\frac{P}{P - r\Delta d}\right)}{\log(1 + r)} - \Delta d. \tag{16}$$

The empirical implementation imposes:

$$P = \text{Minimum payment} + R$$

Robustness Under the Proportional Allocation Rule

The alternative allocation rule assumes the total payment allocated to repayment of an instance of Δd is given by:

$$P = (\text{Minimum payment} + R) \cdot \frac{\Delta d}{d}$$

Figure 11 and Table 7 present the results of this robustness check.

The distribution of consumer surplus for Revolvers features a long left tail, resulting in significantly lower surplus relative to the main results (Figure 8). Nevertheless, the core comparison between net rewards and surplus remains the same. Roughly 60% of Revolvers derive positive surplus from credit cards (Figure 11), whereas fewer than 15% of Revolvers receive positive net rewards.

Figure 11: Consumer Surplus Under an Alternative Allocation Rule

Surplus is calculated assuming that the stream of payments allocated toward an instance of Δd is $P = (\text{Minimum payment} + R) \cdot \frac{\Delta d}{d}$

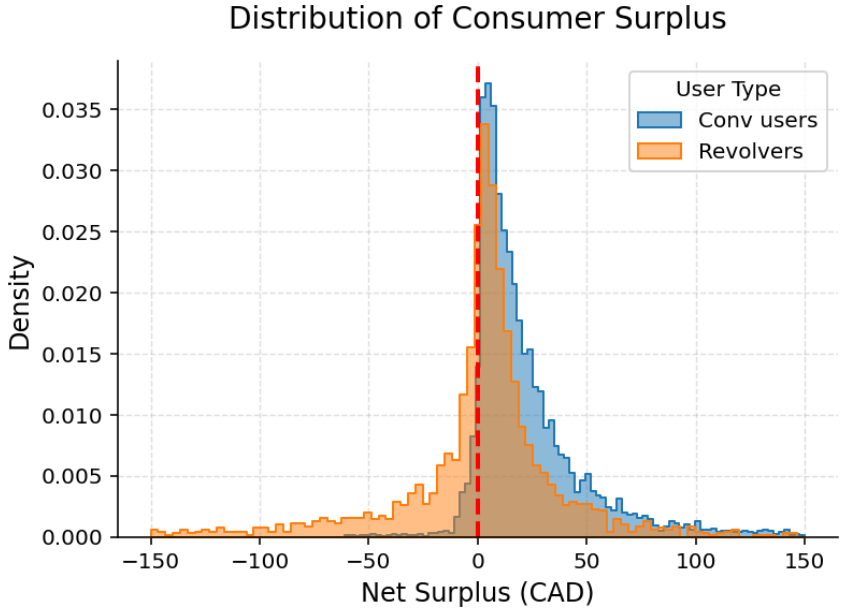


Table 7: Surplus Under an Alternative Allocation Rule by Income Decile

Notes: Consumer surplus is winsorized at the 2.5^{th} and 97.5^{th} percentiles for the averages.

		Income Decile										
Metric	**Type**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Average**
Net welfare (CAD/month)	Conv	8.31	12.61	16.20	16.07	19.11	21.21	25.01	30.54	36.67	49.15	23.49
	Rev	-22.09	-13.60	-12.37	-7.28	-4.89	-7.15	6.76	10.98	17.88	37.90	0.62
	All	-0.50	5.79	8.77	10.94	13.59	15.82	21.36	26.63	33.47	47.58	18.35
$Gini_{CS}$												0.64

9.2 Dynamic Formulation

Environment: The economy consists of a unit mass of finitely lived agents who maximize their expected utility over T periods subject to a discount factor β. Time is discrete and indexed by $t = 0, 1, ..., T$.

At the beginning of each period t, consumers observe their states (y, d), where y and d denote income net of investment decisions and the current outstanding balance, respectively. Given (y, d), agents allocate their income between cash consumption (c), credit card spending (cc), and additional repayment (R) subject to the budget constraint.

Following the literature (Fulford and Schuh, 2024), I assume that cardholders seek to avoid leaving negative wealth and therefore always aim to repay their debt (i.e., $d_T = 0$).[47] The Bellman equation of the problem is given by:

$$V_t(y, d) = \max_{c,cc} \left\{ U\big(c, cc\big) + \beta \mathbb{E}[V_{t+1}(y', d')|cc, R] \right\} \tag{17}$$

subject to :

$$\textit{Debt accumulation} : d' = (1 + r)\Big((1 - \theta)d + cc - R\Big)$$

$$\textit{Budget constraint} : \; y - \theta d = R + c$$

$$\textit{Income process} : \; y' = \bar{y} + \epsilon_t, \; \epsilon_t \overset{iid}{\sim} N(0, \sigma^2)$$

$$\textit{No investment} : \; d' \geq 0$$

$$\textit{Credit limit} : \; d' \leq \bar{D} = k\bar{y}$$

[47] Without such an assumption, cardholders would trivially borrow up to the credit limit.

Two features of the budget constraint warrant further discussion.

First, available income is reduced by θd. This restriction captures the mandatory minimum payment imposed by issuers. In reality, failing to meet the minimum required payment often results in account suspension, forcing credit card spending to be zero. By invoking the Inada condition (i.e., $\lim_{x\to 0} U'(x) = \infty$), the model ensures that agents always optimally pay θd to maintain access to credit cards. Second, credit card spending is not bounded by the available liquid budget (i.e., $y - \theta d$). This absence of a constraint enables cardholders to use credit cards to consume beyond their immediate income, thereby capturing the credit function.

From Continuous to Discrete: Since the income process is exogenous, the allocation of resources between cash consumption, credit card spending, and debt repayment affects future periods solely through the evolution of outstanding debt, d'. This observation motivates the following proposition.

Proposition 2. *The dynamic problem established in Equation (17) can be decomposed into a two-stage decision process. First, consumers determine their optimal level of net borrowing, $\Delta d = cc - R$. Second, conditional on this borrowing decision, they allocate their consumption between cash-based methods and credit cards.*

Proof. We first state the Bellman equation corresponding to Proposition 2. The consumer's problem can be written as:

$$
\begin{aligned}
V_t(y, d) = \max_{\Delta d} \Big\{ & U(c^*, cc^*) + \beta E\left[V_{t+1}(y', d')\right] \Big\} \qquad (18)\\
\text{s.t.} \quad & y' = \bar{y} + \epsilon_t, \quad \epsilon_t \overset{iid}{\sim} N(0, \sigma^2) \\
& d' = (1 + r)\big((1 - \theta)d + \Delta d\big) \\
& 0 \le d' \le \bar{D}
\end{aligned}
$$

where $c^*(d')$ and $cc^*(d')$ are the solutions to:

$$\begin{aligned} \max_{c} \quad & U(c, cc) \\ \text{s.t.} \quad & y - \theta d + \Delta d = cc + c \end{aligned} \tag{19}$$

Since $d' = (1+r)\Big((1-\theta)d + cc - R\Big)$, any pair (cc, R) such that $\tilde{cc} - \tilde{R} = cc - R = \Delta d$ should result in the same continuation value $E[V(y', d')]$. Thus, Equation (17) can be written with Δd as the choice variable. That is,

$$V_t(y, d) = \max_{c, \Delta d} \left\{ U\big(c, cc\big) + \beta \mathbb{E}[V_{t+1}(y', d') | \Delta d] \right\} \tag{20}$$

subject to :

$$\textit{Debt accumulation} : d' = (1+r)\Big((1-\theta)d + \Delta d\Big)$$

$$\textit{Modified budget constraint} : \; y - \theta d + \Delta d = cc + c$$

$$\textit{Income process} : \; y' = \bar{y} + \epsilon_t, \; \epsilon_t \overset{iid}{\sim} N(0, \sigma^2)$$

$$\textit{No investment} : \; d' \geq 0$$

$$\textit{Credit limit} : \; d' \leq \bar{D} = k\bar{y}$$

Since y is exogenous and the law of motion for outstanding balances is identical in the two formulations, any given choice of Δd implies the same continuation value in Equation 18 and Equation 20. To establish equivalence between the two problems, it remains to show that they generate the same optimal within-period allocation, (c^*, cc^*), for each feasible Δd. Once this is shown, the two formulations have the same objective function over Δd and therefore imply the same optimal borrowing choice, Δd^*.

To this end, notice that the FOC with respect to c, as defined by Equation (20), is

$$\begin{aligned}\frac{\partial V}{\partial c} &= \frac{\partial U}{\partial c} + \frac{\partial cc}{\partial c}\frac{\partial U}{\partial cc} + \beta\mathbb{E}\frac{\partial V_{t+1}(y', d')}{\partial c} = 0 \\ &= \frac{\partial U}{\partial c} - \frac{\partial U}{\partial cc} + \beta\mathbb{E}\frac{\partial V_{t+1}(y', d')}{\partial c} = 0\end{aligned}$$

Since $\mathbb{E}[V_{t+1}(y', d')]$ does not depend on c, the FOC with respect to c reduces to:

$$\frac{\partial V}{\partial c} = \frac{\partial U}{\partial c} - \frac{\partial U}{\partial cc} = 0 \tag{21}$$

Assuming that the utility function exhibits diminishing marginal utility in c and cc (i.e., $U' > 0, U'' < 0$), the solution to Equation (21) coincides with the optimal solution of the allocation problem defined in Equation (19). □

Having established equivalence between the original dynamic framework and the two-stage framework, the next step is to illustrate how consumers' preferences for credit card features can be recovered using a discrete choice framework.

Proposition 3. *Under CES preferences over c and cc, that is,*

$$U(c, cc) = U\big(CES(c, cc)\big) = U\big((v_1 c^p + v_2 cc^p)^{\frac{1}{\rho}}\big),$$

consumer demand for cash-based methods and credit cards can be estimated using the discrete-choice model implied by Assumption 1.

Proof. The FOCs of Equation (19) with respect to c and cc are

$$\begin{aligned}\frac{\partial U}{\partial c} &= \frac{\partial U}{\partial CES}\frac{\partial CES}{\partial c} = \lambda, \\ \frac{\partial U}{\partial cc} &= \frac{\partial U}{\partial CES}\frac{\partial CES}{\partial cc} = \lambda.\end{aligned}$$

Therefore, at an interior optimum,

$$\begin{aligned} 1 &= \frac{\partial U/\partial c}{\partial U/\partial cc} \\ &= \frac{\partial CES/\partial c}{\partial CES/\partial cc} \\ &= \frac{v_1 c^{\rho-1}}{v_2 cc^{\rho-1}}. \end{aligned}$$

Rearranging gives

$$\frac{cc}{c} = (\frac{v_2}{v_1})^{\frac{1}{1-\rho}}.$$

Following the literature (Anderson and De Palma, 1992; Ellickson, Grieco, and Khvastunov, 2020; Li, 2023), I impose parametric assumptions on v_2. That is,

$$\begin{aligned} v_1^{\frac{1}{1-\rho}} &= \exp(\sigma\delta_{ic}) \\ v_2^{\frac{1}{1-\rho}} &= \exp(\sigma\delta_{icc}) \\ \sigma &= \frac{\rho}{1-\rho} \end{aligned}$$

Taking the log of $\frac{cc}{c}$ gives the same expression as in Equation (7):

$$\log \frac{cc}{c} = \frac{1}{1-\rho}(\delta_{icc} - \delta_{ic})$$

□

9.3 Definition Of Surplus

Denote by $V_t(\cdot)$ and $H_t(\cdot)$ the value functions with and without access to credit cards, respectively.

The value function with credit cards is given by:

$$
\begin{aligned}
V_t(y, d) = \max_{\Delta d} \Big\{ & U(c^*, cc^*) + \beta E[V_{t+1}(y', d')] \Big\} \\
\text{s.t.} \quad & y' = \bar{y} + \epsilon_t, \quad \epsilon_t \overset{iid}{\sim} N(0, \sigma^2) \\
& d' = (1 + r)\big((1 - \theta)d + \Delta d\big) \\
& 0 \leq d' \leq \bar{D}
\end{aligned}
$$

where c^* and cc^* are solutions to the allocation problem as defined by Equation (19).

The restricted value function under the counterfactual is:

$$
\begin{aligned}
H_t(y, d) = \max_{c} \Big\{ & U(c^*) + \beta E[H_{t+1}(y', d')] \Big\} \\
\text{s.t.} \quad & y' = \bar{y} + \epsilon_t, \quad \epsilon_t \overset{iid}{\sim} N(0, \sigma^2) \\
& d' = (1 + r)(1 - \theta)d \\
& 0 \leq d' \leq \bar{D}
\end{aligned}
$$

where $c^* = y - \theta d$.

Thus, the counterfactual corresponds to an environment in which consumers lose access to credit cards but must still repay their existing outstanding balances. This differs from a counterfactual in which credit cards were never introduced. Such a scenario would imply an initial balance of $d = 0$. In the counterfactual considered here, however, the initial balance d is fixed at the observed level.

Under the debt-runoff counterfactual, the welfare gain from credit cards is measured as

$$
V_t(y, d) - H_t(y, d). \tag{22}
$$

By contrast, in a counterfactual in which credit cards were never introduced, the welfare gain would be measured as

$$
V_t(y, d) - H_t(y, 0).
$$

The latter comparison mechanically sets the outstanding balance to zero and therefore conflates the value of access to credit cards with the wealth effect of eliminating existing debt. While this distinction is moot for Convenience users, whose initial balance is zero, it is consequential for Revolvers, who carry substantial outstanding balances.

9.4 Decomposition Of Consumer Surplus

If the consumer enters period t with balance d, repays a fraction θ, and undertakes new borrowing Δd, then next period's balance is

$$d' = (1 + r)\big[(1 - \theta)d + \Delta d\big].$$

Thus, the continuation value associated with new borrowing Δd is

$$\begin{aligned} V_{t+1}(y', d') - H_{t+1}(y', \tilde{d}) = &\big[V_{t+1}(y', d') - V_{t+1}(y', \tilde{d})\big] \\ &+ \big[V_{t+1}(y', \tilde{d}) - H_{t+1}(y', \tilde{d})\big], \end{aligned} \tag{23}$$

where $\tilde{d}$ denotes an arbitrary starting balance.

Holding access to credit cards fixed, $V_{t+1}(y', d') - V_{t+1}(y', \tilde{d})$ isolates the marginal continuation-value effect of new credit card borrowing. Hence, this term captures the value coming from the credit function.

Payment Function: Consider the payment-function term:

$$V_{t+1}(y', \tilde{d}) - H_{t+1}(y', \tilde{d}).$$

Holding debt fixed at $\tilde{d}$, this term compares the value of expenditure when credit cards are available as a payment instrument with the value of expenditure when only cash-based methods are available.

If the available expenditure in period $t+1$ is

$$Expenditure_{t+1} = y' - \theta\tilde{d},$$

then

$$CES(c, cc) = (v_1 c^{\rho} + v_2 cc^{\rho})^{\frac{1}{\rho}} = Expenditure \cdot \psi_{cc}$$

where $\psi_{cc} = \left(v_1^{\frac{1}{1-\rho}} + v_2^{\frac{1}{1-\rho}} \right)^{\frac{1-\rho}{\rho}}$

Similarly, without credit cards, the CES aggregator yields:

$$CES(c) = Expenditure \cdot \psi_0$$

where $\psi_0 = v_1^{1/\rho}$

To isolate the value generated by the payment function, I impose that future balances are identical across the with-credit-card and without-credit-card environments, so that $d'' = \tilde{d}''$. This restriction applies only to the calculation of $V_{t+1}(y', \tilde{d}) - H_{t+1}(y', \tilde{d})$ and effectively shuts down differences arising from new borrowing. Formally,

$$\begin{aligned} V_{t+1}(y', \tilde{d}) - H_{t+1}(y', \tilde{d}) = {} & U(Expenditure_{t+1}\psi_{cc}) - U(Expenditure_{t+1}\psi_0) \\ & + \beta \mathbb{E}\left[V_{t+2}(y'', \tilde{d}'') - H_{t+2}(y'', \tilde{d}'') \right] \end{aligned} \tag{24}$$

Suppose further that future payment-function gains are sufficiently small that the discounted continuation component is negligible. That is,

$$\sum_{\tau=t+2}^{T} \beta^{\tau-t-1} \left[U(Expenditure_{\tau}\psi_{cc}) - U(Expenditure_{\tau}\psi_0) \right] \approx 0.$$

Thus, the payment-function component can be approximated by its one-period flow value:

$$V_{t+1}(y', \tilde{d}) - H_{t+1}(y', \tilde{d}) \approx U(Expenditure_{t+1}\psi_{cc}) - U(Expenditure_{t+1}\psi_0).$$

Equivalently, this expression can be interpreted as the one-period flow benefit of the payment function.

Assuming further that the underlying utility function is homogeneous of degree 1,

$$U(Expenditure_{t+1}\psi_{cc}) - U(Expenditure_{t+1}\psi_0) = Expenditure_{t+1}(\psi_{cc} - \psi_0)U(1). \quad (25)$$

Thus, under the continuous model, welfare gains from the payment function are identified up to a multiplicative constant. The formula for consumer surplus under a discrete choice framework requires that $U(1) = 1$.[48]

Since $\frac{Expenditure_{t+1}(\psi_{cc} - \psi_0)}{Expenditure_{t+1}} = (\psi_{cc} - \psi_0)$, this term captures the per-unit surplus gains from the introduction of credit cards. Readers interested in how the log-sum formula can appear under this framing are directed to Dubé, Joo, and Kim, 2025.

Credit Function: In period t, the welfare gains from incurring Δd are given by:

$$V_t^{\Delta d>0}(y,d) - V_t^{\Delta d=0}(y,d) = U_t(y - \theta d + \Delta d) - U_t(y - \theta d) + \beta \mathbb{E}\left[V_{t+1}(y', d') - V_{t+1}(y', \tilde{d}')\right],$$

where $\tilde{d}'$ denotes the starting balance in period $t+1$ assuming $\Delta d = 0$.

Assuming a constant shadow price of income (i.e., $U'(c) = \alpha$), the period-$t+1+k$ flow-utility difference is

$$U\left(y_{t+1+k}, d_{t+1+k}\right) - U\left(y_{t+1+k}, \tilde{d}_{t+1+k}\right) = \alpha\theta\left(d_{t+1+k} - \tilde{d}_{t+1+k}\right).$$

The continuation-value difference is

$$\mathbb{E}_t\left[V_{t+1}(y_{t+1}, d_{t+1}) - V_{t+1}(y_{t+1}, \tilde{d}_{t+1})\right] = \alpha\theta \sum_0^{\widetilde{T}} \beta^k \left(d_{t+1+k} - \tilde{d}_{t+1+k}\right),$$

where $\widetilde{T}$ denotes the final period after which Δd is completely paid off.

To isolate the interest cost of borrowing, consider a counterfactual scenario involving an

[48] The most obvious choice is $U(CES) = CES$.

interest-free loan of the same size, Δd_t, with an identical principal-repayment schedule. The difference in the outstanding balance between the two scenarios is:

$$\theta(d_{t+1+k} - \tilde{d}_{t+1+k}) = rb_k$$

where b_k is the part of the remaining outstanding balance attributable to Δd as defined in Appendix 9.1. Thus, the difference in the minimum required payment between these scenarios is generated by the outstanding component of Δd.

The discounted stream of differences in utility yields:

$$\mathbb{E}_t \left[V_{t+1}(y_{t+1}, d_{t+1}) - V_{t+1}(y_{t+1}, \tilde{d}_{t+1}) \right] = -\alpha r \sum_{k=0}^{\widetilde{T}} \beta^k b_k.$$

Note that the term $\sum_{k=0}^{\widetilde{T}} b_k$ captures the total interest charges generated by Δd. From Appendix 9.1, b_k evolves according to:

$$\begin{aligned} b_{k+1} &= (1+r)b_k - P \\ (1+r)b_k - b_{k+1} &= P \\ \Rightarrow \sum_{k=0}^{\tilde{T}} \beta^k \big((1+r)b_k - b_{k+1}\big) &= P \sum_{k=0}^{\tilde{T}} \beta^k \\ \Rightarrow \sum_{k=0}^{\tilde{T}} \beta^k r b_k + \sum_{k=0}^{\tilde{T}} \beta^k (b_k - b_{k+1}) &= P \sum_{k=0}^{\tilde{T}} \beta^k \end{aligned}$$

For ease of calculation, assume $\beta = 1$ so that

$$\sum_{k=0}^{\tilde{T}} r b_k + \sum_{k=0}^{\tilde{T}} (b_k - b_{k+1}) = P(\tilde{T}+1) \sum_{k=0}^{\tilde{T}} r b_k = P(\tilde{T}+1) - \sum_{k=0}^{\tilde{T}} (b_k - b_{k+1})$$

Given $b_0 = \Delta d$ and $b_{\tilde{T}} = 0$, $\sum_{k=0}^{\tilde{T}} (b_k - b_{k+1}) = b_0 - b_1 + b_1 - b_2, \ldots - b_{\tilde{T}} = \Delta d$, which gives:

$$\sum_{k=0}^{\tilde{T}} r b_k = (\tilde{T}+1)P - \Delta d.$$

Thus, the value of the credit function is given by:

$$\begin{aligned} V_t^{\Delta d>0}(y,d) - V_t^{\Delta d=0}(y,d) =& U_t(y-\theta d+\Delta d) - U_t(y-\theta d) + \mathbb{E}\left[V_{t+1}(y',d') - V_{t+1}(y',\tilde{d}')\right] \\ &= \alpha\Delta d - \alpha\big((\tilde{T}+1)P - \Delta d\big). \end{aligned}$$

This expression coincides with the statically derived formula for the value of the credit function. Note that setting $\beta = 1$ places greater weight on the future utility costs of borrowing and therefore provides a lower bound on the liquidity value of credit cards. Relaxing this assumption is rather straightforward, provided that the researcher specifies both a discount factor and a repayment horizon, $\tilde{T}$.

Total consumer surplus: Collecting terms gives the final expression for consumer surplus under the dynamic model, which coincides with the static formulation in Equation (9).

$$\begin{aligned} V_{t+1}(y',d') - H_{t+1}(y',\tilde{d}) &= \left[V_{t+1}(y',\tilde{d}) - H_{t+1}(y',\tilde{d})\right] + \left[V_{t+1}(y',d') - V_{t+1}(y',\tilde{d})\right] \\ &= Expenditure_{t+1}(\psi_{cc} - \psi_0) + \alpha\Delta d - \alpha r\Delta d_t \frac{1-[\beta(1+r)(1-\theta)]^{\widetilde{T}}}{1-\beta(1+r)(1-\theta)}. \end{aligned}$$

10 Appendix

10.1 Variable Construction

Earn rate of Point-Based Cards

Since most issuers operate their own rewards programs, with different point-earn rates and redemption schemes, comparing point-based cards poses a non-trivial challenge. To address this issue, I convert all point-based products into a cashback-equivalent earn rate by multiplying the unweighted average point-earn rate by the unweighted average value per point. Consider the TD First Class Travel Visa Infinite as an example. For this card, consumers earn an average of 5 points per dollar (Table 9), with an average point value of 0.333 ¢ per point (Table 8). The

cashback-equivalent earn rate is therefore $5 \times 0.333 = 1.665$ ¢ per dollar spent, or equivalently 1.665%.

While intuitive, this approach abstracts from the fact that consumers may redeem points across different reward options. For example, low-income Revolvers would likely convert points into statement credits, whereas high-income Convenience users may derive greater value by redeeming points for travel-related rewards. Although this simplification may introduce measurement error, it is nevertheless necessary as the DWPT does not report how consumers redeem their points.

Table 8: Value of TD Reward Points

Source: FinlyWealth Points Calculator

Redemption Option	**Avg. Value**
Expedia® For TD	0.5¢ / pt
Travel	0.44¢ / pt
Statement Credits	0.25¢ / pt
Gift Cards	0.25¢ / pt
Merchandise	0.225¢ / pt

Table 9: TD First Class Visa Travel Infinite Earn Rate

Type of Purchases	**Points per dollar**
Travel through Expedia®	8 pts/$
Groceries	6 pts/$
Recurring bills	4 pts/$
Other purchases	2 pts/$

Source: FinlyWealth Points Calculator

Consumption

Since the survey does not directly report respondents' total consumption or expenditure, I construct this measure by combining respondents' reported credit card spending for "personal purposes" with the share of total spending paid by credit card.[49] Because the DWPT does not define precisely

[49]The exact wording of the question is: "In a typical month, how much do you spend on your credit card(s) for personal spending? Please enter a dollar amount."

what constitutes personal spending, this measure of consumption is admittedly coarse and does not distinguish between durable and non-durable consumption. As a result, the analysis should be interpreted as capturing overall consumption rather than spending on any specific category. Nonetheless, at roughly CAD 2,500 per month, the total expenditure measure aligns well with data on current consumption, defined as total consumption net of housing costs Statistics Canada, 2025.

10.2 Double ML

To provide causal evidence of differences between Revolvers' and Convenience users' preferences for credit card rewards, I estimate the following partially linear model:

$$\text{CC Usage (\% of consumption)} \;=\; g(\mathbf{1}_{\boldsymbol{Rev}}, \boldsymbol{X}) + \nu, \tag{26}$$

$$m(\boldsymbol{X}) + \epsilon > \bar{Z} \Leftrightarrow \mathbf{1}_{Rev} = 1, \tag{27}$$

where $\boldsymbol{X}$ is a high-dimensional vector consisting of card attributes (e.g., reward earn rates, insurance coverage), demographic controls (e.g., income, marital status, household size), and their interactions.

The nonparametric function $g(\boldsymbol{X})$ captures the baseline relationship between card usage and $\boldsymbol{X}$. Similarly, $m(\boldsymbol{X})$ characterizes the non-random component of the borrowing decision. Finally, θ quantifies the difference in credit card usage between Revolvers and Convenience users, conditional on all observable characteristics (i.e., the "treatment effect").

Following the Double/Debiased Machine Learning methodology, I treat m and g as nuisance functions and estimate them using the random forest algorithm.[50] To mitigate regularization bias stemming from the estimated $\hat{m}$ and $\hat{g}$ (Chernozhukov et al., 2018; Bach et al., 2024), I compute the individual-level orthogonal scores as:

$$\tilde{\theta}^{i}_{Revolve} = \hat{g}(1, \boldsymbol{X}_i) - \hat{g}(0, \boldsymbol{X}_i) + \frac{\mathbf{1}_{Rev}(Y_i - \hat{g}(1, \boldsymbol{X}_i))}{\hat{m}(\boldsymbol{X}_i)} - \frac{(1 - \mathbf{1}_{Rev})(Y_i - \hat{g}(0, \boldsymbol{X}_i))}{1 - \hat{m}(\boldsymbol{X}_i)},$$

[50] `sklearn`'s `RandomForestClassifier` and `RandomForestRegressor`.

Assuming $g(D, X) = g(X) + \text{Rewards}_i \cdot \mathbf{1}_{Rev} \cdot \delta_{Rev}$, the Conditional Average Treatment Effect (Semenova and Chernozhukov, 2020) is estimated as:

$$\tilde{\theta}^i_{Revolve} = g(1, X) - g(0, X) = \beta_0 + \delta_{Rev} \cdot \text{Rewards}_i + \xi_i \tag{2}$$

The main parameter of interest, δ_{Rev}, captures the difference in responsiveness with respect to the reward earn rate (i.e., Rewards_i) between Revolvers and Convenience users. Individual-level treatment effects, $\tilde{\theta}^i_{Revolve}$, are estimated using a doubly robust framework (Robins, Rotnitzky, and Zhao, 1994; Imbens and Wooldridge, 2009), which protects against misspecification bias in either the outcome model or the selection model, so long as one is correct.[51]

To assess whether consumer preferences also depend on the specific reward type, I estimate the following analogue of Equations (29)–(30):

$$\text{CC Usage (\% of consumption)} = h(\mathbf{1}_{\boldsymbol{Point}}, \boldsymbol{X}) + \mathbf{1}_{Point}\theta_{Point} + \tilde{\nu}$$
$$k(\boldsymbol{X}) + \tilde{\epsilon} > \bar{P} \Leftrightarrow \mathbf{1}_{Point} = 1$$

where $h(.)$ and $k(.)$ are the equivalents of $g(.)$ and $m(.)$.

The individual-level "treatment effects" (i.e., θ_{Point}) and CATE (i.e., δ_{Point}) are estimated following a procedure similar to that used for $\theta_{Revolve}$ and $\delta_{Revolve}$.

$\delta_{Revolve}$ and δ_{Point} are identified under the assumption of selection on observables (Heckman, Ichimura, and Todd, 1997; Chernozhukov et al., 2018). This assumption implies that, conditional on the vector of control variables $\boldsymbol{X}$, treatment assignments (i.e., $\mathbf{1}_{Revolve}$, $\mathbf{1}_{Point}$) are as if randomly assigned. Formally,

Assumption 3 (Unconfoundedness)**.** $\{Y(0), Y(1)\} \perp D_i|X$

Assumption 3 asserts that, after controlling for all relevant covariates $\boldsymbol{X}$, cardholders do not

[51] If the outcome model is correctly specified, $Y_i(1) - \mathbb{E}[\hat{g}|\boldsymbol{X}, 1] = Y_i(0) - \mathbb{E}[\hat{g}|\boldsymbol{X}, 0] = 0$ and $ATE = \mathbb{E}[\tilde{\theta}^i_{Revolve}] = \mathbb{E}[\hat{g}(1, \boldsymbol{X}_i) - \hat{g}(0, \boldsymbol{X}_i)] = g(1, \boldsymbol{X}_i) - g(0, \boldsymbol{X}_i)$, which is unbiased even if the selection model $\hat{m}(.)$ is misspecified. On the other hand, if $\hat{m}(.)$ is correctly specified, then $\frac{\mathbb{E}[\mathbf{1}_{Revolve}]}{\mathbb{E}[\hat{m}(\boldsymbol{X})]} = 1$ and $ATE = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$.

revolve ($\mathbf{1}_{Revolve}$) or adopt point cards ($\mathbf{1}_{Point}$) based on unobserved factors that also influence their credit card usage intensity. A potential violation of unconfoundedness arises if time-inconsistent consumers revolve strategically to limit consumption (Bertaut, Haliassos, and Reiter, 2009). Under this scenario, the difference in card usage between Revolvers and Convenience users conflates the former's self-control motives with the true heterogeneous responsiveness to rewards, rendering the causal parameter $\delta_{Revolve}$ unidentifiable.

Such a possibility is unlikely in our context, as the self-control argument applies to the overall level of consumption (\$), rather than the composition of payment methods (% of consumption). For example, given a consumption level of \$2,000/month, consumers are free to allocate 50% of that expenditure toward credit cards. Controlling for demographic factors, the difference in credit card usage between Revolvers and Convenience users should therefore arise from heterogeneous preferences for card features, most notably rewards. Likewise, since cashback and point cards differ only in their reward structures, selection into these products is unlikely to be driven by other unobserved characteristics. Because loyalty programs (e.g., AirMiles) offer high potential returns to affluent users via high-value redemption categories such as flight discounts, selection into point cards is predominantly a function of income, which is explicitly controlled for. Figure 12 plots the estimated causal parameters, $\delta_{Revolve}$ and δ_{Points}.

Results

Results indicate that the marginal effect of rewards on credit card usage, measured as a percentage of total consumption, is 13 percentage points (pps) lower for Revolvers than for Convenience users. This pattern is robust across reward types, albeit more pronounced among cardholders collecting cashback than among those earning points (18.9 pps vs. 11.3 pps).

In terms of reward structures, consumers are slightly less responsive to changes in points than to changes in cashback ($\delta_{Points} = -2$). This effect stems primarily from Convenience users ($\delta^{Conv}_{Points} = -1.76$) as the estimated coefficient for the Revolvers subsample is insignificant. Because point earn rates are measured in cashback-equivalent terms, the observed disparity in the marginal effects of different reward types indicates structural differences between the perceived

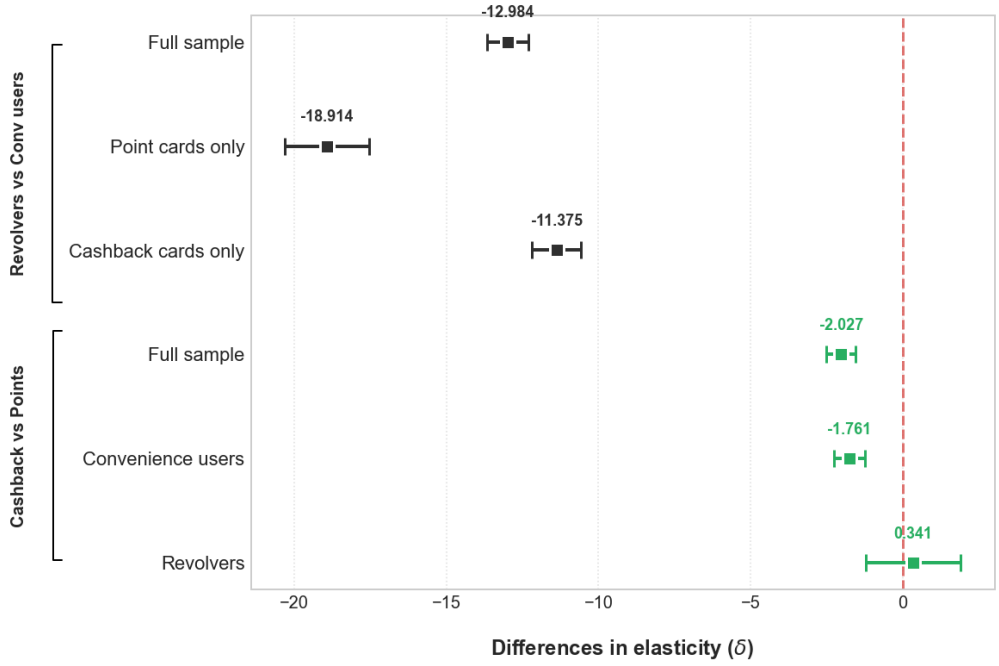
utility of cashback and that of points.[52]

While loyalty programs offer high potential returns to affluent users capable of utilizing high-value reward categories, the lack of a fixed value also exposes cardholders to the risk that issuers adjust the conversion rate arbitrarily (Bureau, 2023). Furthermore, most reward points expire if an account is deemed inactive by the issuer, whereas cashback balances remain accessible insofar as the credit card is valid. Since δ_{Point} reflects the weighted average differential effects of cashback versus reward points across the income distribution, a negative CATE suggests that loyalty programs benefit high-income consumers disproportionately while offering less value to other groups.

The lower responsiveness to rewards among Revolvers is also consistent with their tendency to hold cheaper cards with less generous rebate programs (Table 15). One concern is that this pattern may reflect supply-side restrictions rather than demand-side choices. However, since revolving and non-revolving cardholders report similar credit ratings and debt-to-income ratios (Dao, 2025), both groups should qualify for broadly similar products ex ante. This suggests that differences in reward rates and annual fees are more likely to reflect consumer self-selection than supply-side restrictions.

[52]The point earn rate equals the number of points earned per dollar spent multiplied by the average dollar value per point.

Figure 12: Heterogeneity in Preferences-Double ML



10.3 Additional Discussion On Estimation Of Consumer Preferences

Violations of Assumption 1B

As illustrated in the main text, Assumption 1B bypasses the need to observe specific transaction characteristics, most notably transaction values. This simplification is not completely innocuous, as payment choices could be highly context-dependent. For instance, in high-value transactions, consumers generally prefer credit cards to banknotes (i.e., cash) for convenience and security reasons, whereas banknotes are preferred for small-value purchases (Huynh, 2019). This concern is mitigated by the product nesting, which defines "cash-based methods" to include both banknotes and debit cards. Since debit cards share many of the convenience and security advantages of credit cards but do not typically offer rewards, this nesting reduces the extent to which transaction value mechanically drives the comparison between cash-based methods and credit cards.

Given this product nesting, the primary dimensions of differentiation between cash-based methods and credit cards are the features exclusive to the latter, most importantly reward programs. Because transaction value determines the total dollar amount of rewards earned but not the

marginal utility of a given reward rate (i.e., α_i and β_i), a violation of Assumption 1B should not materially affect the results of this analysis.

Set of Identifiable Preferences

This paper also highlights the set of identifiable preferences when using the discrete choice framework to study demand for payment methods (Ching and Hayashi, 2010; Koulayev et al., 2016). Specifically, the discrete approach can identify preferences only for card features that shift spending across payment alternatives (i.e., "static" features). Preferences for "dynamic" characteristics such as interest rates remain unidentified because they directly affect consumption decisions, thereby violating Assumption 1A. The same restriction applies more broadly to studies that discretize continuous choices (Ellickson, Grieco, and Khvastunov, 2020; Li, 2023): characteristics that may violate analogous conditional-static assumptions should not be included in the discrete choice problem.

To illustrate this limitation, I re-estimate Equation (7) after including the interest rate as an additional card characteristic (Table 10). Since interest rates represent the costs of borrowing, we should expect estimates of preferences for this feature to be negative. In particular, Convenience users, who choose not to borrow, should exhibit strongly negative preferences for interest rates, whereas Revolvers should exhibit less negative preferences. Thus, the coefficient on the interest rate should be negative, while its interaction with revolving status should be positive. The estimates recover the opposite pattern, illustrating that preferences for borrowing costs cannot be identified from the static payment-choice equation.

Table 10

Cashback is the cashback earn rate as a percentage.
Point value is the cashback-equivalent earn rate of points.
Interest rate is the advertised annual interest rate as a percentage.
$\mathbf{1}_{Revolver}$ = 1 for Revolvers.
$\mathbf{1}_{Point}$ = 1 if the primary card earns point-based rewards.

Cashback (%)	1.313*** (.079)
Cashback × *Income*	-.024*** (.008)
Point value	.395*** (.059)
Point value × *Income*	.004 (.005)
No. of insurance benefits	.008 (.006)
Interest rate (%)	**.031***** (.011)
$\mathbf{1}_{Revolver}$ × *Cashback*	-.352*** (.087)
$\mathbf{1}_{Revolver}$ × *Point value*	-.225*** (.056)
$\mathbf{1}_{Revolver}$ × *Insurance*	.048*** (.012)
$\mathbf{1}_{Revolver}$ × *Interest rate*	**-.033***** (.012)
$\mathbf{1}_{Point}$	.457*** (.079)
$\mathbf{1}_{Revolver}$	-.307 (.243)
Constant	-2.847*** (.271)

10.4 Willingness To Pay For Points

I calculate cardholders' willingness to pay (WTP) for points using the standard coefficient-ratio approach:

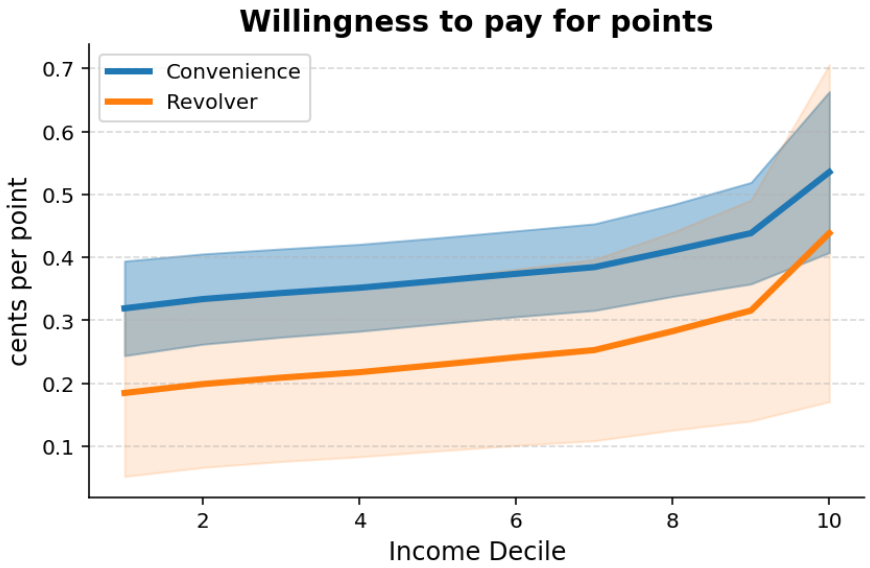
$$WTP_{Point} = \frac{\beta_i}{\alpha_i},$$

where α_i and β_i denote the estimated marginal utilities of cashback and points, respectively. Figure 13 presents the average WTP across income deciles.

Results indicate that WTP_{Point} generally increases with income and rises sharply in the highest income decile. This pattern is consistent with the proposed mechanism underlying the divergence in preferences for cashback and points. However, because the data do not reveal how consumers redeem their points, the evidence remains suggestive rather than conclusive.

Figure 13: Average WTP for points

Standard errors were calculated following the delta method.



10.5 Estimation of s_d

Minimum Required Payment

Based on the applicable credit card agreements,[53] I approximate each respondent's average minimum required payment, $\overline{\theta d}$, using the issuer-specific repayment rule. For respondents outside Quebec whose card agreements specify a payment of $10 plus accrued interest, I calculate:

$$\overline{\theta d} = 10 + \frac{30.5}{365} r d,$$

where r is the annual interest rate expressed as a decimal and d is the average outstanding balance. This calculation abstracts from fees, overdue payments, installment-plan payments, and over-limit amounts, which are not observed in the DWPT.

For Quebec residents with accounts opened before August 1, 2019, I calculate:

$$\overline{\theta d}_t = \max\{10, 0.03d\}.$$

[53] See CIBC, BMO, RBC, American Express, and Scotiabank.

For accounts opened on or after August 1, 2019,

$$\overline{\theta d}_t = \max\{10, 0.05d\}.$$

Predicting Revolvers' Non-Credit Resources

Because the economic interpretation and plausibility of Assumption 3 are discussed in the main text, this appendix focuses on the prediction procedure, including feature selection and model fit. All stages are conducted using the *Convenience-user* subsample, except for the final application of the fitted model to Revolvers.

Gradient Boosting Regressor: The Gradient Boosting Regressor (GBR) is an ensemble machine learning algorithm that sequentially combines multiple weak decision trees into a single, highly accurate predictive model. Each tree is trained to predict the residual errors of the previous trees, incrementally refining the model's overall performance.

For example, consider estimating an outcome y using predictors X. A basic GBR algorithm proceeds as follows:

1. Train Tree 1 on the dependent variable: $\tilde{y} = f(X_i)$
2. Train Tree 2 on the residual: $r_1 = y - \tilde{y} \Rightarrow \hat{r}_1 = h_1(X)$
3. Train Tree 3 on a new residual: $r_2 = r_1 - \hat{r}_1 \Rightarrow \hat{r}_2 = h_2(X)$

The final prediction is then obtained by summing the outputs: $\hat{y} = \tilde{y} + h_1(X) + h_2(X)$.

Feature selection: In principle, GBR can capture nonlinear relationships and interactions among predictors, making prior feature selection unnecessary. Nevertheless, including many weakly informative predictors may increase estimation noise and the risk of overfitting. To avoid these issues, I conduct a preliminary feature-selection stage using LASSO.

I first construct a high-dimensional set of predictors comprising the original covariates, squared terms for nonbinary variables, and all pairwise interactions. I then estimate a LASSO regression with observed expenditure as the dependent variable and retain the selected predictors for use in

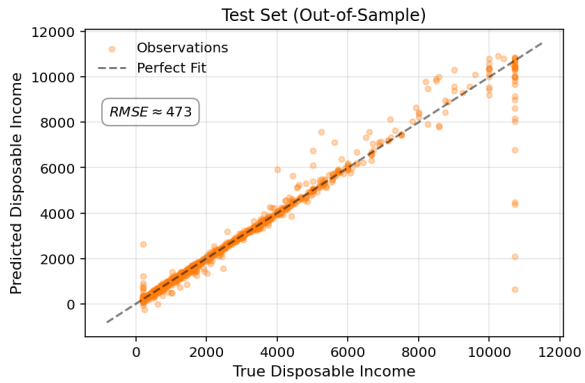
the GBR.[54] The LASSO regularization parameter is selected using five-fold cross-validation.

Model Fit: The model is trained on a 63% random sample of Convenience users, with hyper-parameters selected via five-fold cross-validation using `scikit-learn`'s `RandomizedSearchCV`. Model performance is subsequently evaluated using out-of-sample root mean squared error (RMSE) on the remaining 37% of observations.

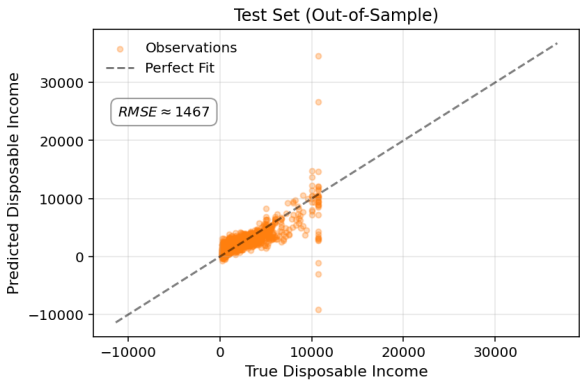
Figure 14 reports the model fit. The GBR predictor performs significantly better than the LASSO predictor on the same set of covariates.

Figure 14: Model Performance

(a) Gradient Boosting Regressor RMSE



(b) Lasso RMSE



Sensitivity Analysis of Assumption 2

Table 11: Robustness to alternative scaling factors

The sensitivity analysis assumes: Robustness factor $\cdot\, \mathbb{E}[\bar{y}_i \mid Z_i, \mathbf{1}_{Rev} = 0] = \mathbb{E}[\bar{y}_i \mid Z_i, \mathbf{1}_{Rev} = 1]$.

		Baseline calibration		$\delta_c = 0$	
Robustness factor	Debt share	Net welfare	$Gini_{\text{CS}}$	Net welfare	$Gini_{\text{CS}}$
0.7	0.281	35.102	0.773	19.201	0.857
0.8	0.206	25.787	0.665	13.317	0.751
0.9	0.123	25.279	0.586	18.025	0.647
1.0	0.033	22.541	0.554	20.710	0.578
1.1	0.014	21.794	0.564	20.890	0.572
1.2	0.010	21.595	0.565	20.947	0.570
2.0	0.003	21.383	0.563	21.163	0.564

[54] Note that $y^{Conv} = Expenditure$.

10.6 Incremental Effects Of Credit Cards

To quantify the impacts of credit cards on welfare inequality, I compare the Gini coefficient of total welfare in a counterfactual economy without credit cards with that in the observed economy with credit cards. Baseline welfare in the absence of credit cards is calculated according to:

$$W_{\text{baseline}} = \frac{\mathbf{v}_i^{\text{without cc}} \cdot (1 - s_d) \cdot \text{Expenditure}_{\text{with credit}}}{\alpha_i}$$

Since consumer surplus is defined as the net welfare gains due to the introduction of credit cards, welfare levels with credit cards are given by:

$$W_{\text{with cc}} = W_{\text{baseline}} + CS$$

The incremental effect of credit cards on welfare inequality is therefore measured as:

$$\frac{Gini_{W_{\text{with cc}}} - Gini_{W_{\text{baseline}}}}{Gini_{W_{\text{baseline}}}}$$

Since baseline welfare depends on specific calibrations of per-unit surplus without credit cards, the magnitude of the difference between the Gini coefficients is highly sensitive to specific calibrations of the average utility of cash-based methods (i.e., δ_c).

Relative to the baseline calibration of δ_c specified in Equation (10), imposing $\delta_c = 0$ would mechanically understate W_{baseline} while leaving CS largely unchanged. Estimates under this assumption therefore provide a conditional upper bound on the incremental effect of credit cards on inequality. Table 12 reports estimates under both the baseline calibration and this upper-bound specification.

Under both calibrations, total welfare remains highly unequal, with Gini coefficients ranging from 0.51 to 0.54. The estimated incremental contribution of credit cards to welfare inequality ranges from 2% under the baseline calibration to 13% under the upper-bound specification. Thus, although inequality in total welfare remains substantial, credit cards play a rather limited role in

shaping this inequality.

Table 12: Incremental Effect of Credit Cards on Inequality

Notes: The baseline specification calibrates $\delta_c = \max\{0, \Xi_c - \Xi_{cc}\}$.
Gini coefficients are calculated following Raffinetti, Siletti, and Vernizzi, 2015 to accommodate negative observations.

	Baseline calibration	$\delta_c = 0$
Welfare without credit cards, W_{baseline}	63.79	13.22
Net welfare gain from credit cards, CS	22.87	20.74
Welfare with credit cards, $W_{\text{with cc}}$	86.66	33.96
$Gini_{CS}$	.553	.596
$Gini_{Rewards}$	.791	.791
$Gini_{W_{\text{baseline}}}$	.499	.479
$Gini_{W_{\text{with cc}}}$	.509	.541
Δ Gini coefficient relative to $Gini_{Rewards}$	55.4%	46.2%
ΔGini coefficient relative to W_{baseline}	2.0%	12.9%

10.7 Additional Tables And Figures

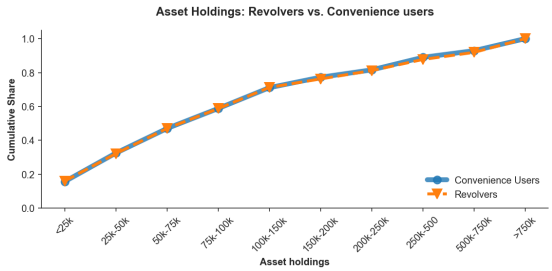
Table 13: Share of primary card

The primary card is defined as the most often used credit card.
Share is calculated as the share of spending/outstanding balance on the primary card.

Primary share (%)	Mean	Stdev	p25	p50	p75
Credit card spending	80.8	26.6	66.7	97.1	1
Outstanding balance	76.4	34.1	55.6	1	1

Figure 15: Cumulative Distributions Of Assets And Liabilities

(a) Asset holdings



(b) Financial Liabilities

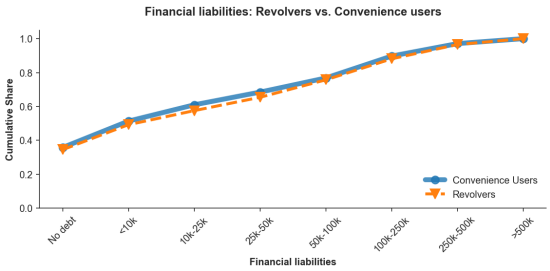


Figure 16: Per-unit surplus: Convenience users vs. Revolvers

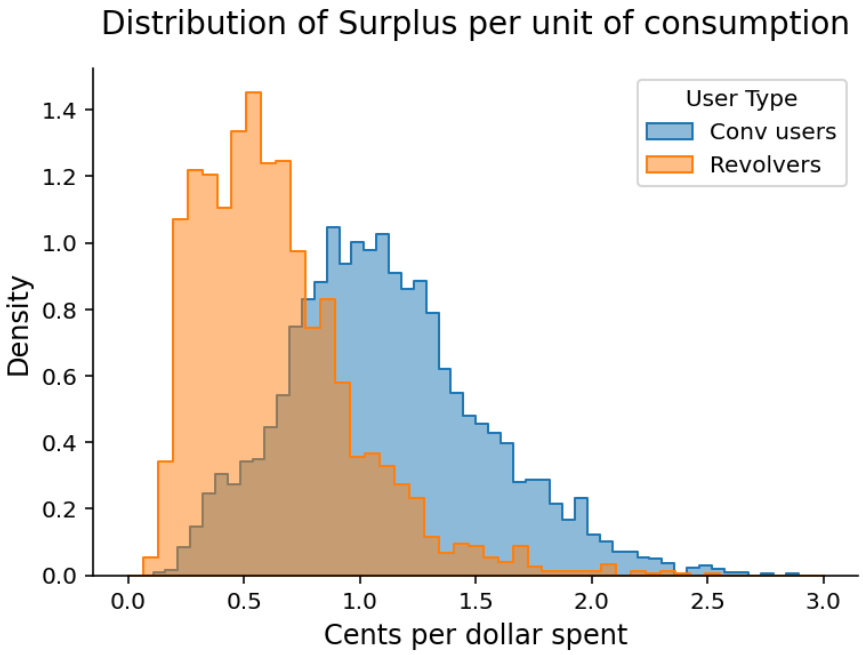


Figure 17: Average Share of Debt-Funded Expenditure Among Revolvers

The steady-state approximation assumes $\frac{d'}{(1+r)} = (1-\theta)d + \Delta d = d \Rightarrow \Delta d = \theta d$.

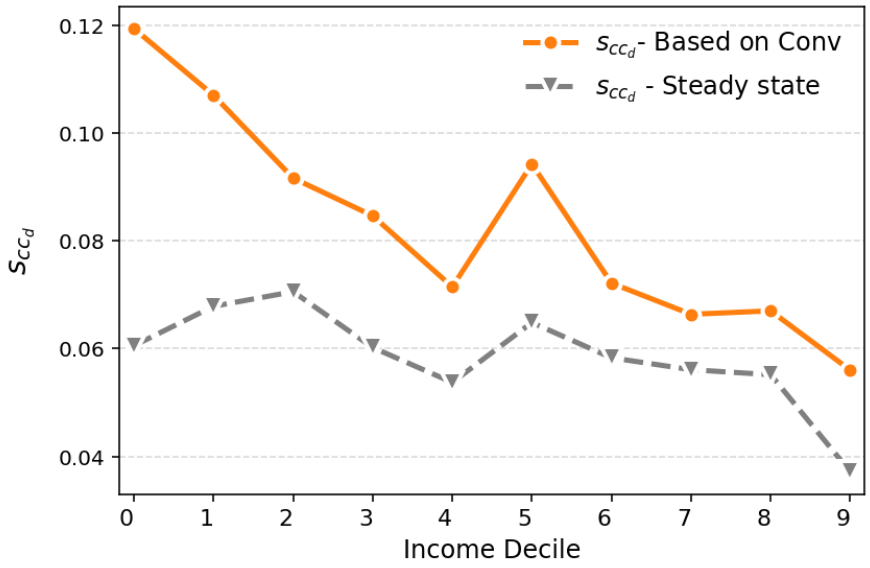


Figure 18: Survey Question: "Please tell us you have Line of Credit/ Loan"

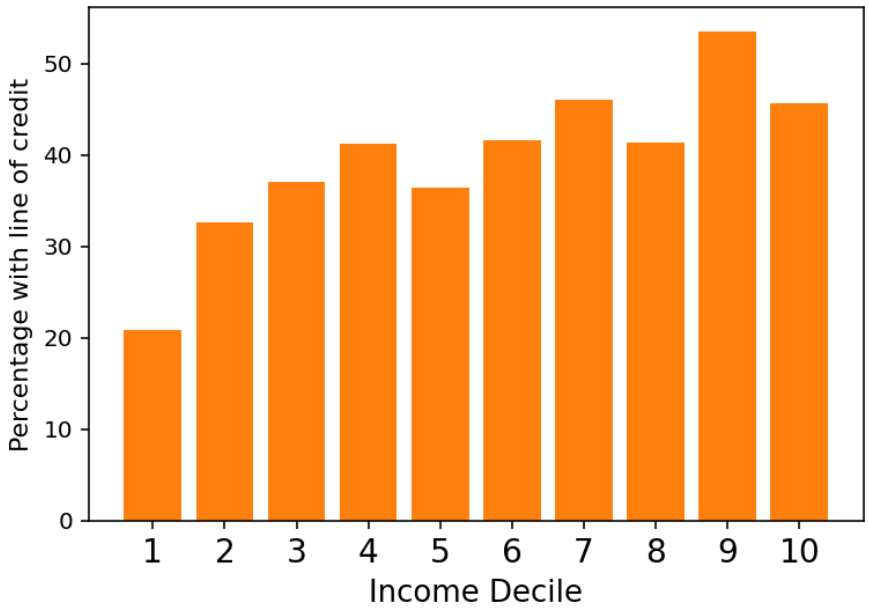


Table 14: Determinants of Annual Fees

Notes: The table reports OLS estimates from a regression of annual fees on rewards scale, insurance coverage, and the interest rate. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Annual fees
Rewards scale	48.432***
	(1.975)
No. of insurance benefits	12.941***
	(0.640)
Interest rate	-0.226
	(0.330)
Constant	-52.403***
	(7.001)
Observations	10,309
R^2	0.335
Adjusted R^2	0.334

Table 15: Characteristics of primary cards: Revolvers vs. Convenience users

	Avg. Reward Rate (%)		Avg. Annual Fee ($)		Avg. Interest (%)		Avg. Limit ($)		Avg. Utilization (%)	Avg. No. of Insurance Benefits (#)		Share with a point card	
Quintile	Conv.	Rev.	Conv.	Rev.	Conv.	Rev.	Conv.	Rev.	Rev.	Conv.	Rev.	Conv.	Rev.
1st (Bottom 20%)	1.07	0.86	33.41	29.02	20.91	20.93	12,913	12,995	56.92	3.33	3.14	0.55	0.49
2nd Quintile	1.19	0.96	45.46	45.97	21.01	20.84	17,111	17,547	49.82	3.90	3.78	0.58	0.52
3rd Quintile	1.30	1.06	60.00	52.54	20.89	20.60	20,726	20,034	32.99	4.47	4.03	0.60	0.54
4th Quintile	1.36	1.18	67.02	59.23	20.98	20.70	21,590	21,428	36.11	4.70	4.31	0.60	0.60
5th (Top 20%)	1.61	1.22	105.77	65.32	21.12	20.29	27,731	26,560	24.68	5.96	4.43	0.71	0.57

Notes: Conv. = Convenience users; Rev. = Revolvers.

Reward rates are expressed as percentages. The limit is the average total credit limit across all cards. Utilization is the balance divided by the limit.

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