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Debt Relief Programs and Money Left on the Table: Evidence from Canada's Response to COVID-19

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Abstract

This paper analyzes the effectiveness of debt-relief programs targeting short-run household liquidity constraints implemented in Canada in response to the COVID-19 pandemic. These programs allowed individuals to push off mortgage and credit card payments and cut in half interest rates on credit card debt. Using credit bureau data, we document that, despite potential savings above $4 billion, enrollment was limited: 24% for mortgages and 7% for credit cards. By exploiting the richness of our data set, we provide evidence that close to 80% of individuals were unaware of the credit card relief program while others faced important fixed non-monetary costs preventing uptake.

Topics: Credit and credit aggregates; Coronavirus disease (COVID-19); Debt management
JEL codes: H5, G31

1 Introduction

In this paper, we study the effectiveness of debt-relief programs targeting short-run household liquidity constraints implemented in Canada following the COVID-19 outbreak. Backed by the federal government, the banking regulator, and the Canada Mortgage and Housing Corporation (CMHC), financial institutions offered a number of options to borrowers to alleviate their financial obligations in a context of job losses and economic insecurity. Similar programs were implemented in other countries throughout the world, including as part of the CARES Act in the United States. Based on a rich account-level data set, we show that despite the fact that these programs offered important savings to Canadians who opted in, enrollment was low. In addition, we document that this outcome was mainly due to a mix of limited information about the programs and fixed non-monetary costs associated with enrollment. In a context where the debt-relief programs were implemented to minimize personal defaults and help stabilize the economy, these findings have important policy implications.

Our focus is on two specific debt-relief programs that gave the opportunity to borrowers to directly or indirectly realize savings on outstanding credit card debt. The first program allowed credit card borrowers to defer the minimum payment on their outstanding balances and to cut the interest rate on their revolving debt (roughly) in half. The second made it possible for individuals to pause their mortgage payments for up to six months and use the freed-up cash flow to pay back high-interest-rate credit card debt.

In theory, anyone carrying a positive credit card balance could benefit from these deferral programs. However, in practice there were two important features of the programs that may have limited their effectiveness. First, their existence may not have been sufficiently publicized. Details on the credit card deferral programs were initially difficult to find. The mortgage deferral program was more widely promoted, but even its existence may not have been known to all. In other words, there may have been an *informational friction* preventing take-up.[1] Second, there may have been certain real or perceived non-

[1] A number of authors have studied informational frictions in the context of small U.S. firms (not) taking advantage of the Paycheck Protection Program during the pandemic, c.f. Humphries et al. (2020).

monetary *fixed costs* associated with program enrollment. For instance, the onus was on borrowers to formally request support from their financial institution. Hence, the eventual success of these programs hinged crucially on the extent to which individuals *opted in*. However, doing so required some effort or *hassle cost* on the part of borrowers.[2] With reported wait-times in the hours at the launch of the deferral programs, many individuals might have given up.[3] Previous work in household finance has shown that hassle costs often cause some to forgo potential savings.[4] Another potential fixed cost associated with enrollment is *reputation*—if individuals believe that applying for a deferral will impact their ability to access credit in the future, they might forgo enrollment.

Our analysis of enrollment in these programs is based on comprehensive data from TransUnion©, a national credit bureau company that provides the Bank of Canada with monthly anonymized updates on the credit portfolios of Canadians, including contract-level information on mortgages and credit cards. For each individual, the data set contains information on the lender, outstanding balance, payment obligations, credit limits, and additional variables on a large range of credit products (credit cards, mortgages, student loans, etc.). For each product, it also contains information on whether individuals obtained a deferral.

Using these very detailed data, we document two main findings. First, we identify important aggregate potential savings from the two deferral policies under study—more than $4 billion. These savings stem from the 34% of credit card holders who do not pay their credit card debt in full every period (so called "revolvers"), carrying average

[2]Lambrecht and Tucker (2012) define hassle costs as the non-monetary effort and inconvenience a customer incurs in setting up, maintaining or disposing of a product or service. Hviid and Shaffer (1999), Marshall (2015), and Grubb (2015) all point out that hassle costs can lead individuals to make sub-optimal choices.

[3]In an appearance before the Standing Committee on Finance on July 7, 2020, the Financial Consumer Agency of Canada described the difficulty faced by consumers to access deferral programs. They reported wait-times of between 1 and 4.5 hours, with some claiming it took days to get through (https://www.canada.ca/en/financial-consumer-agency.html). This is consistent with statements made via Twitter by financial institutions reporting long wait-times, asking for patience, and directing clients to make online appointments. See, for example, https://twitter.com/rbc/status/1241817076521734145?lang=en.

[4]In the mortgage market see, for instance, Woodward and Hall (2012) and Allen et al. (2019). In addition, see Hortaçsu and Syverson (2004) for the role of search frictions in the market for mutual funds, Stango and Zinman (2015) in the credit card market and Argyle et al. (2019) for auto loans.

monthly balances of \$8,920. The typical interest rate on these balances is about 20%. On their own, the savings from the available interest-rate reduction are worth about \$1 billion. In addition, mortgagors could use the extra liquidity from deferred low-interest mortgage payments to pay back their high-interest credit card debt.[5] A conservative estimate of aggregate potential savings in interest costs from doing so is \$3.35 billion. Our second finding is that despite the size of the combined potential savings, only a minority of revolvers took advantage of the opportunity: only 7% of them chose to defer on at least one credit card, while 24% deferred on their mortgage. Together, the considerable potential savings but low take-up rates suggest that Canadians did not take full advantage of the deferral programs and left significant "money on the table".[6]

However, these aggregate findings mask important heterogeneity. Looking at take-up rates of the credit card deferral program along the distribution of potential savings reveals that, even amongst revolvers, many would save relatively little from a deferral: the median potential savings is \$108 over three months. Hence, even moderate hassle costs could discourage borrowers from enrolling. Not surprisingly, we find that take-up rates for each of the first five deciles of potential savings are very low, ranging from 4% to 6%. In contrast, take-up rates are higher for the top five deciles of potential savings. In the top decile, average potential savings are above \$750 and take-up rates are around 19%. Yet, while higher, deferral probabilities for those at the top of the potential savings distribution remain quite low. This relationship is robust to the inclusion of various controls.

We then take advantage of our rich data set to study the potential reasons behind the limited enrollment in the credit card deferral program. We begin by discarding supply-side explanations: denial rates on deferral requests were less than 3%, and we find no evidence that banks limited access to debt-relief programs or "punished" customers for deferring.[7] On the demand side, we assess the importance of information frictions by

[5]The same is also true for auto-loan deferrals, although we do not consider these here. The dispersion in auto-loan interest rates is substantial and we lack data on individual-level loan rates.

[6]These findings are consistent with those in Gross and Souleles (2002), Stango and Zinman (2009), Andersen et al. (2015), Agarwal and Yao (2015), Ponce et al. (2017), Gathergood et al. (2019), Baugh et al. (2020), Keys and Wang (2019), Agarwal et al. (2017), among others, who study the extent to which households optimally manage their debt.

[7]Rejection rates were 0.4% for mortgages and 2.6% for credit cards. See https://www.canada.ca/

comparing the deferral decisions of individuals who were more likely to have been aware of the programs relative to those of their peers. First, we consider individuals with student loans. Since these were automatically deferred and loan holders were directly informed by the government that their payments would be frozen, we believe that it is reasonable to think that these individuals were more aware than others about debt-deferral options. Indeed, we find that take-up along the distribution of potential savings is higher for these individuals, ranging from 4% to 26%, compared to 4% to 19% for the overall sample.

Second, we zoom in on borrowers with multiple revolving cards and who deferred on at least one of them. Deferring on one card signals awareness—for these borrowers, information frictions cannot explain their decision not to defer on all their cards, hinting at a role for real or perceived non-monetary costs associated with program enrollment. To get a sense of the degree of awareness to the program and the size of the fixed cost of deferring, we contrast deferral behavior on multiple credit cards from the same bank versus from rival banks. We find much higher take-up within bank than across banks. This is sensible since the hassle cost of deferring at a particular bank, conditional on having already deferred on one card from that bank, should be minimal. In contrast, if a card holder has deferred a card from a rival bank, the information friction is not present yet the fixed cost of deferral remains. Studying jointly these sub-samples, we estimate that roughly 80% of borrowers were unaware of the program. Finally, we quantify the fixed cost of deferral using a sub-sample of borrowers who have non-deferred credit cards issued by banks different from the issuers of their deferred cards. On average, fixed costs should lie between the potential saving from non-deferred and deferred credit cards, which are on average $114 and $312 over three months, respectively.

Our findings suggest that the effectiveness of debt-deferral programs depends on the extent to which people are aware of them and how easy they are to use. One way to ensure greater awareness would be through greater advertising by consumer protection agencies, similar to the increase in advertising by deposit insurance agencies during the financial crisis and pandemic.[8] Furthermore, making it easier for individuals to access

`en/financial-consumer-agency/corporate/COVID-19/bank-relief-measures.html`.

[8] The Canada Deposit Insurance Corporation, for example, substantially increased their advertising

debt-relief programs would increase enrollment. This could be done by facilitating online applications with classic behavioral “nudges”, or by making opt-in the default option.

Our paper is related to recent empirical work analyzing the impact of stabilization policies designed to affect the household balance sheet and focusing on debt relief (see, for instance, Agarwal et al. (2011), Agarwal et al. (2017), Agarwal et al. (2020), Di Maggio et al. (2017), Ganong and Noel (2017), Maturana (2017), Kruger (2018), Mueller and Yannelis (2020)). The closest paper to ours is Cherry et al. (2021) who, like us, use credit bureau data to study take-up of loan deferral programs. They document that by October 2020, debt forbearance allowed U.S. consumers to defer roughly $43 billion in debt payments. Take-up was significant for student loans, but only around 4.6% for revolving loans (credit cards and personal lines of credit) and 9% for mortgages. Their analysis considers supply-side factors hindering take-up, namely the importance of making the program mandatory from the point of view of lenders. By contrast, in Canada, although the programs were not mandatory, they were almost uniformly implemented by lenders for political and reputational reasons. Therefore, our focus is instead on demand-side frictions related to awareness of the programs and ease of enrollment, which prevented consumers from signing up. Low take-up is also easier to rationalize in their context, since credit card deferrals were not always linked with rate cuts as in the Canadian case.

The paper proceeds as follows. Section 2 describes the deferral programs and the institutional setting. In Section 3 we present the TransUnion data set. Sections 4 and 5 contain our analysis of potential savings and take-up rates, while Section 6 describes and quantifies the main impediments to enrollment. Section 7 concludes.

2 The deferral programs

The COVID-19 shock occurred against a backdrop of record household debt levels: one-third of Canadians already reported in 2019 that they struggled or were unable to make required monthly payments on their debt (2019 Canadian Financial Capability Survey).

budget at the start of the pandemic. See their 2020 annual report.

In this context, policymakers were concerned that the pandemic and its aftermath would leave many incapable of meeting their financial obligations.[9,10]

The focus of some of these programs was to transfer cash directly to individuals to help meet immediate obligations. Other programs were aimed at helping businesses stay afloat by subsidizing wages and rent payments. The Canada Emergency Response Benefit (CERB) provided a $2,000 per month taxable benefit for Canadians over the age of 15 who were not working because of COVID-19 (but did not quit work) and had employment income of at least $5,000 in 2019. The program was initially announced to last four months, but was subsequently extended into 2021. The Canada Child Benefit program made a one-time payment of $300 per child, and personal income tax deadlines were extended. The government also introduced the Canada Emergency Wage Subsidy (CEWS), which provided support for businesses to minimize layoffs. Subject to some restrictions and caps, the CEWS provided employers with a subsidy worth 75% of wages paid out to employees. The government introduced the Canada Emergency Student Benefit—providing students who could not find work with a taxable benefit of $1,250 per month for May through August. Finally, the government mailed cheques to seniors (those aged 65 and over) of up to $500 tax-free. By most accounts these programs were very generous: household disposable income, for example, in the second quarter of 2020 was 16% higher than in the second quarter of 2019 (Statistics Canada Table: 36-10-0112-0), and the largest increase in income was for the lowest income quintile.

In addition to these programs, which were meant to supplement lost or reduced labor income and shield the asset side of individuals' balance sheets, the government worked with financial institutions and regulators to facilitate several debt-relief programs.[11] These debt-relief programs allowed individuals to defer payment on mortgages, credit cards, personal loans, auto loans, and lines of credit. In addition, federal and provincial governments automatically paused payments on student loans. Financial institutions worked closely

[9] See https://www150.statcan.gc.ca/n1/daily-quotidien/200420/dq200420b-eng.htm.

[10] That said, we observe an increase in savings by households who continue full-time work but have fewer expenses. The average savings rate in Canada went from about 3% pre-pandemic to 7.6% in 2020Q1 and 28.2% by 2020Q2. In the U.S., savings peaked at 33.7%.

[11] The Office of the Superintendent of Financial Institutions (OSFI) rules governing the treatment of deferrals are here: https://www.osfi-bsif.gc.ca/Eng/fi-if/in-ai/Pages/FRI20200828_let.aspx.

with the credit bureaus to ensure that deferral decisions would not negatively affect credit scores, and therefore impede the ability of their clients to access credit in the future. Our focus is on two of these programs: mortgage and credit card deferrals.

For mortgages, the vast majority of lenders provided some level of debt relief for their clients. The typical program offered the possibility of deferral for up to six months.[12] Monthly payments were paused while interest continued to accrue, effectively extending the amortization period of the loan.[13] Financial institutions also provided debt relief and interest-rate reductions on most credit cards. Although some lenders offered up to a six-month deferral, the majority were for three months. A credit card deferral is simply a stop on the minimum payment due. Interest continues to accrue, and individuals can continue using the card so long as it is below the credit limit. The main benefit from a credit card deferral is that most lenders simultaneously offered an interest-rate reduction of up to 50% on new and outstanding purchases. Some financial institutions, such as Vancity Credit Union, went so far as to lower rates to zero. Interestingly, a credit card deferral also offered individuals a "fresh start" by removing flags on past-due accounts from their records. Hence, individuals with accounts that are past due can benefit from a deferral both through lower rates and a fresh start.

3 Data

In this section, we start by presenting our main data source, the TransUnion© credit bureau data set. We then describe a number of supplementary data sources.

3.1 Credit data

The Bank of Canada receives monthly anonymized credit report updates from TransUnion© on the population of Canadians with a credit product. We use a 1% random sample, re-

[12]Financial institutions have stated a possibility of extension, but with stricter underwriting standards. OSFI has stated that the special capital treatment for deferred loans extends only to January 31, 2021.

[13]This is different from the CARES Act implemented in the U.S. In that case, interest did not accrue on federally- and GSE-backed mortgages.

sulting in 303,838 individuals with complete credit data between January 1, 2009, and November 15, 2020. The data set is structured such that for each individual, we observe all of their credit products, including those that are no longer active. This allows us to observe account-level information for credit cards, mortgages, lines of credit, utilities, student loans, auto loans (both bank and dealer loans), demand loans, and installment loans.[14] For each product we observe the lender as well as an individual's product-level outstanding balance, monthly payment obligation, credit limit, opening date, billing date, payment date and, most importantly, a *deferral flag*. We define a borrower as a *deferrer* on a specific product type—credit card, mortgage, etc.—if at least one credit account in the product category was marked with a deferral flag in any month between March and September 2020. Most of the deferrals were granted before July 2020.[15]

3.2 Neighborhood-level data

While the TransUnion© data set is very rich, borrower-level characteristics are, unfortunately, limited to the borrower's age, credit score and postal code of primary residence. For this reason, we complement our analysis with neighborhood-level information. We define a neighborhood as the first three digits of an individual's postal code, referred to as "Forward Sortation Area" (henceforth FSA). There are over 1,600 FSAs in Canada. The average number of households in an FSA is 8,000, ranging from zero to over 60,000.

FSA-level employment data. Given that debt-relief policies were put in place to shield individuals' balance sheets from severe employment and income shocks, one could expect deferral decisions to be driven in part by job loss. As pointed out in Lemieux et al. (2020), there was a 15% decline in employment between February and April 2020, and nearly half of job losses were in the bottom earnings quartile. If lower-income earners are more constrained, we would expect a large take-up of deferral programs.

To circumvent the fact that we have no information on borrowers' employment status

[14] TransUnion© does not have the entire population of credit products since some lenders do not report. Mortgages are by far the least reported product, yet we still capture over 85% of mortgages in Canada.

[15] Table A.1 in the Appendix provides the distribution of deferral lengths for credit cards and mortgages.

in the TransUnion© data set, we make use of data from Statistics Canada. Statistics Canada does not provide monthly employment change data at the FSA level, only at the province-industry level.[16] FSA-level employment shares at the industry level are available from the 2016 Census. We use a shift-share methodology based on these two sources to determine the approximate employment change at the FSA level, and then assign to each borrower the employment change of their FSA. Specifically, we define dN_{jt} as the employment change in FSA j belonging to province k in month t:

$$dN_{jt} = \sum_{l} \omega_{jl} dN_{klt}, \tag{1}$$

where ω_{jl} is the share of FSA j's employment in industry l in 2016, and $dN_{klt} = \ln\left(N_{klt}/N_{klt-1}\right)$ is the year-over-year change in employment in province k for industry l. Figure 1 plots the within-province variation in the year-over-year employment changes across FSAs. There is both substantial between- and within-province variation. In our regression analysis, we study the impact of employment change on the decision to defer.

FSA-level CERB data We have access to the total number of unique applications by FSA for CERB, an income-replacement program for pandemic-related job loss. Employment and Social Development Canada (ESDC) reported that as of October 4, 2020, there had been 8.9 million unique applicants. Figure 2 shows the dispersion in the CERB application rate (applicants as a fraction of the labor force) across FSAs in each province. The average application rate is 22.2% and the standard deviation is 7.6%. While applying to CERB is negatively correlated with our measure of employment change—worse employment shocks are correlated with more CERB applicants—there is much more heterogeneity across provinces in CERB application rates than in unemployment.

[16] Statistics Canada publishes unadjusted monthly industry employment data for each province (`https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410035501`). There are 15 industry categories: Agriculture, forestry, fishing, mining, quarrying, oil and gas; Utilities; Construction; Manufacturing; Wholesale and retail trade; Transportation and warehousing; Information, culture and recreation; Finance, insurance, real estate, rental and leasing; Professional, scientific and technical services; Business, building and other support services; Educational services; Health care and social assistance; Accommodation and food services; Other services (except public administration); Public administration.

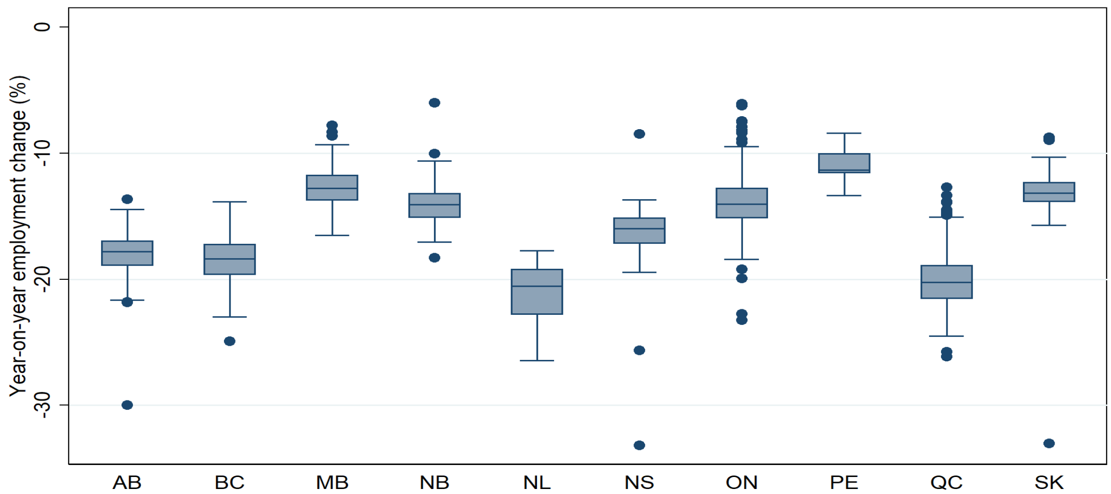


Figure 1: FSA-level employment change from April 2019 to April 2020

Notes: This figure plots the distribution of year-over-year employment changes across FSAs within the ten Canadian provinces. Across 1,609 FSAs, the average employment change is -16.6%, and the standard deviation is 3.5%.

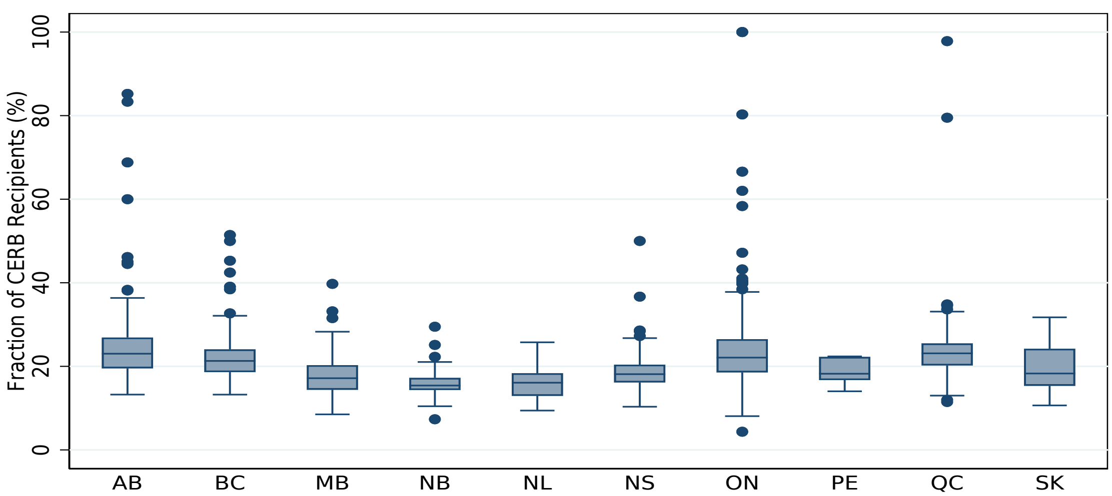


Figure 2: FSA-level fraction of CERB applicants in April 2020

Notes: This figure plots the distribution of the CERB application rate (fraction of labor force applying for CERB) across FSAs within the ten Canadian provinces. Across 1,609 FSAs, the average CERB application rate is 22.2%, and the standard deviation is 7.6%.

Other FSA-level data. To control for FSA-level wealth and savings, we calculate average investment income and average savings in Tax-Free Savings Accounts (TFSA) using individual tax statistics published by the Canada Revenue Agency for the 2017 tax year.[17] We also include the average after-tax income from the 2016 Census. Finally, another factor that could affect enrollment in debt-relief programs is financial literacy. We proxy FSA-level financial literacy using the fraction of the population aged 25 to 64 years with a college or university degree from the 2016 Census.[18]

3.3 Summary statistics

Table 1 summarizes the unique number of active accounts in our 1% sample randomly drawn from the TransUnion© data set. We calculate the fraction of accounts receiving deferrals between March 2020 and September 2020 for our two products of interest: credit cards and mortgages. We also present this information for student loans, since we use these in our analysis. The top two rows are for all accounts, whereas the bottom two focus on active accounts with a positive payment required. For the 286,115 individuals in our sample reported on April 1, 2020, we observe 499,228 credit cards and 59,417 mortgages. The majority of accounts have a positive payment required. Mortgages are the product type most likely to be deferred by individuals: 14.98% of mortgages were deferred at some point between March 2020 and September 2020, compared to just 2.28% for credit cards with a positive balance. Finally, nearly all student loans are deferred. Student loans were automatically put into deferral by both levels of government (federal and provincial). The 10% of student loans not in deferral are non-government loans.

Credit cards: deferrers vs non-deferrers. Table 2 provides key summary statistics for individuals with a credit card. We report on individuals with a deferral separately from those without. The aggregated credit card limit for the average deferrer is $22,730, while it is $16,680 for a non-deferrer. Individuals deferring have on average more cards—2.5 versus 1.8—and significantly higher utilization rates; their outstanding balance relative to

[17]TFSAs are registered investment accounts that allow for tax-free gains. Achou et al. (2020) find, based on a survey of Quebec households, that only 9.8% of individuals accessed their TFSA in the first couple of months of the pandemic—and draw-downs of registered accounts were even lower.

[18]In addition to census-level education, we looked at Canadian responses to the 2003 International Adult Literacy and Skills Survey. Unfortunately, 2003 was the latest year for the survey, and there was no correlation at the FSA-level between literacy scores reported in this survey and debt-relief take-up.

Table 1: Summary statistics of credit accounts

Using account-level data from TransUnion©, this table presents the deferral probabilities for credit cards, mortgages, and student loans. The top two rows are all accounts, whereas the bottom two rows are all accounts with positive payments required, which implies positive balances for credit cards and mortgages. Student loan accounts can have positive balances but zero required payments in the six-month non-repayment period.

	Cards	Mortgages	Student loans
		All accounts	
Pr(Deferral) (%)	1.55	14.96	89.48
Observations	499,228	59,417	19,129
		All positive accounts	
Pr(Deferral) (%)	2.28	14.98	90.59
Observations	321,149	59,261	12,112

the limit is close to 63%, compared to 28% for non-deferrers. Individuals with a deferral flag are also younger and have lower credit scores.

One reason for the lower credit score is that 13.1% of deferrers have an account that is at least 30 days past due in the period just prior to the start of the pandemic (i.e., the borrower failed to meet the minimum required payment). As highlighted in Section 2, a credit card deferral removes past-due flags on an individual's account. A deferral therefore offers a "fresh-start", i.e., an additional incentive to defer relative to individuals with up-to-date accounts.[19] We also find that 10% of individuals with a deferral have student loans, compared to 6% for non-deferrers. The higher fraction with student loans could arise for at least two reasons. First, these individuals have more debt and might therefore consider that the benefits of deferring relative to the costs are higher. Second, since the debt-relief program for student loans featured automatic enrollment, it is conceivable that individuals with student debt are more aware of their ability to defer on other products. We analyze these effects in Section 5.

Finally, Table 2 includes FSA-level characteristics. There do not appear to be significant differences in the FSAs in which deferrers and non-deferrers live in terms of after-tax household income, savings, or changes in employment as a result of the pandemic.

[19]Generally, past-due accounts will lead to lower credit scores and higher interest rates. In our quantification of the benefits from deferral, we ignore the advantages to borrowers of having a reset on their credit report. This is because our sample period is still within the COVID-19 pandemic.

Table 2: Summary statistics of credit card holders by deferral flag

This table presents summary statistics for credit card holders in TransUnion©—columns (1)-(3) are for non-deferrers and columns (4)-(6) are for deferrers. Limit is the maximum allowable credit on a card. Balance is the current amount outstanding. Utilization is balance divided by limit. Payment required is the minimum amount due by the cards' billing date. Payment made is the actual payment to the card issuer by the reporting date. Total debt is the sum of credit across all products. Total obligation is the sum of monthly payments required. The variable Past-due is an indicator variable equal to 1 for borrowers who have at least one account past due in the three months prior to the onset of COVID-19 in Canada, and 0 otherwise. Credit score is a measure of creditworthiness. Age is the account holder's age in years. No. of accounts and No. of cards are the total number of accounts and cards, respectively. There are also four indicator variables, $I(\cdot)$. They are equal to 1 if the individual owns the product listed in the brackets. There are five FSA-level variables: income is the average 2015 after-tax income (2016 Census); investment income and TFSA savings are calculated from 2017 individual tax statistics—and are total investment income and funds in the TFSA, respectively; education is the percentage of people with at least a college degree in the population aged 25-64 years; employment change is the year-over-year employment change calculated using the shift-share approach in Section 3.2; fraction of CERB applicants is the number of CERB applicants in April 2020 divided by the labor force. There are 229,366 non-deferrers and 6,714 deferrers.

	Non-deferral			Deferral		
	Mean	Median	SD	Mean	Median	SD
Limit ($1,000)	16.68	11.00	18.98	22.73	15.50	24.76
Balance ($1,000)	3.66	1.07	7.52	12.92	7.00	16.50
Utilization (%)	28.14	11.10	33.74	63.42	76.90	36.35
Payment required ($)	83.49	24.67	256.08	257.21	156.00	305.41
Payment made ($)	1870.98	852.33	4316.81	1840.52	722.00	4067.14
Total debt ($1,000)	188.19	61.00	302.70	220.14	78.44	328.84
Total obligation ($1,000)	0.90	0.36	1.59	1.35	0.86	1.58
Past-due (%)	3.21	0.00	17.63	13.11	0.00	33.75
Credit score	778.61	820.33	99.81	686.08	694.33	113.26
Age	49.23	48.75	17.87	45.39	44.42	15.03
No. of accounts	3.29	3.00	2.25	4.38	4.00	2.82
No. of cards	1.81	1.00	1.17	2.50	2.00	1.72
I(student loan)	0.06	0.00	0.24	0.10	0.00	0.30
I(line of credit)	0.40	0.00	0.49	0.44	0.00	0.50
I(personal loan)	0.30	0.00	0.46	0.45	0.00	0.50
I(mortgage)	0.19	0.00	0.39	0.23	0.00	0.42
FSA income ($1,000)	91.96	86.19	27.21	91.98	86.19	26.66
FSA invest income ($1,000)	5.07	3.51	7.76	5.05	3.41	8.73
FSA TFSA saving ($1,000)	8.18	7.93	2.86	7.92	7.61	3.00
FSA education (%)	54.99	54.12	13.82	54.93	53.92	13.62
FSA employment change	-0.17	-0.16	0.03	-0.17	-0.16	0.03
Fraction of CERB applicants	0.23	0.23	0.06	0.24	0.23	0.07

Revolvers vs convenience users. For credit cards, it is convenient to sort individuals into two types: (i) revolvers and (ii) convenience users. Revolvers are individuals who do not typically make their full credit card payments. More specifically, we treat a credit card as *revolving* if in the previous three months it was never paid in full and the average payment-to-balance ratio was less than 90%. At the individual level, a revolver is defined as a borrower with at least one revolving card. Approximately 34% of credit card holders in our sample are revolvers. The remainder are convenience users; those who use their credit card at the point-of-sale but do not carry a balance.

Table 3 breaks down the sample into revolvers and convenience users. Revolvers hold substantial credit card debt—close to $9,000 spread over 2.1 cards. Revolvers are twice as likely to defer their mortgage as convenience users and seven times more likely to defer their credit card. Revolvers are also more likely to have a student loan and a personal loan (mostly auto). Finally, revolvers tend to live in markets with lower education attainment, average income and savings than convenience users. This last point motivates our decision to control for local-market factors in the regression analysis of Section 5.

Mortgages: deferrers vs non-deferrers. Table 4 provides key summary statistics for mortgage borrowers. First, we find that about 15.5% of mortgage holders defer their payments. This is consistent with aggregate numbers reported by CMHC—the primary mortgage insurer in Canada. On average, mortgage deferrers have larger mortgages and more non-mortgage debt—in terms of both the original loan amount (395- versus 302-thousand dollars) and current balance (347- versus 249-thousand dollars). The consequence is that average monthly payments are higher for deferrers ($1,924) than for their peers ($1,559). These systematic differences point to the potential importance of liquidity constraints as a driver of the mortgage deferral decision.

Table 4 also includes neighborhood-level characteristics. Unlike for credit cards, there are notable market-level differences between mortgage deferrers and non-deferrers. In particular, we find that deferrers live in neighborhoods with higher income but less savings. This is not as surprising as it might seem: deferrers tend to have high loan-to-value (LTV) mortgages, meaning that they are insured by the government. Insured mortgages are required to meet an income stress-test (Clark and Li (2019)). A buffer, therefore, is already built into the mortgage. For new homebuyers to have a high LTV, they must have sufficiently high income in order to demonstrate they can make monthly payments significantly higher than their current payment.

Table 3: Summary statistics: revolving and convenience credit card users

This table presents summary statistics for two types of credit card holders in TransUnion©—the first three columns are for revolvers and the last three columns are for convenience users. Variables are defined in the header of Table 2. The only new variables are I(defer card) and I(defer mortgage | mortgage). These are indicator variables equal to 1 if the individual deferred a credit card or mortgage, respectively.

	Revolving			Convenience		
	Mean	Median	SD	Mean	Median	SD
Limit ($1,000)	17.78	11.40	20.30	17.75	12.70	19.25
Balance ($1,000)	8.92	4.87	11.83	1.65	0.59	3.75
Utilization (%)	60.72	68.20	34.50	12.92	5.20	19.86
Payment required ($)	198.26	114.00	408.24	31.88	13.33	106.77
Payment made ($)	1229.49	500.00	2506.75	2215.80	1144.33	4975.55
Total debt ($1,000)	181.43	67.76	259.62	204.63	63.50	334.05
Total obligation ($1,000)	1.18	0.71	1.78	0.80	0.12	1.52
Past-due (%)	8.82	0.00	28.35	0.92	0.00	9.56
Credit score	703.59	718.00	113.20	811.60	840.00	71.93
Age	47.21	46.50	15.41	50.60	50.83	18.55
No. of accounts	3.82	3.00	2.50	3.21	3.00	2.19
No. of cards	2.12	2.00	1.42	1.79	1.00	1.10
I(student loan)	0.09	0.00	0.28	0.05	0.00	0.23
I(line of credit)	0.39	0.00	0.49	0.42	0.00	0.49
I(personal loan)	0.43	0.00	0.49	0.23	0.00	0.42
I(mortgage)	0.21	0.00	0.41	0.18	0.00	0.38
I(defer card)	0.07	0.00	0.25	0.01	0.00	0.11
I(defer mortgage | mortgage)	0.24	0.00	0.43	0.11	0.00	0.31
FSA income ($1,000)	90.49	85.49	24.62	94.45	88.13	28.91
FSA invest income ($1,000)	4.57	3.29	6.61	5.53	3.77	8.35
FSA TFSA saving ($1,000)	7.75	7.49	2.67	8.44	8.09	2.96
FSA education (%)	53.49	52.62	13.04	56.78	56.28	13.64
FSA employment change	-0.16	-0.16	0.03	-0.16	-0.16	0.03
Fraction of CERB applicants	0.23	0.23	0.06	0.23	0.23	0.06
Observations	73,948			141,754		

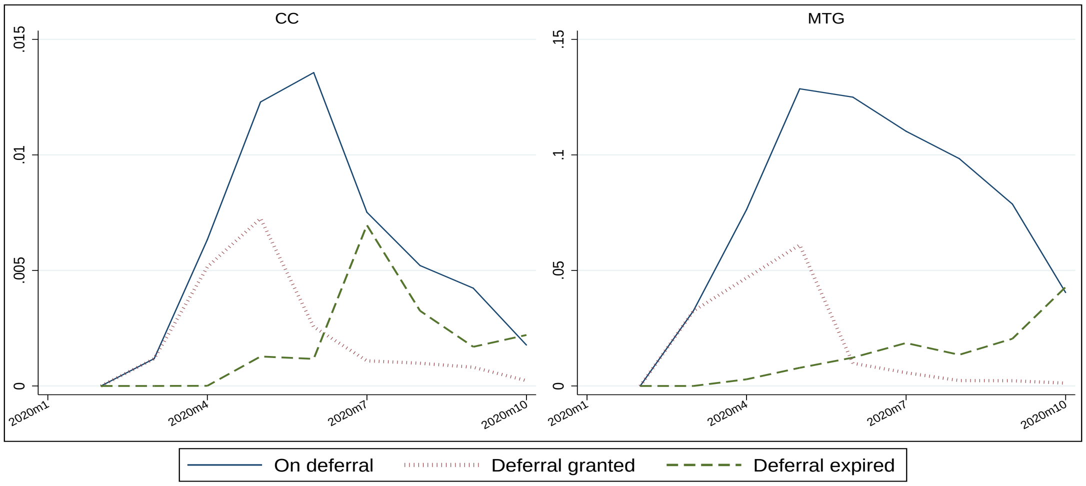
Table 4: Summary statistics of mortgage borrowers by deferral flag

This table presents summary statistics for individuals with a mortgage as reported in TransUnion©—the first three columns are for non-deferrers and the last three columns are for deferrers. Variables are defined in the header of Table 2.

	Non-deferral			Deferral		
	Mean	Median	SD	Mean	Median	SD
Limit ($1,000)	301.54	239.20	262.83	394.60	301.48	350.49
Balance ($1,000)	248.85	192.82	236.95	346.89	262.89	319.78
Utilization (%)	78.98	86.32	21.41	85.76	89.85	14.46
Payment required ($)	1558.88	1274.00	2330.79	1923.81	1531.44	1556.94
Total debt ($1,000)	428.76	337.61	361.62	525.37	404.35	451.08
Total obligation ($1,000)	2.10	1.75	1.75	2.81	2.28	2.91
Past-due (%)	0.59	0.00	7.64	1.59	0.00	12.50
Credit score	788.82	825.33	89.49	731.58	759.00	110.91
Age	50.53	50.00	13.35	48.89	48.17	12.03
No. of accounts	5.14	5.00	2.49	5.79	5.00	2.91
No. of cards	1.89	2.00	1.40	2.13	2.00	1.63
No. of mortgages	1.19	1.00	0.56	1.28	1.00	0.74
I(student loan)	0.03	0.00	0.16	0.04	0.00	0.20
I(line of credit)	0.73	1.00	0.45	0.71	1.00	0.46
I(personal loan)	0.43	0.00	0.50	0.57	1.00	0.50
FSA income ($1,000)	91.53	86.26	24.82	93.54	88.00	25.73
FSA invest income ($1,000)	4.77	3.41	7.59	4.81	3.43	6.46
FSA TFSA saving ($1,000)	8.07	7.77	2.78	7.80	7.49	2.73
FSA education (%)	53.87	53.05	13.70	53.39	52.77	13.40
FSA employment change	-0.17	-0.17	0.03	-0.17	-0.17	0.03
Fraction of CERB applicants	0.23	0.22	0.06	0.24	0.23	0.07
Observations	41,901			7,683		

Enrollment over time. Figure 3 shows the debt-relief take-up rate evolution from March until October 2020. We can see that most deferrals were initiated in the months of April and May, with much lower numbers in the summer as the Canadian economy was coming out of lock-downs. The active stock of deferrals peaked in June for credit cards and May for mortgages. Finally, Figure 3 also displays the rate at which deferrals were terminated. For example, we see that most credit card deferrals expired after three months, with a jump in terminations in July. On the other hand, mortgage deferrals lasted up to six months, with a slow increase in terminations throughout the sample period.

Figure 3: Program take-up rate over time



Notes: For each product category, the solid line shows the fraction of accounts on deferral in each month. The dotted line displays the fraction of accounts entering deferrals in each month. The dashed line is the fraction of accounts exiting deferrals in each month.

4 Potential and actual savings

In this section, we quantify the potential savings that borrowers could have achieved by deferring their credit cards and/or mortgages. We also provide more information on the extent to which they enrolled in the deferral programs.

4.1 Potential savings from debt-relief measures

Debt-relief measures aimed at individuals were broadly available during the spring and summer of 2020. The objective was to allow individuals to lighten their debt obligations at a time of large employment losses and economic insecurity. Some of these measures, such as deferral programs for mortgages and student loans, were designed as intertemporal substitution vehicles: while debtors could pause their payments for a few months, it implied a higher balance once the deferral period was over. In contrast, other options, such as reductions on credit card interest charges, offered unambiguous savings to borrowers.

We focus on the potential savings on credit card interest charges stemming from two channels. We explain each in turn using numerical examples. Moreover, using our data, we quantify their size for each credit card revolver and calculate the aggregate potential savings. Note that for these calculations, we only use information from March 2020—the last period before deferrals took effect. We use the one-month calculation as a benchmark, and then aggregate across borrowers and over time.[20]

Potential savings from credit card deferrals. The first channel allowed individuals to cut in half the interest rate paid on their revolving credit card balances and to defer the minimum payment due. An individual opting into this deferral program would typically see her interest rate (APR) cut from 20.99% to 10.99%, generating significant potential savings. As an example, consider an individual with a $9,000 outstanding balance and a typical APR.[21] Over three months, the cost in accrued interest if rates were held constant would be $472. Deferral would lower the interest charge by $225, and the minimum payment (3% of outstanding balance) would be deferred for three months.[22]

To quantify the size of these potential savings, we consider the set of revolvers with *eligible balances* who could benefit from rate reductions.[23,24] Each observation carried a positive eligible balance in March 2020. We calculate the potential savings as interest cost savings on the outstanding eligible balances in March 2020 from a one-month rate reduction, assuming interest rates were reduced from 20.99% to 10.99%.

Aggregating across all credit card accounts, we estimate that the aggregate potential savings for Canadians from the one-month interest charge differential is $3.42 million in the 1% sample. Summing over the population and taking into account the fact that most

[20] Recall that deferred accounts were "frozen". We therefore do not see current outstanding balances during the deferral period—only before and after the deferral.

[21] For easy comparison, we use a $9,000 outstanding balance throughout our examples illustrating the calculations of potential savings. From Table 3, the outstanding balance of an average revolver is $8,920.

[22] See https://www.ratehub.ca/blog/credit-card-payment-deferrals-COVID-19/, accessed November 4, 2020, for a description of the rate reductions by banks. See Figure B.1 in the Appendix for a histogram of the rates offered by credit card companies between 2016 and 2019.

[23] We define eligible balances as revolving balances held by borrowers in *eligible* lenders offering rate reductions. We define eligible lenders as those having at least 0.5% of their credit card accounts in deferral in any month between March and September 2020. These criteria eliminate card issuers that do not offer deferral programs—for example, retail stores like Best Buy and Walmart and charge cards like American Express. The list of eligible lenders is consistent with the counterpart reported in regulatory data.

[24] Table A.3 in the Appendix shows the summary statistics of this sample.

of the lenders allow rate reductions for up to three months, the aggregate potential savings for the Canadian population from rate reductions in three months are \$1.03 billion.

Potential savings through mortgage deferrals. The second source of savings is indirect. Mortgagors were given the opportunity to pause their regular payments. This strategy only defers debt obligations for a few months: in fact, the debt burden increases during the deferral period, as missed interest payments accrue to the principal. Individuals can, however, use this option strategically: by stopping their payments on low-interest mortgages, they can reroute the extra liquidity towards high-interest-rate credit card balances. For example, consider a revolver carrying a \$9,000 balance and paying \$1,500 monthly towards her mortgage. Suppose that the interest rate for her credit card and mortgage are 20.99% and 2.99%, respectively.[25] If the borrower chooses to defer the mortgage payment by one month and apply the extra \$1,500 to her credit card balance, the one-month savings in interest cost would be \$21.25. The total savings from this debt-consolidation strategy depend on how long the borrower expects it to take to pay off the credit card balance. If we assume that without debt consolidation the borrower needs 18 months to pay off the entire balance of \$9,000, the total savings will be \$382.50 from a one-month mortgage deferral. If the borrower chooses a mortgage deferral period of six months, the total savings from debt consolidation are approximately \$2,295.

With the help of our data set, we can quantify the size of potential savings from deferring mortgage obligations at low interest rates in order to make additional payments on high-interest revolving credit card balances.[26] Specifically, we simplify the calculation by assuming a 20.99% credit card interest rate and a 2.99% mortgage interest rate. We then compute the interest cost savings in one month from the following debt-consolidation strategy: deferring one monthly mortgage payment and using the deferred amount to pay down the outstanding revolving balance in March 2020.

The monthly aggregate potential savings from this strategy are equal to approxi-

[25] Among revolvers who also own a mortgage, the average monthly mortgage payment is just over \$1,500. The average interest rate of the outstanding residential mortgage balances in months between January 2020 to March 2020 is 2.99%. See Statistics Canada Table 10-10-0006-01, https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1010000601.

[26] See Table A.4 for summary statistics for the set of revolvers with a mortgage.

mately \$0.31 million in our 1% sample. Since most lenders offer mortgage deferrals up to six months and borrowers normally pay off their revolving balances in no less than 18 months,[27] a conservative estimate of aggregate potential savings in interest costs amounts to \$3.35 billion ($100 \times 18 \times 6 \times \$0.31$ million).

Overall potential savings. Aggregating over the two debt-relief policies yields total potential savings of close to \$4.4 billion. This is a sizeable amount. Importantly, however, debt-relief programs are only effective at addressing short-term liquidity constraints if individuals choose to opt in. This is what we turn our attention to next.

4.2 Take-up rate of credit relief measures and actual savings

We have shown that the two government-backed programs provided the possibility of significant aggregate savings on credit card debt for Canadians. Yet, we documented in Section 3 that they were not particularly popular: the aggregate deferral rate for credit cards was 2.3%, and 15% for mortgages. Before exploiting the substantial heterogeneity across individuals that hides behind these aggregate statistics, we quantify the size of *actual* and *realized* savings in our sample.

To do so, we compute the savings obtained for each credit card that benefited from a reduced interest rate. Specifically, for each revolver's eligible credit card accounts in deferral, we calculate the interest cost savings from three-month rate reductions on the outstanding balance in March 2020. Aggregating across all revolvers, we obtain a total amount of actual savings of \$0.11 billion. This represents only a small fraction of the potential savings, which we previously valued at \$1.03 billion. For mortgage deferrals, we cannot determine the actual savings since we do not observe how borrowers use their deferred mortgage payments. Nevertheless, we can calculate an upper bound on the savings from mortgage deferrals, assuming that revolvers apply all of their deferred mortgage payments towards their credit card balances. In this case, the actual savings amount to \$0.97 billion while the potential savings are \$3.35 billion. Note, however, that from the

[27] In our data, less than one-third of revolvers are able to pay off their revolving balances in 18 months.

data we can see that 24.5% of revolvers with mortgage deferrals continued making some payments towards their mortgages (consistent with Cherry et al. (2021)). Therefore, in practice, actual savings are lower than the theoretical upper bound of $0.97 billion.

Overall actual savings. Aggregating over the two debt-relief policies yields total actual savings of close to $1.1 billion, or roughly 25% of total potential savings. In other words, borrowers "left on the table" at least 75% of the potential savings from the debt-relief programs offered to them during the pandemic.

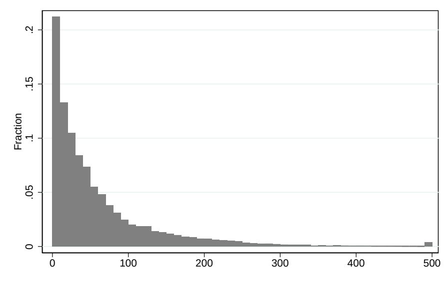
5 Heterogeneity in potential savings and take-up rates

The aggregate potential savings presented in Section 4 mask an important degree of heterogeneity across borrowers. This can been seen in Figure 4, which plots the overall distribution of monthly potential savings at the individual level from credit card rate reductions (top two panels) and from mortgage deferrals (bottom two panels). Looking at the potential savings from rate reductions, it is clear that most borrowers face relatively limited gains from enrollment: only about 25% of individuals have a potential savings greater than $80 per month. Even once we restrict our sample to individuals with potential savings in excess of $80 per month (panel (b)), we continue to see significant heterogeneity across individuals.

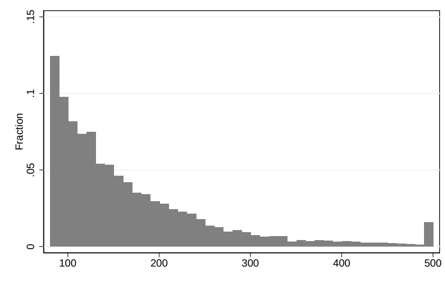
Next, we investigate the relationship between potential savings and enrollment. Table 5 shows take-up rates across the distribution of potential savings from either credit card (Panel A) or mortgage (Panel B) deferrals. Panel C isolates individuals with a past-due flag on their record. While enrollment in the credit card deferral program is between 4% and 6% for the lower half of the distribution (average potential savings between $2.23 and $30.09 per month), it reaches 19% in the top decile (potential savings of $254.92 on average). For the mortgage deferral program, the enrollment rate for revolvers ranges from 15% to 38%. There are two important takeaways from Table 5. First, deferrals increase with potential savings. Second, while higher, the deferral probability for those at the top of the potential savings distribution is still low.

Figure 4: Distribution of potential savings from credit cards and mortgage deferral

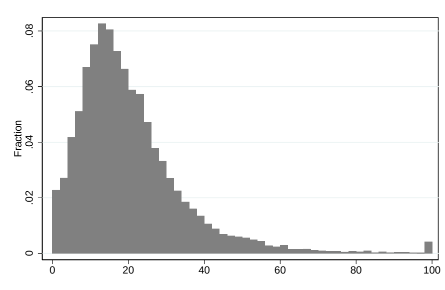
(a) CC - Potential Savings, all non-zero



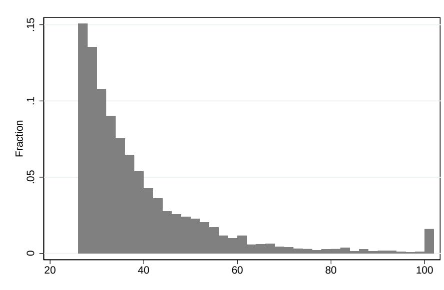
(b) CC - Potential Savings, > $80



(c) MTG - Potential Savings, all non-zero



(d) MTG - Potential Savings, > $25



Notes: 1. For each revolver with a positive eligible balance in March 2020, we calculate the one-month interest cost saving from a rate reduction of 10% on the balance. Borrowers with potential savings above $500 are lumped into the $500 bin. 2. For each revolver who holds a credit card and mortgage, we calculate the one-month interest cost saving from deferring one mortgage payment and paying down the revolving balance on the credit card. We assume that the interest rates for credit cards and mortgages are 20.99% and 2.99%, respectively. Borrowers with potential savings above $100 are lumped into the $100 bin.

Finally, we look at the deferral decisions of individuals who had past-due credit card accounts entering the pandemic. We would expect these borrowers to have a higher incentive to enroll since obtaining a credit card deferral meant the removal of past-due flags on an individual's account. A deferral therefore offered a "fresh-start", i.e., an additional incentive to defer relative to individuals with up-to-date accounts. Our results, reported in Panel C of Table 5, indicates that these borrowers were indeed about twice as likely to enroll in the credit card deferral program than their peers, with take-up rates between 7% and 38% as a function of potential savings.

The positive relationship between potential savings and take-up is a stylized fact that

Table 5: Take-up rates by potential savings

This table presents the deferral probability and average potential savings for ten deciles (DI) along the potential savings ($) distribution for (A) credit card deferrals, (B) mortgage deferrals, and (C) credit card deferrals amongst borrowers with past-due credit card accounts, respectively. The calculation of potential savings is explained in the note of Figure 4.

Panel A: Credit card deferral										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer CC)	0.04	0.04	0.05	0.06	0.06	0.07	0.08	0.11	0.13	0.19
Potential	2.22	6.80	12.69	20.39	30.09	41.92	57.81	81.09	124.96	254.92
Obs.	5420	5393	5404	5407	5404	5413	5402	5407	5406	5407

Panel B: Mortgage deferral										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer MTG)	0.15	0.17	0.19	0.23	0.23	0.24	0.26	0.26	0.32	0.38
Potential	3.69	8.13	11.05	13.59	16.07	18.89	22.14	26.08	32.36	53.64
Obs.	1500	1493	1501	1504	1502	1506	1495	1497	1502	1500

Panel C: Past-due revolvers' credit card deferral										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer CC)	0.07	0.11	0.12	0.13	0.10	0.18	0.15	0.24	0.23	0.38
Potential	2.47	6.81	12.39	20.33	29.92	41.89	57.63	81.26	123.10	257.84
Obs.	728	626	563	474	445	489	439	421	393	339

will guide us in identifying potential frictions that explain low overall enrollment. This relationship could, however, be driven by other factors. For example, individuals with high potential savings may be those most likely to be past due on their debt payments, since they carry high revolving balances. These borrowers also have a higher incentive to defer, for example to take advantage of the "fresh start" offered by deferrals. Similar intuition applies to other factors such as credit scores, income or unemployment risk. Based on a regression analysis, we therefore investigate whether the relationship between potential savings and enrollment is robust to the inclusion of other factors that could explain deferral decisions. The general specification of our cross-sectional regression is:

$$I(C_i) = \beta_0 + X_i'\Phi + \varepsilon_i, \tag{2}$$

where $I(C_i) \in \{I(rate)_i, I(defer)_i\}$, depending on the regression. $I(rate)_i = 1$ if individual i benefited from an interest-rate reduction between March 2020 and September 2020 on at least one of her credit cards, while $I(defer)_i = 1$ if the borrower i has applied for a mortgage payment deferral. The vector X_i includes individual-level as well as FSA-level explanatory variables. In some of the regressions, we allow for lender fixed effects to capture potentially (unobserved) supply-side determinants of debt relief.[28] Region fixed effects are also sometimes included—there is strong evidence of persistent regional effects in the levels of financial distress (c.f. Keys et al. (2020)).

Results from the estimation of equation (2) for enrollment in credit card and mortgage deferral programs are reported in Tables 6 and 7, respectively. Overall, we find that the positive relationship between enrollment and potential savings is robust to the inclusion of a host of controls, including lender or region fixed effects. In analyzing the regression results, we initially focus on borrower-level variables before discussing FSA-level factors.

The main takeaway is that the potential savings variable is both statistically and economically significant in all specifications. This is consistent with Table 5 which shows that individuals with higher potential savings from credit card deferrals enroll at higher rates. The coefficient estimates imply that a one standard deviation increase in potential saving from a rate reduction ($80.87) raises the probability of an individual deferring on at least one credit card by about 4.5 pps, depending on the specification. In addition, we find that a one standard deviation increase in potential saving ($15.44) increases the probability of a mortgage deferral by more than 3 pps.

Our results also indicate that credit history matters for enrollment, with individuals with higher credit scores less likely to defer. The differences are economically large. For example, according to our estimates, a borrower with a credit score above 800 is about 4 pps less likely to defer on a credit card than an individual with a credit score between 620 and 710, all else being equal. For mortgage deferrals, this difference is about 13 pps. We also find that age is negatively correlated with credit card deferrals, with borrowers above

[28]For example, Cherry et al. (2021) document lower deferral rates among shadow banks relative to traditional banks. Since we have the identities of each lender we are able to control for lender-specific fixed effects. For borrowers with multiple credit cards from different banks, we define the main lender as the one offering the highest potential savings from a rate reduction or mortgage deferral. Although most lenders provide details of their programs, not all do. For example, Vancity lowered the interest rate to zero on all credit card deferrals: the potential savings for their customers, therefore, are higher than what we capture by assuming rates are cut to 10.99%. Unfortunately we do not observe this level of detail for all lenders. The fixed effect therefore captures systematic variations in take-up rates across lenders.

65 least likely to enroll in the program. The effect is less significant, both statistically and economically, for mortgage deferral decisions.

Not surprisingly, given that a deferral removes past-due flags on an individual's account, we find that borrowers with credit card accounts that were past due in the three months prior to the onset of the pandemic were between 4.2 and 4.6 pps more likely to defer on a credit card. In addition, a higher number of credit cards tends to be associated with a higher probability of deferral on *at least* one credit card. In terms of other credit products, our results indicate that total debt and debt obligations are positively related with the decision to defer on a mortgage during the pandemic, but not credit cards. Given that most household debt is composed of mortgages, the individuals most likely to defer their payments are those with higher balances, all else being equal. In addition, we document that borrowers who also have a student loan are about 2.5 pps more likely to defer on a credit card than their peers, a finding that we exploit in the next section.

Next, we turn our attention to factors measured at the FSA level. Tables 6 and 7 suggest that the number of CERB applicants is positively related to take-up of deferral programs: the coefficients on this variable are always significant at the 1% level and positive, indicating that locations that experienced more applications to the income-replacement program saw higher take-up rates on average. The effect is also economically significant. For instance, compare an FSA with a fraction of CERB applicants equal to 20% to another at 30%. According to our estimates in Table 6, this is associated with a 1.1 to 1.5 pp higher take-up rate for credit card deferral in the hardest-hit FSA, all else being equal (unconditional average of 8%). For mortgages deferrals, the impact is twice as high, ranging from 2.2 to 2.7 pps (unconditional average of 24%).

Our employment-change variable is generally not statistically significant, a sign that the CERB variable is a better proxy of income loss. Lastly, we find that the average level of education at the FSA level is positively related to enrollment in the credit card debt-relief program, but not mortgage deferrals. In addition, total income is statistically significant at the 5% level in only one specification, and the amount of tax-free savings (TFSA) is never significant once we include region fixed effects.

Table 6: Linear probability regression for credit card deferral

This table presents estimation results from equation 2. The dependent variable $I(rate)_i$ equals 1 if the borrower deferred at least one credit card. There are 54,046 observations. CS is credit score, and the omitted category is credit scores less than 620. A region is defined by the first digit of a borrower's postal code. Quebec and Ontario are split into three and five regions, respectively. Each of the other provinces has only one region. The omitted age category is under 35. We do not report the coefficient on I(personal loans) since it is insignificant in all credit card and mortgage specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at FSA level.

	(1)	(2)	(3)	(4)	(5)
Potential saving ($1,000)	0.58***	0.59***	0.47***	0.58***	0.47***
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)
CS 620-710	-0.036***	-0.037***	-0.039***	-0.037***	-0.039***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
CS 710-800	-0.063***	-0.063***	-0.069***	-0.063***	-0.069***
	(0.0038)	(0.0038)	(0.0039)	(0.0038)	(0.0039)
CS 800+	-0.078***	-0.078***	-0.086***	-0.078***	-0.086***
	(0.0040)	(0.0040)	(0.0041)	(0.0040)	(0.0041)
Age 35-50	-0.011***	-0.010**	-0.00019	-0.010**	-0.00013
	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0033)
Age 50-65	-0.022***	-0.020***	-0.0098**	-0.020***	-0.0094**
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Age 65+	-0.038***	-0.035***	-0.029***	-0.035***	-0.028***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Past-due	0.046***	0.045***	0.042***	0.045***	0.042***
	(0.0055)	(0.0055)	(0.0053)	(0.0055)	(0.0053)
No. of cards	0.0099***	0.0092***	0.010***	0.0091***	0.010***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Log total debt	0.0014	0.0015	-0.0029*	0.0015	-0.0026
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Log total obligation	-0.0023	-0.0017	0.0029*	-0.0015	0.0028*
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0014)
I(student loan)	0.024***	0.024***	0.023***	0.024***	0.025***
	(0.0054)	(0.0054)	(0.0053)	(0.0055)	(0.0053)
I(line of credit)	0.014***	0.013***	0.0039	0.013***	0.0043
	(0.0033)	(0.0034)	(0.0033)	(0.0034)	(0.0033)
I(mortgage)	0.0041	0.0041	0.0043	0.0047	0.0046
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Log FSA income		-0.0100	-0.0091	-0.014	-0.013
		(0.0080)	(0.0079)	(0.0099)	(0.0096)
Log FSA invest income		0.00057	0.00058	0.0021	0.0022
		(0.0029)	(0.0029)	(0.0034)	(0.0034)
Log FSA TFSA saving		0.0066	0.0081	0.0049	0.0056
		(0.0060)	(0.0059)	(0.0072)	(0.0069)
FSA education (%)		0.00029*	0.00023	0.00031	0.00023
		(0.00014)	(0.00013)	(0.00016)	(0.00015)
FSA employment change		-0.0020	-0.085*	-0.11	-0.095
		(0.042)	(0.041)	(0.099)	(0.096)
Fraction of CERB applicants		0.15***	0.13***	0.12***	0.11***
		(0.021)	(0.020)	(0.026)	(0.025)
Constant	0.072***	0.068	0.027	0.11	0.071
	(0.0089)	(0.095)	(0.093)	(0.12)	(0.12)
Lender FE	N	N	Y	N	Y
Region FE	N	N	N	Y	Y
Adjusted R-squared	0.053	0.055	0.078	0.055	0.079

Table 7: Linear probability regression for mortgage deferral

This table presents estimation results from equation 2. The dependent variable $I(defer)_i$ equals 1 if the borrower deferred at least one mortgage. There are 14,999 observations. CS is credit score, and the omitted category is credit scores less than 620. A region is defined by the first digit of a borrower's postal code. Quebec and Ontario are split into three and five regions, respectively. Each of the other provinces has only one region. The omitted age category is under 35. We do not report the coefficient on I(personal loans) since it is insignificant in all credit card and mortgage specifications. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at FSA level.

	(1)	(2)	(3)	(4)	(5)
Potential saving ($1,000)	2.08***	2.05***	2.09***	2.13***	2.15***
	(0.34)	(0.34)	(0.35)	(0.33)	(0.34)
CS 620-710	-0.059***	-0.057***	-0.057***	-0.056***	-0.056***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
CS 710-800	-0.14***	-0.14***	-0.14***	-0.14***	-0.14***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
CS 800+	-0.19***	-0.19***	-0.20***	-0.19***	-0.19***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age 35-50	0.023	0.023*	0.024	0.024*	0.024*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age 50-65	-0.0098	-0.0067	-0.0069	-0.0044	-0.0050
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age 65+	-0.037*	-0.032*	-0.029*	-0.029*	-0.027
	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)
Past-due	-0.0043	-0.0058	-0.0057	-0.0065	-0.0065
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
No. of mortgages	-0.015*	-0.013	-0.016*	-0.013	-0.015*
	(0.0072)	(0.0073)	(0.0072)	(0.0073)	(0.0072)
Log total debt	0.037***	0.031**	0.035***	0.031**	0.032**
	(0.0098)	(0.010)	(0.010)	(0.010)	(0.011)
Log total obligation	0.039***	0.039***	0.039***	0.039***	0.039***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
I(student loan)	0.011	0.017	0.019	0.014	0.017
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
I(line of credit)	-0.039***	-0.035***	-0.037***	-0.035***	-0.038***
	(0.0081)	(0.0081)	(0.0083)	(0.0081)	(0.0082)
Log FSA income		0.067*	0.055	-0.024	-0.022
		(0.029)	(0.029)	(0.033)	(0.034)
Log FSA invest income		0.015	0.014	-0.0043	-0.0084
		(0.010)	(0.010)	(0.011)	(0.011)
Log FSA TFSA saving		-0.059**	-0.048*	-0.0080	-0.0011
		(0.019)	(0.019)	(0.023)	(0.023)
FSA education (%)		-0.00014	-0.00016	0.00052	0.00060
		(0.00044)	(0.00044)	(0.00050)	(0.00051)
FSA employment change		-0.68***	-0.69***	-0.40	-0.42
		(0.13)	(0.14)	(0.29)	(0.30)
Fraction of CERB applicants		0.27***	0.27***	0.22**	0.23**
		(0.068)	(0.069)	(0.082)	(0.082)
Constant	-0.43***	-0.89**	-0.97**	-0.19	-0.36
	(0.091)	(0.33)	(0.34)	(0.41)	(0.42)
Lender FE	N	N	Y	N	Y
Region FE	N	N	N	Y	Y
Adjusted R-squared	0.066	0.073	0.086	0.077	0.090

6 Impediments to enrollment

In the previous section, we documented important heterogeneity in potential savings across individuals. We also found that those who stood to gain more deferred in larger numbers, a relationship robust to the inclusion of various controls. However, even at the highest levels of potential savings, enrollment was low. In this section, we investigate a number of possible impediments to enrollment that are consistent with these findings and attempt to quantify their relative importance.

Note that for the rest of our analysis, the focus is on credit card deferrals. This program, which provided more direct savings through lower interest rates, allows us to perform a more precise analysis and gives us the opportunity to quantify the relative importance of various potential frictions.

6.1 Potential explanations

We start by ruling out a variety of supply-side factors that could have played a role. For instance, one concern might be that the low take-up rate is in fact caused by banks' refusal to approve credit relief for a significant portion of their customers. Agarwal et al. (2011) and Agarwal et al. (2017) show the important role that securitization and loan-servicing played in limiting the supply of credit and hence the effectiveness of the U.S. mortgage refinancing program, HAMP. While in theory banks could deny requests for deferral, in practice this happened only in rare instances. Given the extent of political intervention and the reputational risk that refusals may have entailed for financial institutions, mortgage and credit card deferral requests were nearly universally accepted with overall denial rates for each product below 3%. Furthermore, requesting a deferral did not involve any monetary costs—this factor therefore cannot explain the low take-up rates, the way it may rationalize limited refinancing (see, for instance, Defusco and Mondragon (2020)). Lastly, we should point out that it is very unlikely the reason revolvers did not defer their credit cards was because they had somehow paid off their credit card debt: less than 10% of revolvers became convenience users within four months of March 2020.

Next, we turn our attention to two broad alternative explanations. These impediments to enrollment meet two conditions that need to be satisfied in order to be consistent with the evidence presented so far. They should (i) not be proportional to potential savings, and (ii) be large enough to rationalize low enrollment.

Information frictions. First, it is conceivable that a significant portion of Canadians were not aware of the existence of these programs or that they were eligible, let alone the potential savings from enrolling. This was particularly true of the credit card deferral program, which was not as well publicized as mortgage deferrals. The suggestive evidence in Figure A.1 using Google Trends appears to confirm this disparity.

Limited publicity alone could rationalize low overall take-up rates. Information frictions, however, could also explain the positive relationship between potential savings and take-up rate. Under the theory of rational inattention, limited time and/or cognitive ability implies that economic agents devote most of their attention to factors that matter most to them. In this context, we would expect borrowers with very large credit card balances to be more likely to be informed (or to seek information) about opportunities to lower their interest charges.

Non-monetary fixed costs. With the exception of student loans, Canadians had to opt into all debt-relief programs. Enrollment required the holder to formally request support from their financial institution. Doing so may have involved real or perceived non-monetary fixed costs. In particular, there may have been a time or hassle cost associated with enrollment. The media reported long wait-times linked to the process of contacting financial institutions to request a deferral.[29]

Individuals may also have perceived there to be future hassle costs associated with repairing their credit profile (due to potential reputational effects). Borrowers might have been concerned that a deferral would leave a blemish on their credit history, possibly affecting their ability to borrow in the future. Horvath et al. (2020) document that in the United States, many credit card holders, especially riskier borrowers, had their credit restricted during the pandemic. Hence, it might have been ex ante rational for individuals

[29]See https://www.ratehub.ca/blog/COVID-19-and-your-mortgage/.

to be reluctant to defer for fear of damaging their credit score or seeing their credit limits impacted.

Non-monetary fixed costs such as hassle or reputational costs are arguably independent of the size of potential savings, and therefore could rationalize our finding that take-up rates are positively correlated with the size of potential savings, which capture the benefits from deferral. In other words, borrowers who would benefit most from enrollment were more willing to put up with the fixed costs of requesting it.

6.2 Quantifying the role of enrollment frictions

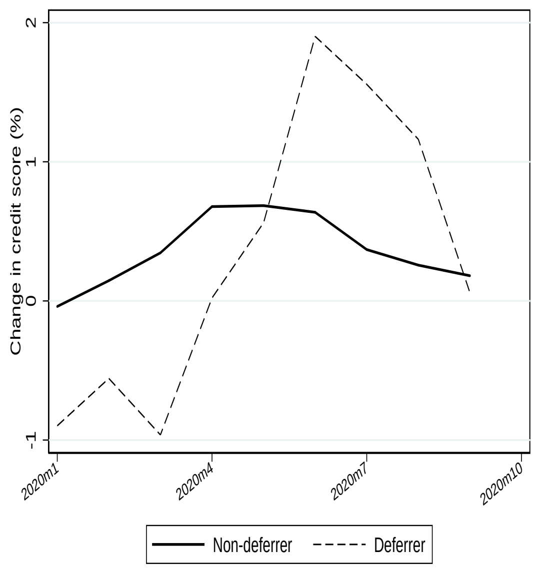
In this section, we present empirical evidence that confirms the role played by each of these frictions and allows us to quantify their relative importance.

Evidence from the actual evolution of credit scores/limits. We start by examining whether deferrals had an impact on credit limits and scores. The objective is to see whether it was rational ex post for borrowers to be concerned that enrollment could carry with it a reputational effect, possibly limiting their ability to access credit in the future. Our findings suggest that this was not the case. First, banks were explicitly prohibited from allowing the deferral decision to influence credit histories, and the two credit agencies (Equifax© and TransUnion©) collaborated to ensure that deferrals did not impact credit scores. Second, we look at the evolution of credit scores. Figure 5 shows that prior to COVID-19, average credit scores were falling for both deferrers and non-deferrers in our sample. Credit scores increase throughout the spring and summer, then continue increasing, albeit at a slower rate, in the fall of 2020. The larger variation in the change in scores for deferrers is due to entry and exit of individuals. Specifically, deferrers in Figure 5 are individuals who deferred between March and August and resumed payments in or before September. While credit scores are supposed to be held constant during the deferral period, they can start to change again post-deferral. Since people are entering and exiting at different times, the average score is a mix of people in and out of deferral.

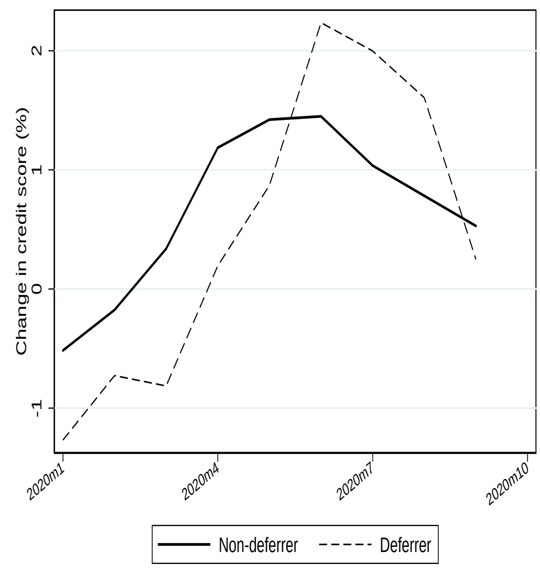
Even if their credit scores were not affected, individuals may still have been concerned

Figure 5: Credit scores in TransUnion©

This figure uses individual-level data from TransUnion© to construct quarter-over-quarter changes in individual credit scores. We drop borrowers who are still on deferral in September 2020 since their credit scores are not updated. In addition, this figure focuses on the scores of borrowers with no opened or closed accounts during 2020m1-2020m9. Panel (a) compares individuals with a deferral flag at some point in the sample to those who never have a deferral flag. Panel (b) shows the comparison among revolving credit card users.



(a) All Credit Card Users



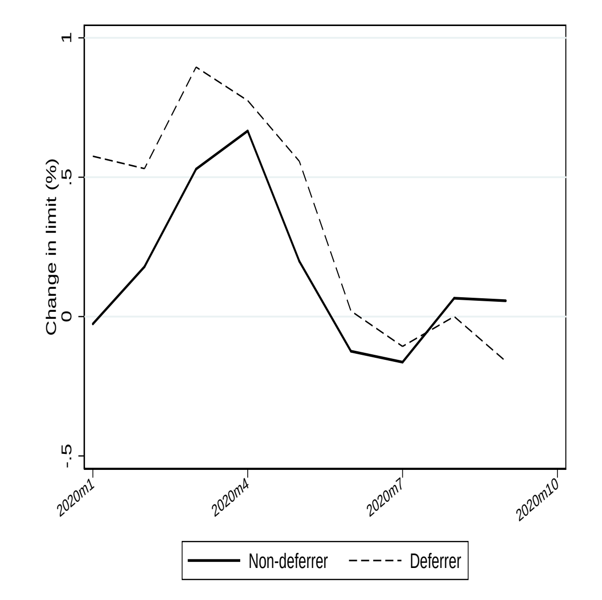
(b) Revolving Credit Card Users

that banks would lower their credit card limits. Fulford (2015) presents evidence of substantial variability in credit limits in the U.S. and argues that this can help explain why a substantial fraction of Americans simultaneously hold high-interest debt and low-interest savings. Horvath et al. (2020) show that in the U.S. many credit card holders, especially riskier borrowers, had their credit restricted during the pandemic.

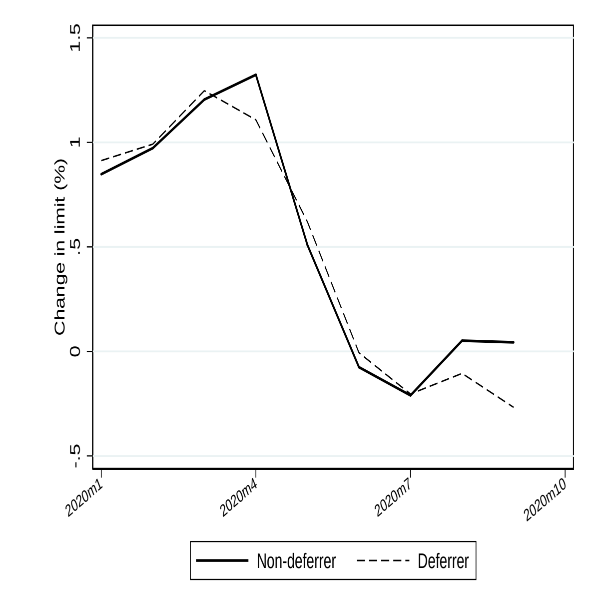
In the Canadian context, we find that credit limits were indeed lowered during the pandemic period. However, as is shown in Figure 6, the decline is (i) small at less than 1%, and (ii) broad-based, with no evidence that it was more acute for borrowers who deferred. Moreover, since we focus on limit changes of existing accounts, the credit limit decrease was not driven by lower limits on new credit cards or account closures. The number of new products fell sharply at the time (see Figure B.1, panel (c), in the Appendix). In any

Figure 6: Credit card limits in TransUnion©

This figure uses individual-level data from TransUnion© to construct quarter-over-quarter changes in the maximum allowable credit summed across all cards. We dropped borrowers who are still on deferral in September 2020 since their limits are not updated. In addition, this figure focuses on the limit change of borrowers' existing accounts—we dropped borrowers who opened or closed accounts during 2020m1-2020m9. Panel (a) compares individuals with a deferral flag at some point in the sample to those who never have a deferral flag. Panel (b) shows the comparison among revolving credit card users.



(a) All Credit Card Users



(b) Revolving Credit Card Users

given year, approximately 10% of credit card accounts are closed. The majority (60%) are closed at the request of customers, with the remainder being "cancelled", which is a catch-all term that mostly captures bank-initiated cancellations. See Table A.2 in the Appendix.[30]

In summary, we do not find convincing evidence that banks directly or indirectly limited access to debt-relief programs or "punished" customers for enrolling. That being said, our analysis is naturally limited to the *actual* impact on credit access: we cannot rule out that borrowers decided not to defer due a *perceived* possibility of reputation harm associated with the decision, or that they were unaware of the true impact from these

[30]Bank-initiated closures are tied to accounts being past due. In our regression analysis below we control for accounts that are past due.

programs on their credit scores. This explanation would in principle be compatible with the heterogeneity documented in Table 5: only those with the largest potential savings would be willing to suffer the perceived reputation cost of deferral.

Evidence from holders of student loans. According to the information friction explanation, borrowers may simply not have been aware of the existence or characteristics of these programs, or believed that they would not qualify. To investigate this possibility, we analyze the deferral decisions of a population that should have been better informed about the existence of debt-relief programs. Specifically, we consider the credit card deferral decisions of individuals who also had student loans, since student loans were automatically deferred: loan holders were notified by the government that their payments would be frozen unless they opted to continue paying. Given this policy, it is reasonable to assume that individuals with student loans were more aware than the general public about deferral programs.

Table 8 reports deferral rates along deciles of the potential savings distribution only for individuals with student loans. This distribution is very similar to the one for the broader sample presented earlier in Table 5, except for a lower average in the top decile. Take-up rates, on the other hand, are generally higher for student loan holders, ranging from 4% to 26%, compared to 4% to 19% for the overall sample of revolvers. Overall, these findings suggest that awareness mattered for take-up: the information provided to student loan holders through automatic deferral led to a higher enrollment probability. Nonetheless, even in this more informed population, take-up rates remained low across the board.

Evidence from holders of multiple cards. Another set of individuals who should be program-aware are those who have multiple cards and have deferred on at least one. In other words, when thinking about the account-level deferral decision, an individual that has deferred on one account is clearly aware of the program when making the decision to defer or not on another. Hence, we focus on the 11,437 revolvers in our sample who had multiple cards eligible for rate reduction programs. Of these, only 359 deferred all eligible cards; 1,300 deferred some but not all cards; and the remainder chose not to defer any.

Table 8: Take-up rate by potential savings—student loan holders

Focusing on individuals with a student loan, this table presents the deferral probability, potential savings, and actual savings for ten deciles (DI) along the potential savings distribution.

	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer CC)	0.04	0.08	0.07	0.10	0.07	0.13	0.14	0.14	0.16	0.26
Potential	2.28	6.70	12.65	20.35	29.70	41.79	57.65	81.34	124.24	226.61
Actual	0.12	0.38	0.82	1.81	1.68	4.53	6.64	10.19	17.18	50.23
Obs	436	453	501	501	514	476	445	455	388	265

Table 9: Revolvers' deferred and non-deferred credit cards

This table presents the potential savings (PS) and utilization rates for two types of credit card accounts—those with a deferral flag and those without—held by multiple-card holders who defer on some but not all of their accounts. The variable I(big 7) is the fraction of accounts issued by one of the largest seven credit card lenders. The seven largest credit card issuers are: Bank of Montreal, Bank of Nova Scotia, Canadian Imperial Bank of Commerce, National Bank of Canada, Royal Bank of Canada, Toronto Dominion Bank, and Caisse Desjardins. The variable I(same lender) is the fraction of non-deferral accounts with the same bank as one of the deferral accounts. For each borrower who has non-deferred cards issued by rival lenders, lenders that are different from the issuing banks of the deferred cards, we also infer the bounds of their fixed cost from the potential savings in deferred and non-deferred accounts.

	count	mean	sd	p5	p25	p50	p75	p95
				Deferral				
Potential savings	1300	86.48	77.44	5.26	27.81	63.13	124.01	248.16
Utilization (%)	1300	85.31	22.70	29.71	79.02	96.76	100.00	100.00
I(big 7)	1300	0.87	0.32	0.00	1.00	1.00	1.00	1.00
				Non-deferral				
Potential savings	1300	50.85	50.73	3.81	16.06	36.68	67.21	153.38
Utilization (%)	1300	80.93	25.55	21.39	72.12	93.10	99.10	100.00
I(big 7)	1300	0.51	0.47	0.00	0.00	0.50	1.00	1.00
I(same lender)	1300	0.11	0.29	0.00	0.00	0.00	0.00	1.00
PS - same lender	177	66.80	72.39	6.13	19.75	41.19	83.99	244.12
PS - rival lenders	1190	48.70	47.85	3.67	15.36	35.32	66.17	148.13
				Fixed cost bounds				
Lower bound	856	114.39	118.58	7.70	32.45	78.60	151.24	340.90
Upper bound	856	312.16	245.85	31.83	126.03	243.73	444.86	824.40

Our analysis focuses mainly on the 1,300 individuals who deferred on some but not all of their cards. We start by addressing a potential concern: that the reason some borrowers defer on only a subset of their cards is that the non-deferred cards are secondary accounts with low potential savings. To investigate this possibility, Table 9 compares the potential savings on deferred versus non-deferred accounts for the 1,300 credit card revolvers. We see that the average potential savings on a deferred account is $86 whereas it is $51 for a non-deferred account. In other words, while potential savings are lower for these accounts, they are non-negligible.

Table 10: Account-level take-up rate by potential savings

This table presents the potential and actual savings for ten deciles (DI) along the potential savings distribution. The statistics are at the account level. Panel A is all eligible credit card accounts. Panel B are accounts whose owners have deferrals at the same bank. Panel C are accounts whose owners have deferrals at rival banks.

Panel A: All eligible credit card accounts										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer)	0.03	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.12	0.15
Potential	2.16	6.51	11.61	18.44	26.51	36.72	47.95	65.88	96.31	184.89
Actual	0.07	0.26	0.50	0.91	1.31	2.21	3.39	5.01	11.36	29.68
Observations	6894	6875	6887	6883	6877	6884	6893	6885	6887	6884

Panel B: Accounts whose owners have deferrals at the same bank										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer)	0.80	0.58	0.72	0.69	0.68	0.69	0.75	0.80	0.77	0.82
Potential	1.92	6.98	12.00	18.86	26.44	36.97	46.62	66.07	96.84	198.43
Actual	1.55	3.98	8.53	13.05	18.11	25.00	34.85	52.63	75.37	160.65
Observations	25	50	36	68	44	87	67	84	110	159

Panel C: Accounts whose owners have deferrals at rival banks										
	DI1	DI2	DI3	DI4	DI5	DI6	DI7	DI8	DI9	DI10
I(defer)	0.05	0.12	0.14	0.23	0.22	0.28	0.29	0.31	0.49	0.60
Potential	2.48	6.71	11.69	18.29	26.56	36.71	47.66	66.50	96.59	195.24
Actual	0.13	0.78	1.55	4.20	5.85	10.22	13.67	20.55	47.29	119.97
Observations	117	170	186	178	230	269	220	283	339	344

Since multiple-card holders were aware of the program, information frictions cannot explain their decision to defer on some but not all their cards. Therefore, the most probable explanation is real or perceived fixed non-monetary costs. To get a sense of the relative importance of information frictions and fixed costs, we proceed to an account-level analysis. First, Panel A of Table 10 is the equivalent of Table 5 at the account instead of individual level. The takeaways are the same at the two levels of aggregation: take-up rates are low overall but are increasing in the level of potential savings.

Second, we look separately at the extent to which multiple credit card accounts from the same bank or from rival banks are deferred. Statistics are presented in panels B and C of Table 10. We consider all of the eligible credit cards owned by the 1,659 individuals in our sample that defer on at least one card. More specifically, for each credit card account, we observe whether the card holder has a deferred card from the same bank or from a rival bank.

Panel B focuses on credit card accounts whose owners have deferred at the same bank. Since they defer, they must be aware of the program. Moreover, the fixed cost of deferring at a particular bank, given that the borrower has already deferred on another card from the same bank, should be very low. Consistent with this intuition, we see that take-up rates are at least 58% in every decile potential savings distribution, with most being over 70%. Our findings, therefore, suggest that with no information friction and no fixed cost, the deferral probability is very high regardless of potential saving levels. This supports our initial decision to focus on these two frictions.[31]

Next, Panel C focuses on cards whose owners have deferred at a different bank. Again there is no information friction, since the borrower is sufficiently aware of the program to defer on at least one card. In this case, however, deferral at the different bank would involve an additional fixed cost. Consistent with the presence of fixed costs, we find the typical pattern first observed in Table 5: take-up is low overall, and the deferral probability is positively correlated with potential savings.

By comparing Panel C with the unconditional deferral probability shown in Panel

[31]A comment is in order about the fact that deferral is not equal to 100% for this sample. This can be explained by three factors. First, although the fixed costs of deferring a second card at the same bank would have been much lower, they may not be zero. Second, there may have been concern about one's reputation from deferring multiple cards at the same bank. Finally, it is possible that individuals deferred on high-rate cards, while additional cards had lower rates. The last explanation seems unlikely since there were relatively few low-rate cards available. Panels (a) and (b) of Figure B.1 in the Appendix shows that there are very few low-rate cards in the market.

A, we can estimate the fraction of uninformed borrowers. The unconditional deferral probability can be expressed as follows:

$$\begin{aligned}\Pr(\text{defer}) &= \Pr(\text{defer}|\text{informed})\Pr(\text{informed}) + \Pr(\text{defer}|\text{uninformed})\Pr(\text{uninformed}) \\ &= \Pr(\text{defer}|\text{informed})\Pr(\text{informed}). \end{aligned} \tag{3}$$

The second equality follows because $\Pr(\text{defer}|\text{uninformed}) = 0$. Irrespective of potential savings, Panels C and A of Table 10 show that $\Pr(\text{defer}|\text{informed}) = 32\%$ and $\Pr(\text{defer}) = 7\%$, respectively. Therefore, an estimate of $\Pr(\text{informed})$ would be 7/32, which is about 22%.[32] In other words, about 78% of the borrowers are either unaware of the deferral program or too concerned about the potential reputation effects. At higher potential saving levels, the estimated probability of being informed is slightly higher, close to 25%.

Furthermore, we can estimate the distribution of fixed costs using a sub-sample of borrowers who have non-deferred credit cards issued by banks different from the issuers of their deferred cards. These people had to be aware of the possibility of deferral yet did not want to pay the fixed cost of deferring a rival-bank account. We denote borrower i's fixed cost C_i. We can infer the lower bound $\underline{c}_i$ and upper bound $\bar{c}_i$ from the potential savings of their deferred and non-deferred accounts. For example, consider a borrower i who deferred a card issued by bank A, for which the one-month potential savings from a rate reduction is \$100. Suppose further that the same borrower did not defer cards issued by banks B and C, for which the one-month potential savings are \$80 and \$50, respectively. In this case, given the potential savings from a three-month rate reduction, the fixed cost upper bound is $\bar{c}_i = \$100 \times 3 = \$300$ and the lower bound is $\underline{c}_i = \$80 \times 3 = \$240$. Otherwise, we should have observed different deferral decisions.

Table 9 shows the inferred lower and upper bounds of fixed costs.[33] Since we do not

[32] Equation 3 implicitly assumes that, conditional on being informed, the deferral of each card is independent of other cards. This is not the case if the other cards owned by the card holder are issued from the same bank. As a robustness check, we exclude borrowers holding multiple cards from a same bank in the calculation. The estimated Pr(informed) is 20%.

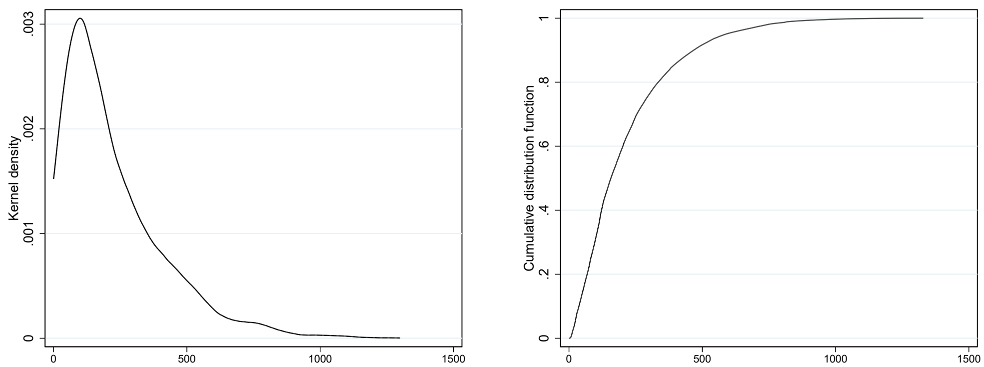
[33] There are 1,190 borrowers with non-deferred cards from rival banks. However, for 28% of them, the potential savings from non-deferred cards are greater than those from deferred cards. One possibility is that these non-deferred cards carry low rates to start with and hence cannot benefit from the rate reduction programs. We dropped such borrowers since we cannot obtain an effective lower bound of

observe individual-level fixed costs, in order to approximate the fixed cost distribution we make the following simplifying assumption: $C_i \sim U[\underline{c}_i, \bar{c}_i]$. The cumulative distribution function of the fixed cost is then approximated by the following:

$$\Pr(C \leq c) = \frac{\sum_{i=1}^{856} I(\bar{c}_i \leq c) + \sum_{i=1}^{856} I(\underline{c}_i \leq c \leq \bar{c}_i) Prob(C_i \leq c)}{856}. \tag{4}$$

Figure 7 displays the approximated fixed cost distribution. The mean is \$213.75 and the median is \$157.18. The 5th and 95th percentiles are \$22.84 and \$587.43, respectively.

Figure 7: Approximated distribution of fixed costs



Takeaway. Our analysis of the credit card deferral programs has confirmed the importance of information frictions and fixed non-monetary costs of enrollment for explaining the low take-up of the program. Our calculations suggest that 80% of individuals were not aware of the program or how to access it, and that even for those who were informed, many faced significant non-monetary fixed costs that prevented them from enrolling.

6.3 Evidence from account-level regressions

While our previous exercises allowed us to quantify the importance of the two types of frictions, they do not account for the role of possible confounding factors. We use a

their fixed costs. This yields a sample of 856 borrowers. For borrowers holding multiple deferred or non-deferred cards, we use the least upper bound inferred from deferred cards and the greatest lower bound inferred from non-deferred cards.

regression analysis to show that the results are robust to the inclusion of a variety of fixed effects and controls.

Table 11 presents results from regressions with specifications broadly similar to those discussed in Section 5 and that include a similar set of controls. An important distinction, however, is that the analysis is now performed at the *account* instead of the *borrower* level. We therefore cluster standard errors at the borrower level.

The results of interest for this section can be found in the first two lines of Table 11. The variable I(same-bank) is an indicator equal to 1 if the credit card owner has a deferred card at the same bank, 0 otherwise. The positive and significant coefficients across all specifications confirm our earlier finding: borrowers are more likely to defer payments on a specific credit card if they already have a deferred card at the same bank. This is sensible: these individuals are not only by definition informed about the deferral program, but they have also already "paid" the non-monetary cost associated with deferral, such as time spent on the phone with their bank.

The other variable of interest, I(rival-bank), is equal to 1 if the credit card owner has a deferred card at a *rival* bank, 0 otherwise. While the coefficients on this variable are again positive and statistically significant at the 0.1% level across all regressions, they are smaller in size. This is consistent with the intuition developed in the previous section: while these borrowers are aware of the debt-relief program, they are less willing to pay the additional non-monetary fixed costs associated with deferring at a different bank. In other words, one of the two frictions remains potent. As a result, they are less likely to defer than the same-bank individuals.

Table 11: Linear probability regression for account-level credit card deferral

The dependent variable is the binary decision to defer a credit card. There are 68,829 observations. PS is potential savings. I(same-bank) and I(rival-bank) are indicator variables equal to 1 if the card owner owns a deferred card at the same bank or at some rival bank, respectively. CS is credit score, and the omitted category is scores under 620. A region is defined by the first digit of a borrower's postal code. Quebec and Ontario are split into three and five regions, respectively. Each of the other provinces has only one region. The omitted age category is under 35. We do not report the coefficient on I(personal loans) since it is insignificant. We do not report the FSA-level coefficients due to space constraints. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at borrower level.

	(1)	(2)	(3)	(4)	(5)
I(same-bank)	0.64***	0.64***	0.60***	0.64***	0.60***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
I(rival-bank)	0.22***	0.22***	0.23***	0.22***	0.23***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Potential savings ($1,000)	0.63***	0.64***	0.48***	0.63***	0.48***
	(0.024)	(0.024)	(0.025)	(0.024)	(0.025)
CS 620-710	-0.026***	-0.027***	-0.027***	-0.026***	-0.027***
	(0.0029)	(0.0029)	(0.0028)	(0.0029)	(0.0028)
CS 710-800	-0.045***	-0.045***	-0.047***	-0.044***	-0.048***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
CS 800+	-0.055***	-0.054***	-0.060***	-0.054***	-0.060***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Age 35-50	-0.0099***	-0.0092***	0.00046	-0.0092***	0.00047
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Age 50-65	-0.017***	-0.016***	-0.0064*	-0.016***	-0.0062*
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Age 65+	-0.027***	-0.025***	-0.018***	-0.024***	-0.018***
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Past-due	0.037***	0.037***	0.037***	0.037***	0.037***
	(0.0054)	(0.0054)	(0.0052)	(0.0054)	(0.0052)
No. of Cards	-0.0032**	-0.0037***	-0.0034***	-0.0038***	-0.0033***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Log total debt	0.0018	0.0017	-0.0022*	0.0016	-0.0020
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Log total obligation	-0.0043***	-0.0037**	0.00077	-0.0034**	0.00070
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
I(student loan)	0.018***	0.017***	0.016***	0.017***	0.017***
	(0.0039)	(0.0040)	(0.0039)	(0.0040)	(0.0039)
I(line of credit)	0.0089***	0.0084***	-0.00011	0.0083***	0.00014
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
I(mortgage)	0.0021	0.0022	0.0019	0.0027	0.0022
	(0.0026)	(0.0026)	(0.0026)	(0.0027)	(0.0026)
Constant	0.076***	0.098	0.058	0.10	0.073
	(0.0074)	(0.074)	(0.074)	(0.096)	(0.095)
Lender FE	N	N	Y	N	Y
Region FE	N	N	N	Y	Y
FSA characteristics	N	Y	Y	Y	Y
Adjusted R-squared	0.13	0.13	0.16	0.13	0.16

7 Conclusion

The economic response to COVID-19 was quick and broad. In this paper we focus on two debt-relief programs: credit card and mortgage deferrals. Using individual-level credit account data, we document that despite substantial potential savings from deferring and optimizing their debt portfolio, the majority of Canadian credit card revolvers did not enroll in the programs. We calculate that despite the potential to save approximately $4 billion in interest over six months, only 7% of credit card revolvers chose to defer, while 24% deferred on their mortgage. Actual savings were therefore about 11% of potential. Together, the considerable potential savings and low take-up rates suggest that Canadians left significant money on the table.

After ruling out supply-side reasons, we focus on potential demand-side reasons to explain the low take-up rates. We find that the majority of Canadians were either unaware of their ability to re-optimize their debt during the pandemic or faced too high a non-monetary cost of applying. The size of these fixed (hassle) costs are consistent with results in other credit markets. Our findings suggest that if debt-deferral programs are to be effective during a crisis, then they need to be visible and easy to use.

Better publicity of programs and how they work is crucial if there is to be sizeable take-up. For instance, we estimate in our context that take-up rates would be on the order of 32% if people were informed. Increased information and assistance interventions have been shown to be effective in other areas of financial planning. See Beshears et al. (2013) for retirement savings, Hastings and Weinstein (2008) for school choice, Bettinger et al. (2012) for college financial aid, Bertrand and Morse (2011) for payday borrowing, Stango and Zinman (2014) for overdraft fees, and Finkelstein and Notowidigdo (2019) for nutritional assistance. To increase take-up rates even further, financial institutions should make it easier for individuals to access debt-relief programs. One example would be to facilitate online applications and aid with classic "nudges" (c.f. Benartzi et al. (2017)); for example, auto-selecting "yes" on an opt-in box within a debt deferral application form.

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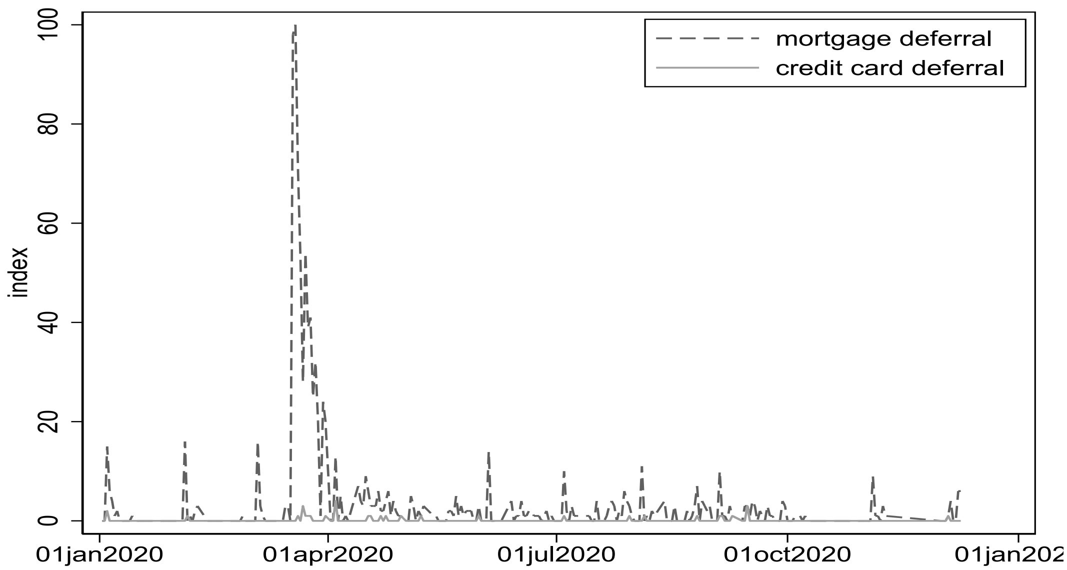
A Additional tables and figures

This appendix includes additional tables and figures.

Figure A.1: Search for deferrals using Google Trends



Notes: The dashed line is the Google trends index for the search word "mortgage deferral" and the solid line is for the search word "credit card deferral". The graph is indicative of the much larger awareness of mortgage deferrals relative to credit card deferrals.

Figure A.1 uses Google Trends to plot the search-intensity for credit card and mortgage deferral programs. Table A.1 shows the distribution of deferral periods for credit cards and mortgages in the TransUnion© data, where the deferral period is calculated as the number of months marked with a deferral flag. The deferral period is treated as unknown for accounts that are still on deferral in October 2020. Due to the immense complexity of implementing a nation-wide deferral program, some banks had trouble reporting deferral flags at the start of the pandemic. Table A.1, therefore, underestimates the actual deferral length. Table A.2 describes the characteristics of cancelled credit cards. Sixty percent of cards are cancelled at the request of the account holder. Table A.3 presents summary statistics for the set of revolvers with *eligible balances* who could benefit from rate reductions. Table A.4 presents summary statistics for the set of revolvers who could benefit from a mortgage deferral.

Table A.1: Distribution of months in deferral

Using account-level data from TransUnion©, this table presents the distribution of months in deferral for credit cards and mortgages. Row percentages are in parentheses. We conservatively label most as "unknown"—the vast majority of these are likely six months.

Product	1	2	3	4	5	6	Unknown	Total
Credit cards	1006	2616	1611	633	474	365	1098	7803
	(12.9)	(33.5)	(20.6)	(8.1)	(6.1)	(4.7)	(14.1)	(100.0)
Mortgages	533	1264	673	1295	1120	1638	2559	9082
	(5.9)	(13.9)	(7.4)	(14.3)	(12.3)	(18.0)	(28.2)	(100.0)

Table A.2: Characteristics of cancelled cards for those deferring a different credit card

Characteristics of cancelled cards is based off of the narrative codes reported to TransUnion©. Percentages are in parenthesis. In this table a payment is considered late if it is at least 60 days past due.

Narrative	I(payment late)	I(payment on time)	Total
Cancelled	223	287	510
	(90.65)	(28.42)	(40.61)
Customer requested	23	723	746
	(9.35)	(71.58)	(59.39)
Total	246	1,010	1,256

Table A.3: Summary statistics: revolvers with positive potential savings from rate reduction

This table presents summary statistics for individuals with a revolving credit card as reported in TransUnion©. Variables are defined in the header of Table 2.

	No card deferral			Card deferral		
	Mean	Median	SD	Mean	Median	SD
Limit ($1,000)	18.40	12.00	20.78	24.39	17.00	25.65
Payment required ($)	207.51	123.33	409.92	329.85	235.17	328.80
Payment made ($)	1242.13	526.67	2528.14	1486.31	620.17	3145.88
Balance ($1,000)	9.49	5.35	11.99	17.17	11.55	18.09
Utilization (%)	62.38	70.01	33.25	77.39	89.98	27.36
Revolving balance ($1,000)	8.69	4.84	11.14	15.70	10.44	16.65
Eligible balance ($1,000)	7.09	4.04	9.01	13.21	8.62	14.22
Potential saving	59.05	33.66	75.12	110.10	71.83	118.53
Total debt ($1,000)	182.58	70.25	259.03	216.75	82.88	300.02
Total obligation ($1,000)	1.20	0.73	1.73	1.47	1.00	1.54
Past-due (%)	8.37	0.00	27.69	17.12	0.00	37.67
Credit score	703.63	718.00	112.29	657.25	663.00	106.00
Age	47.45	46.75	15.29	45.42	44.92	14.06
No. of accounts	3.87	3.00	2.51	4.61	4.00	2.86
No. of cards	2.17	2.00	1.43	2.67	2.00	1.80
No. of mortgages	0.26	0.00	0.56	0.28	0.00	0.57
I(student loan)	0.08	0.00	0.27	0.11	0.00	0.31
I(line of credit)	0.40	0.00	0.49	0.45	0.00	0.50
I(personal loan)	0.43	0.00	0.50	0.48	0.00	0.50
I(mortgage)	0.21	0.00	0.41	0.24	0.00	0.43
FSA income ($1,000)	90.29	85.48	24.34	92.36	86.41	26.79
FSA invest income ($1,000)	4.54	3.27	6.50	5.12	3.41	9.93
FSA TFSA saving ($1,000)	7.72	7.43	2.65	7.86	7.52	3.14
FSA education (%)	53.19	52.23	12.98	54.76	53.78	13.38
FSA employment change	-0.17	-0.16	0.03	-0.16	-0.16	0.03
Fraction of CERB applicants	0.23	0.23	0.06	0.24	0.23	0.07
Observations	49,571			4,492		

Table A.4: Summary statistics: revolvers with positive potential savings from mortgage deferral

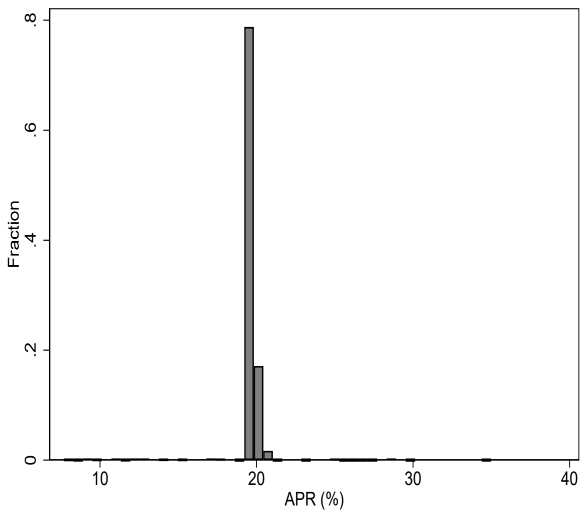
This table presents summary statistics for individuals with a revolving credit card and a mortgage, as reported in TransUnion©. Variables are defined in the header of Table 2.

	No mortgage deferral			Mortgage deferral		
	Mean	Median	SD	Mean	Median	SD
Limit ($1,000)	24.49	18.00	23.52	25.24	17.50	26.18
Payment required ($)	230.74	145.33	369.34	296.02	194.83	446.64
Payment made ($)	1740.75	766.67	3248.67	1879.55	712.33	4187.22
Balance ($1,000)	11.07	6.74	13.35	14.50	9.14	16.81
Utilization (%)	52.47	51.63	33.36	65.04	73.72	32.31
Revolving balance ($1,000)	9.70	5.59	12.23	12.69	7.82	14.92
Potential saving	19.24	16.49	13.72	24.70	20.50	19.30
Total debt ($1,000)	395.20	331.35	284.94	486.89	392.44	376.11
Total obligation ($1,000)	2.26	1.96	1.77	2.86	2.43	2.48
Past-due (%)	6.01	0.00	23.77	9.85	0.00	29.80
Credit score	739.70	763.00	97.48	694.12	701.67	103.69
Age	51.33	51.17	12.32	48.95	48.33	11.24
No. of accounts	5.88	5.00	2.62	6.30	6.00	2.84
No. of cards	2.43	2.00	1.54	2.62	2.00	1.69
No. of mortgages	1.17	1.00	0.53	1.22	1.00	0.63
I(student loan)	0.04	0.00	0.19	0.05	0.00	0.21
I(line of credit)	0.73	1.00	0.44	0.69	1.00	0.46
I(personal loan)	0.56	1.00	0.50	0.65	1.00	0.48
Mortgage balance ($1,000)	236.28	193.89	191.31	324.69	259.08	272.52
Mortgage obligation ($1,000)	1.46	1.25	0.98	1.81	1.49	1.32
I(defer card)	0.04	0.00	0.20	0.19	0.00	0.39
FSA income ($1,000)	90.72	86.04	22.86	93.70	88.68	24.94
FSA invest income ($1,000)	4.41	3.24	6.79	4.71	3.39	6.93
FSA TFSA saving ($1,000)	7.75	7.51	2.63	7.64	7.29	2.76
FSA education (%)	52.53	51.59	12.70	53.13	52.47	13.10
FSA employment change	-0.16	-0.16	0.03	-0.17	-0.17	0.03
Fraction of CERB applicants	0.23	0.22	0.06	0.24	0.23	0.07
Observations	11,365			3,635		

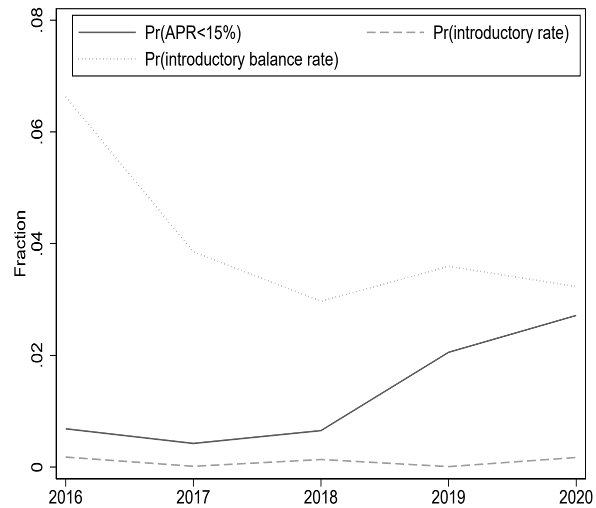
B Mintel credit card offers data

We use data collected by the marketing firm Mintel for the period 2016 to 2020. Mintel tracks and reports on household spending patterns across 34 countries. Our Canadian sample consists of credit card solicitations from a panel of over 1,300 households. Figure B.1 plots four pieces of information. Panel (a) plots the distribution of interest rates (APR) on all credit cards offered to households via mail. Panel (b) has three lines. First, the solid line is the fraction of cards sent in the mail that offer an interest rate below 15%. The dashed line shows the fraction of cards that have a low-rate introductory offer on new purchases. Finally, the dotted line shows the fraction of cards that have a low-rate introductory offer on balance transfers. Panel (a) consists of solicitations between January 2016 and December 2019, whereas panel (b) shows solicitations from January 2016 to September 2020. Panel (c) plots the year-over-year growth rate in the number of credit card solicitations from 2016 to 2020. Panel (d) plots the distribution of credit card fees for the set of cards offered between 2016 and 2020.

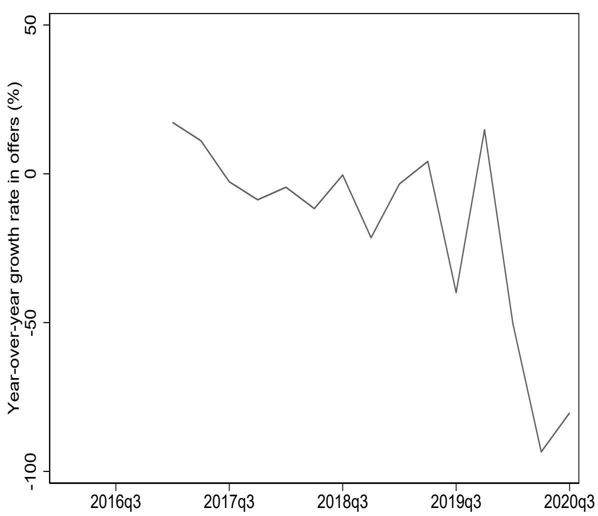
Figure B.1: Credit card offers



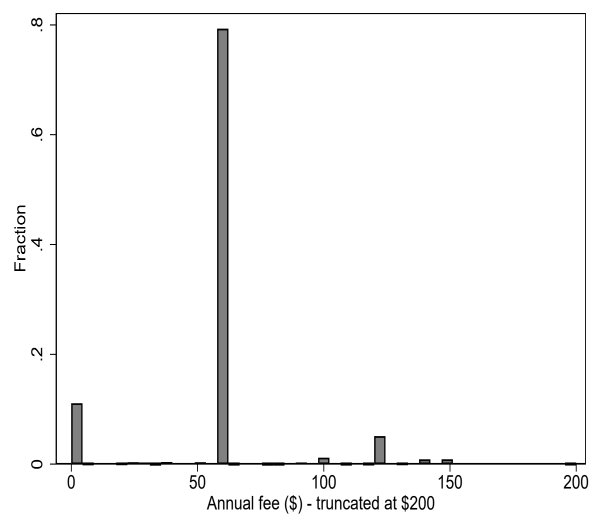
(a) APR (%)



(b) Low rate cards



(c) YoY growth in offers (%)



(d) Annual fees