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.

Résumé. Nous analysons l’efficacité de mesures d’allégement financier aux emprunteurs mises en place par les institutions financières canadiennes durant la pandémie de COVID-19. Ces mesures offraient aux ménages l’occasion de repousser leurs paiements hypothécaires ou de cartes de crédit. À l’aide de données sur les comptes de crédit individuels, nous documentons que malgré le fait que ces programmes offraient des économies potentielles de plus de 4 milliards de dollars, les taux de recours ont été...
faibles: 24 % pour les prêts hypothécaires et 7 % pour les cartes de crédit. Nous montrons également que près de 80 % des individus n’étaient pas au courant du programme d’allègement pour les cartes de crédit alors que d’autres n’ont pas déposé de demande en raison de la présence de coûts non monétaires fixes.

JEL classification: D12, D14, G28, G51

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, enrolment was low. In addition, we document that this outcome was due mainly to a mix of limited information about the programs and fixed non-monetary costs associated with enrolment. 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 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-monetary fixed costs associated with program enrolment. For instance,

¹ A number of authors have studied informational frictions in the context of small US firms (not) taking advantage of the Paycheck Protection Program during the pandemic; see, for instance, Humphries et al. (2020).
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 \textit{opted in}. However, doing so required some effort or \textit{hassle cost} on the part of borrowers.\textsuperscript{2} With reported wait times in the hours at the launch of the deferral programs, many individuals might have given up.\textsuperscript{3} Previous work in household finance has shown that hassle costs often cause some to forgo potential savings.\textsuperscript{4} Another potential fixed cost associated with enrolment is \textit{reputation}—if individuals believe that applying for a deferral will impact their ability to access credit in the future, they might forgo enrolment.

Our analysis of enrolment in these programs is based on comprehensive data from TransUnion\textsuperscript{©}, 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 cardholders who do not pay their credit card debt in full every period (so called “revolvers”), carrying average 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

\textsuperscript{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 suboptimal choices.

\textsuperscript{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 (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, www.twitter.com/rbc/status/1241817076521734145?lang=en.

\textsuperscript{4} In the mortgage market see, for instance, Woodward and Hall (2012) and Allen et al. (2019). In addition, see Hortac\c{c}su 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.
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: 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 among 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%. 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 enrolment 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 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. Because 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

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\(^5\) The same is also true for automobile loan deferrals, although we do not consider these here. The dispersion in automobile 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 et al. (2015), Ponce et al. (2017), Gathergood et al. (2019), Baugh et al. (2021), Keys and Wang (2019) and Agarwal et al. (2017b), 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 www.canada.ca/en/financial-consumer-agency/corporate/COVID-19/bank-relief-measures.html.
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 enrolment. To get a sense of the degree of awareness of the program and the size of the fixed cost of deferring, we contrast deferral behaviour on multiple credit cards from the same bank vs. from rival banks. We find much higher take-up within bank than across banks. This is sensible because 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 cardholder has deferred a card from a rival bank, the information friction is not present yet the fixed cost of deferral remains. Jointly studying these subsamples, we estimate that roughly 80% of borrowers were unaware of the program. Lastly, we quantify the fixed cost of deferral using a subsample 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. Furthermore, making it easier for individuals to access debt-relief programs would increase enrolment. This could be done by facilitating online applications with classic behavioural “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. 2017a, Agarwal et al. 2020, Di Maggio et al. 2017, Ganong and Noel 2017, Maturana 2017, Kruger 2018 and 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 US 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

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8 The Canada Deposit Insurance Corporation, for example, substantially increased their advertising budget at the start of the pandemic. See their 2020 annual report.
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 enrolment, which prevented consumers from signing up. Low take-up is also easier to rationalize in their context because 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 enrolment. 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). In this context, policy-makers 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. Others aimed to help 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 who had 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. As of October 3, 2020, total CERB and employment insurance payments totalled $81.64 billion.11 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. As of March 7, 2021, the value of approved subsidies was $69.31 billion.12

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9 See 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 US, savings peaked at 33.7%.
11 See www.canada.ca/en/services/benefits/ei/claims-report.html.
12 See www.canada.ca/en/revenue-agency/services/subsidy/emergency-wage-subsidy/cews-statistics.html.
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. Lastly, 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 36-10-0112-01), 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 labour income and shield the asset side of individuals’ balance sheets, the government worked with financial institutions and regulators to facilitate several debt-relief programs.13 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 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.

Most lenders provided some level of debt relief for their mortgage clients. The typical program offered deferral for up to six months.14 Monthly payments were paused while interest continued to accrue, effectively extending the loan amortization period.15 Financial institutions also provided debt relief and interest-rate reductions on most credit cards. Some lenders offered up to a six-month deferral, but 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 through both lower rates and a “fresh start.” It should also be noted that there is no real reason to think that individuals

13 The Office of the Superintendent of Financial Institutions (OSFI) rules governing the treatment of deferrals are available at www.osfi-bsif.gc.ca/Eng/fi-if/in-ai/Pages/FRI20200828_let.aspx.

14 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.

15 This is different from the CARES Act implemented in the US. In that case, interest did not accrue on federally and GSE-backed mortgages.
might defer in order to take on more debt (moral hazard). The exception to this is the possibility that individuals might defer, increase their spending and then declare bankruptcy. So far, there is little evidence that this is taking place. In fact, insolvencies fell dramatically in Canada during the pandemic.\textsuperscript{16}

The mortgage and credit card deferral programs imposed no cost on taxpayers because the programs were offered through Canadian financial institutions. This is in contrast to CERB and CEWS, which were implemented by the federal government. Because payments were deferred as opposed to cancelled, the costs to financial institutions were not huge, although clearly there was some loss of revenue (for instance from lower credit card interest rates). Furthermore, there were perceived to be some benefits too; by allowing borrowers to push off payments, it was thought that a large number of defaults might be avoided.

3. Data

In this section, we start by presenting our main data source, the TransUnion\textsuperscript{©} 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\textsuperscript{©} on the population of Canadians with a credit product. We use a 1\% random sample, resulting 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 instalment loans.\textsuperscript{17} 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 important, 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.\textsuperscript{18}

\textsuperscript{16} See www.ic.gc.ca/eic/site/bsf-osb.nsf/eng/br04435.html.

\textsuperscript{17} TransUnion\textsuperscript{©} does not have the entire population of credit products because some lenders do not report. Mortgages are by far the least reported product, yet we still capture over 85\% of mortgages in Canada.

\textsuperscript{18} Table A1.1 in the appendix provides the distribution of deferral lengths for credit cards and mortgages.
3.2. Neighbourhood-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 neighbourhood-level information. We define a neighbourhood 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, containing from zero to over 60,000 households. The average number of households in an FSA is 8,000.

**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 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.¹⁹ 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 \( t \):

\[
dN_{jt} = \sum_l \omega_{jl} dN_{klt},
\]

where \( \omega_{jl} \) is the share of FSA \( j \)'s employment in industry \( l \) in 2016 and \( dN_{klt} = \ln \left( \frac{N_{klt}}{N_{klt-1}} \right) \) 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

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¹⁹ Statistics Canada publishes unadjusted monthly industry employment data for each province ([https://doi.org/10.25318/1410035501-eng](https://doi.org/10.25318/1410035501-eng)). There are 15 industry categories: (1) agriculture, forestry, fishing, mining, quarrying, oil and gas; (2) utilities; (3) construction; (4) manufacturing; (5) wholesale and retail trade; (6) transportation and warehousing; (7) information, culture and recreation; (8) finance, insurance, real estate, rental and leasing; (9) professional, scientific and technical services; (10) business, building and other support services; (11) educational services; (12) health care and social assistance; (13) accommodation and food services; (14) other services (except public administration) and (15) public administration.
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 labour force) across FSAs in each province. The average application rate is 22.2% and the standard deviation is 7.6%. While applying for 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.

**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 accessed from Canada Revenue Agency for the 2017 tax year.  

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20 See [www.canada.ca/en/revenue-agency/programs/about-canada-revenue-agency-cra/income-statistics-gst-hst-statistics/individual-tax-statistics-fsa/individual-tax-statistics-fsa-2019-edition-2017-tax-year.html](http://www.canada.ca/en/revenue-agency/programs/about-canada-revenue-agency-cra/income-statistics-gst-hst-statistics/individual-tax-statistics-fsa/individual-tax-statistics-fsa-2019-edition-2017-tax-year.html). TFSA is an investment account in Canada, which provides tax-free gains. Achou et al. (2020) find, on the basis of 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.
We also include the average after-tax income from the 2016 Census. Lastly, another factor that could affect enrolment 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.\textsuperscript{21}

### 3.3. Summary statistics

Table 1 summarizes the unique number of active accounts in our 1% sample randomly drawn from the TransUnion\textsuperscript{©} 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 because 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 with just 2.28% for credit cards with a positive balance. Lastly, nearly all student loans are deferred. Student loans were automatically

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{FSA-level fraction of CERB applicants in April 2020}
\end{figure}

\textbf{NOTES:} This figure plots the distribution of the Canada Emergency Response Benefit (CERB) application rate (fraction of labour force applying for CERB) across forward sortation areas (FSAs) in the 10 Canadian provinces. Across 1,609 FSAs, the average CERB application rate is 22.2\%, and the standard deviation is 7.6\%.

\textsuperscript{21} 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.
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 vs. 1.8—and significantly higher utilization rates; their outstanding balance relative to the limit is close to 63%, compared with 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. 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, because the debt-relief program for student loans featured automatic enrolment, it is conceivable that individuals with student

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**TABLE 1**

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

**NOTES:** 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.

22 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.
Debt-relief programs and money left on the table 21

TABLE 2
Summary statistics of credit cardholders by deferral flag

|                      | 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 ($)     | 1,870.98 | 852.33 | 4,316.81| 1,840.52 | 722.00 | 4,067.14|
| Total debt ($1,000)  | 188.19 | 61.00  | 302.70| 220.14 | 78.44  | 328.84|
| Total obligation ($) | 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 |
| Number of accounts   | 3.29  | 3.00   | 2.25  | 4.38  | 4.00   | 2.82  |
| Number 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  |

NOTES: This table presents summary statistics for credit cardholders in TransUnion©—the first three columns are for non-deferrers and the last three columns 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 amount 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 had 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. “Number of accounts” and “number of cards” are the individual’s total number of accounts and cards, respectively. There are also four indicator variables, I(·). They are equal to 1 if the individual owns the product listed in the brackets. There are five FSA-level variables: (i) income is the average 2015 after-tax income (2016 Census), (ii) investment income and tax-free savings account (TFSA) savings—calculated from 2017 individual tax statistics—are total investment income and funds in the TFSA, respectively, (iii) education is the percentage of people with at least a college degree in the population aged 25 to 64, (iv) employment change is the year-over-year employment change calculated using the shift-share approach in section 3.2 and (v) fraction of Canada Emergency Response Benefit (CERB) applicants is the number of CERB applicants in April 2020 divided by the labour force. There are 229,366 non-deferrers and 6,714 deferrers. SD = standard deviation. FSA = forward sor- tation area.

debt are more aware of their ability to defer on other products. We analyze these effects in section 5.

Lastly, 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.

**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 cardholders 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 automobile). Lastly, 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 ($395,000 vs. $302,000) and current balance ($347,000 vs. $249,000). 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 neighbourhood-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 neighbourhoods 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 2021). 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.
Enrolment 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 lockdowns. The active stock of deferrals peaked in June for credit cards and May for mortgages. 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.

Table 3
Summary statistics: Revolving and convenience credit card users

|                     | 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 ($)    | 1,229.49 | 500.00 | 2,506.75 | 2,215.80 | 1,144.33 | 4,975.55 |
| Total debt ($1,000) | 181.43 | 67.76  | 259.62 | 204.63 | 63.50  | 334.05 |
| Total obligation ($1,000) | 1.18   | 0.71   | 1.78  | 0.80   | 0.12   | 1.52  |
| Past due (%)        | 8.82   | 0.00   | 28.35 | 0.92   | 0.00   | 9.56  |
| Credit score        | 703.59 | 718.00 | 113.20 | 811.60 | 840.00 | 71.93 |
| Age                 | 47.21  | 46.50  | 15.41 | 50.60  | 50.83  | 18.55 |
| Number of accounts  | 3.82   | 3.00   | 2.50  | 3.21   | 3.00   | 2.19  |
| Number of cards     | 2.12   | 2.00   | 4.12  | 1.79   | 1.00   | 1.10  |
| I(student loan)     | 0.09   | 0.00   | 0.28  | 0.05   | 0.00   | 0.23  |
| I(line of credit)   | 0.39   | 0.00   | 0.49  | 0.42   | 0.00   | 0.49  |
| I(personal loan)    | 0.43   | 0.00   | 0.49  | 0.23   | 0.00   | 0.42  |
| I(mortgage)         | 0.21   | 0.00   | 0.41  | 0.18   | 0.00   | 0.38  |
| I(defer card)       | 0.07   | 0.00   | 0.25  | 0.01   | 0.00   | 0.11  |
| I(defer mortgage | mortgage) | 0.24   | 0.00   | 0.43  | 0.11   | 0.00   | 0.31 |
| FSA income ($,000)  | 90.49  | 85.49  | 24.62 | 94.45  | 88.13  | 28.91 |
| FSA invest income ($,000) | 4.57   | 3.29   | 6.61  | 5.53   | 3.77   | 8.35 |
| FSA TFSA saving ($,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 |        |       |

NOTES: This table presents summary statistics for two types of credit cardholders 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. SD = standard deviation. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit.

Enrolment 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 lockdowns. The active stock of deferrals peaked in June for credit cards and May for mortgages. 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.
### TABLE 4
Summary statistics of mortgage borrowers by deferral flag

|                  | Non-deferral |          |          | Median |          | SD  |          |          | Median |          | SD  |          |
|------------------|--------------|----------|----------|--------|----------|-----|----------|----------|--------|----------|-----|----------|
| Limit ($1,000)   | 301.54       | 239.20   | 262.83   | 394.60 | 301.48   | 350.49 |
| Balance ($1,000) | 248.85       | 192.82   | 236.95   | 346.89 | 262.89   | 319.78 |
| Utilization (%)  | 78.98        | 86.32    | 21.41    | 85.76  | 89.85    | 14.46  |
| Payment required ($) | 1,558.88     | 1,274.00 | 2,330.79 | 1,923.81 | 1,531.44 | 1,556.94 |
| 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  |
| Number of accounts | 5.14        | 5.00     | 2.49     | 5.79   | 5.00     | 2.91   |
| Number of cards  | 1.89         | 2.00     | 1.40     | 2.13   | 2.00     | 1.63   |
| Number 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  |          |       |

**NOTES:** 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. SD = standard deviation. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit.

![Figure 3](image-url)

**FIGURE 3** Program take-up rate over time

**NOTE:** 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 and the dashed line is the fraction of accounts exiting deferrals in each month. CC = credit card. MTG = mortgage.
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 use information only 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.\(^2\)

**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 (annual percentage 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.\(^3\) 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.\(^4\)

\(^2\) Recall that deferred accounts were “frozen.” We therefore do not see current outstanding balances during the deferral period—only before and after the deferral.

\(^3\) 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.

\(^4\) See [www.ratehub.ca/blog/credit-card-payment-deferrals-COVID-19/](http://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 A2.1 in the appendix for a histogram of the rates offered by credit card companies between 2016 and 2019.
To quantify the size of these potential savings, we consider the set of revolvers with eligible balances who could benefit from rate reductions.\textsuperscript{26,27} 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 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.

\textit{Potential savings through mortgage deferrals}

The second source of savings is indirect. Mortgagors were given the opportunity to pause their regular payments. This strategy defers debt obligations only for a few months; in fact, the debt burden increases during the deferral period because 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 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.\textsuperscript{28} 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 the borrower needs 18 months to pay off the entire balance of $9,000 without debt consolidation, the total savings will be $382.50 from a one-month mortgage deferral. If the

\textsuperscript{26} 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.

\textsuperscript{27} Table A1.3 in the appendix shows the summary statistics of this sample.

\textsuperscript{28} 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, available at www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1010000601.
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.\textsuperscript{29} 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 approximately $0.31 million in our 1% sample. Because most lenders offer mortgage deferrals up to six months and borrowers normally pay off their revolving balances in no less than 18 months,\textsuperscript{30} a conservative estimate of aggregate potential savings in interest costs amounts to $3.35 billion (100×18×6×$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 effective at addressing short-term liquidity constraints only 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 because we do not observe how borrowers use

\textsuperscript{29} See table A1.4 for summary statistics for the set of revolvers with a mortgage.

\textsuperscript{30} In our data, fewer than one third of revolvers are able to pay off their revolving balances in 18 months.
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, we can see from the data 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, we clearly see that most borrowers face relatively limited gains from enrolment: 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 enrolment. 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 enrolment 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 enrolment 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.

Lastly, 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 enrol because 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
enrol 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 will guide us in identifying potential frictions that explain low overall enrolment. 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 because 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 enrolment is robust to the inclusion of other factors that could explain deferral decisions. The general specification of our cross-sectional regression is

\[ I(C_i) = \beta_0 + X_i \Phi + \varepsilon_i, \]  

(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

![Distribution of potential savings from credit cards and mortgage deferral](image)

**FIGURE 4** Distribution of potential savings from credit cards and mortgage deferral

**NOTES:** 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. 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.
|                  | DI1 | DI2 | DI3 | DI4 | DI5 | DI6 | DI7 | DI8 | DI9 | DI10 |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| Panel A: Credit card deferral |     |     |     |     |     |     |     |     |     |      |
| 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|41.92|57.81|81.09|124.96|254.92|
| Observations     | 5,420| 5,393| 5,404| 5,407| 5,404| 5,413| 5,402| 5,407| 5,406| 5,407|
| Panel B: Mortgage deferral |     |     |     |     |     |     |     |     |     |      |
| 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|
| Observations     | 1,500| 1,493| 1,501| 1,504| 1,502| 1,506| 1,495| 1,497| 1,502| 1,500|
| Panel C: Past-due revolvers’ credit card deferral |     |     |     |     |     |     |     |     |     |      |
| 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|
| Observations     | 728| 626| 563| 474| 445| 489| 439| 421| 393| 339 |

**NOTES:** Panels A, B and C of this table present the deferral probability and average potential savings for 10 deciles (DI) along the potential savings ($) distribution for, respectively, credit card deferrals, mortgage deferrals and credit card deferrals among borrowers with past-due credit card accounts. The calculation of potential savings is explained in the notes to figure 4. CC = credit card. MTG = mortgage.
and September 2020 on at least one of her credit cards, while $I(\text{defer})_i = 1$ if the borrower $i$ has applied for a mortgage payment deferral. The vector $X_i$ includes individual-level and 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.\footnote{For example, Cherry et al. (2021) document lower deferral rates among shadow banks relative to traditional banks. Because 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.} Region fixed effects are also sometimes included—there is strong evidence of persistent regional effects in the levels of financial distress (see, for instance, Keys et al. 2020).

Results from the estimation of equation (2) for enrolment in credit card and mortgage deferral programs are reported in tables 6 and 7, respectively. Overall, we find that the positive relationship between enrolment 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 enrol 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 enrolment, 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 65 least likely to enrol 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
|                  | (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)  | (0.0053)  | (0.0053)  |
| Number 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        | No        | No        | Yes       | No        | Yes       |
| Region FE        | No        | No        | No        | Yes       | Yes       |
| Adjusted R-squared | 0.053     | 0.055     | 0.078     | 0.055     | 0.079     |

**NOTES:** 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. The omitted category is credit scores (CSs) below 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. All other provinces have only one region. The omitted age category is under 35. We do not report the coefficient on $I(personal loans)$ because 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. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit. FE = fixed effect.
|                                | (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) |
| Number 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                      | No      | No      | Yes     | No      | Yes     |
| Region FE                      | No      | No      | Yes     | No      | Yes     |
| Adjusted R-squared             | 0.066   | 0.073   | 0.086   | 0.077   | 0.090   |

**NOTES:** This table presents estimation results from equation (2). The dependent variable \(I(\text{defe}r)\) equals 1 if the borrower deferred at least one mortgage. There are 14,999 observations. The omitted category is credit scores (CSs) below 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. All other provinces have only one region. The omitted age category is under 35. We do not report the coefficient on \(I(\text{personal loans})\) because 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. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit. FE = fixed effect.
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 enrolment 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.

6. Impediments to enrolment

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, enrolment was low. In this section, we investigate a number of possible impediments to enrolment 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. (2017a) show the important role that securitization and loan servicing played in limiting the supply of credit and hence the effectiveness of the US 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 enrolment 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 enrolment.

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 were. The suggestive evidence in figure A1.1 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. enrolment 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 enrolment. The
media reported long wait times linked to the process of contacting financial institutions to request a deferral.32

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 cardholders, especially riskier borrowers, had their credit restricted during the pandemic. Hence, it might have been ex ante rational for individuals 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 enrolment were more willing to put up with the fixed costs of requesting it.

6.2. Quantifying the role of enrolment 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 enrolment 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. Because people are entering and exiting at different times, the average score is a mix of people in and out of deferral.

32 See www.ratehub.ca/blog/COVID-19-and-your-mortgage/.

36 J. Allen, R. Clark, S. Li and N. Vincent
Even if their credit scores were not affected, individuals may still have been concerned that banks would lower their credit card limits. Fulford (2015) presents evidence of substantial variability in credit limits in the US 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 US, many credit cardholders, 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, because 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 panel (c) of appendix figure A2.1). In any 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 captures mostly bank-initiated cancellations. See table A1.2 in the appendix.33

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

FIGURE 5  Credit scores in TransUnion©
NOTES: 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 because 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 have never had a deferral flag. Panel (b) shows the comparison among revolving credit card users.

Even if their credit scores were not affected, individuals may still have been concerned that banks would lower their credit card limits. Fulford (2015) presents evidence of substantial variability in credit limits in the US 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 US, many credit cardholders, especially riskier borrowers, had their credit restricted during the pandemic.

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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

33 Bank-initiated closures are tied to accounts being past due. In our regression analysis below, we control for accounts that are past due.
impact on credit access: we cannot rule out that borrowers decided not to defer because of a perceived possibility of reputation harm associated with the decision or because they were unaware of the true impact from these 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 because 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
**TABLE 8**  
Take-up rate by potential savings – Student loan holders

|       | 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|
| Observations | 436  | 453  | 501  | 501  | 514  | 476  | 445  | 455  | 388  | 265  |

**NOTE:** Focusing on individuals with a student loan, this table presents the deferral probability, potential savings and actual savings for 10 deciles (DI) along the potential savings distribution.
generally higher for student loan holders, ranging from 4% to 26%, compared with 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 enrolment 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 and 1,300 deferred some but not all cards; the remainder chose not to defer any.

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

| TABLE 9 |
| --- |
| Revolvers' deferred and non-deferred credit cards |

|                      | Count | Mean  | SD  | p5   | p25  | p50  | p75  | p95  |
|----------------------|-------|-------|-----|------|------|------|------|------|
| **Deferral**         |       |       |     |      |      |      |      |      |
| Potential savings    | 1,300 | 86.48 | 77.44 | 5.26 | 27.81 | 63.13 | 124.01 | 248.16 |
| Utilization (%)      | 1,300 | 85.31 | 22.70 | 29.71 | 79.02 | 96.76 | 100.00 | 100.00 |
| I(big 7)             | 1,300 | 0.87  | 0.32 | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| **Non-deferral**     |       |       |     |      |      |      |      |      |
| Potential savings    | 1,300 | 50.85 | 50.73 | 3.81 | 16.06 | 36.68 | 67.21 | 153.38 |
| Utilization (%)      | 1,300 | 80.93 | 25.55 | 21.39 | 72.12 | 93.10 | 99.10 | 100.00 |
| I(big 7)             | 1,300 | 0.51  | 0.47 | 0.00 | 0.00 | 0.50 | 1.00 | 1.00 |
| I(same lender)       | 1,300 | 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   | 1,190 | 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 |

**NOTES:** 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 cardholders 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 seven largest credit card lenders. These 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. p = percentile.
investigate this possibility, table 9 compares the potential savings on deferred vs. 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.

Because multiple cardholders 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 cardholder 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. Because 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.34

Next, panel C focuses on cards whose owners have deferred at a different bank. Again there is no information friction because 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.

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34 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. Lastly, it is possible that individuals deferred on high-rate cards, while additional cards had lower rates. The last explanation seems unlikely because there were relatively few low-rate cards available. Panels (a) and (b) of figure A2.1 in the appendix shows that there are very few low-rate cards in the market.
|       | DI1  | DI2  | DI3  | DI4  | DI5  | DI6  | DI7  | DI8  | DI9  | DI10 |
|-------|------|------|------|------|------|------|------|------|------|------|
| **Panel A: All eligible credit card accounts** |      |      |      |      |      |      |      |      |      |      |
| 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 | 6,894 | 6,875 | 6,887 | 6,883 | 6,877 | 6,884 | 6,893 | 6,885 | 6,887 | 6,884 |
| **Panel B: Accounts whose owners have deferrals at the same bank** |      |      |      |      |      |      |      |      |      |      |
| 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   | 44   | 87   | 67   | 84   | 110  | 159  |      |
| **Panel C: Accounts whose owners have deferrals at rival banks** |      |      |      |      |      |      |      |      |      |      |
| 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  |

**NOTES:** This table presents the potential and actual savings for 10 deciles (DI) along the potential savings distribution. The statistics are at the account level. Panel A is all eligible credit card accounts. Panel B is accounts whose owners have deferrals at the same bank. Panel C is accounts whose owners have deferrals at rival banks.
By comparing panel C with the unconditional deferral probability shown in panel A, we can estimate the fraction of uninformed borrowers. The unconditional deferral probability can be expressed as follows:

\[
\Pr(\text{defer}) = \Pr(\text{defer|informed})\Pr(\text{informed}) + \Pr(\text{defer|uninformed})\Pr(\text{uninformed})
\]

\[
= \Pr(\text{defer|informed})\Pr(\text{informed}).
\]

(3)

The second equality follows because \(\Pr(\text{defer|uninformed}) = 0\). Irrespective of potential savings, panels C and A of table 10 show that \(\Pr(\text{defer|informed}) = 32\%\) and \(\Pr(\text{defer}) = 7\%\), respectively. Therefore, an estimate of \(\Pr(\text{informed})\) would be \(7/32\), which is about \(22\%\).\(^{35}\) 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 subsample 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 \(c_i\) 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 \(\bar{c}_i = \$100\times3 = \$300\) and the lower bound is \(c_i = \$80\times3 = \$240\). Otherwise, we should have observed different deferral decisions.

Table 9 shows the inferred lower and upper bounds of fixed costs.\(^{36}\) Because we do not observe individual-level fixed costs, in order to

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\(^{35}\) 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 cardholder 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 \(\Pr(\text{informed})\) is \(20\%\).

\(^{36}\) 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 because we cannot obtain an effective lower bound of 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.
approximate the fixed cost distribution, we make the following simplifying assumption: $C_i \sim U[\xi_i, \eta_i]$. The cumulative distribution function of the fixed cost is then approximated by the following:

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

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.

**Takeaway.** Our analysis of the credit card deferral programs has confirmed the importance of information frictions and fixed non-monetary costs of enrolment 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 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 also

### TABLE 11
Linear probability regression for account-level credit card deferral

|                | (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+        | −0.099*** | −0.092*** | 0.000064* | −0.016*** | −0.0062* |
|                | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| Age (35,50)    | −0.017*** | −0.016*** | −0.00664* | −0.016*** | −0.0062* |
|                | (0.0027) | (0.0027) | (0.0027) | (0.0027) | (0.0027) |
| Age (50,65)    | −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) |
| Number of cards | −0.0032*** | −0.0037*** | −0.0034*** | −0.0033*** | −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) |
| Leader FE      | No        | No        | Yes       | No        | Yes       |
| Region FE      | No        | No        | No        | Yes       | Yes       |
| Adjusted R-squared | 0.13     | 0.13     | 0.16      | 0.13     | 0.16     |

**NOTES:** The dependent variable is the binary decision to defer a credit card. There are 68,829 observations. 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. 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. All other provinces have only one region. The omitted age category is under 35. We do not report the coefficient on I(personal loans) because it is insignificant. We do not report the FSA-level coefficients because of space constraints. *p<0.05, **p<0.01, ***p<0.001. Standard errors clustered at borrower level. FSA = forward sortation area. CS = credit score. FE = fixed effects.
have 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.

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 enrol 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” (see, for instance, Benartzi et al. 2017), for example, auto-selecting “yes” on an opt-in box within a debt deferral application form.
Appendix A1: Additional tables and figures

Figure A1.1 uses Google Trends to plot the search intensity for credit card and mortgage deferral programs. Table A1.1 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 nationwide deferral program, some banks had trouble reporting deferral flags at the start of the pandemic. Table A1.1 therefore underestimates the actual deferral length. Table A1.2 describes the characteristics of cancelled credit cards. Sixty percent of cards are cancelled at the request of the account holder. Table A1.3 presents summary statistics for the set of revolvers with eligible balances who could benefit from rate reductions. Table A1.4 presents

![Figure A1.1](image-url)

**FIGURE A1.1** Search for deferrals using Google Trends

**NOTES:** The dashed line is the Google Trends index for the search words “mortgage deferral” and the solid line is for the search words “credit card deferral.” The graph is indicative of the much larger awareness of mortgage deferrals relative to credit card deferrals.

**TABLE A1.1**

| Product   | 1          | 2          | 3          | 4          | 5          | 6          | Unknown | Total |
|-----------|------------|------------|------------|------------|------------|------------|---------|-------|
| Credit    | 1,006      | 2,616      | 1,611      | 633        | 474        | 365        | 1,098   | 7,803 |
| cards     | (12.9)     | (33.5)     | (20.6)     | (8.1)      | (6.1)      | (4.7)      | (14.1)  | (100.0)|
| Mortgages | 533        | 1,264      | 673        | 1,295      | 1,120      | 1,638      | 2,559   | 9,082 |
|           | (5.9)      | (13.9)     | (7.4)      | (14.3)     | (12.3)     | (18.0)     | (28.2)  | (100.0)|

**NOTES:** 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.
### TABLE A1.2
Characteristics of cancelled cards for those deferring a different credit card

| 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  |

**NOTES:** Characteristics of cancelled cards are based on 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.

### TABLE A1.3
Summary statistics: Revolvers with positive potential savings from rate reduction

|                        | No card deferral | Card deferral |
|------------------------|------------------|---------------|
| **Limit ($1,000)**     | 18.40            | 24.39         |
| **Payment required ($)** | 207.51          | 329.85        |
| **Payment made ($)**   | 1,242.13         | 1,486.31      |
| **Balance ($1,000)**   | 9.49             | 17.17         |
| **Utilization (%)**    | 62.38            | 77.39         |
| **Revolving balance ($1,000)** | 8.69        | 15.70         |
| **Eligible balance ($1,000)** | 7.09         | 13.21         |
| **Potential saving**   | 59.05            | 110.10        |
| **Total debt ($1,000)** | 182.58           | 216.75        |
| **Total obligation ($1,000)** | 1.20       | 1.47          |
| **Past due (%)**       | 8.37             | 17.12         |
| **Credit score**       | 703.63           | 657.25        |
| **Age**                | 47.45            | 45.42         |
| **Number of accounts** | 3.87             | 4.61          |
| **Number of cards**    | 2.17             | 2.67          |
| **Number of mortgages**| 0.26             | 0.28          |
| **I(student loan)**    | 0.08             | 0.11          |
| **I(line of credit)**  | 0.40             | 0.45          |
| **I(personal loan)**   | 0.43             | 0.48          |
| **I(mortgage)**        | 0.21             | 0.24          |
| **FSA income ($1,000)**| 90.29            | 92.36         |
| **FSA invest income ($1,000)** | 4.54       | 5.12          |
| **FSA TFSA saving ($1,000)** | 7.72       | 7.86          |
| **FSA education (%)**  | 53.19            | 54.76         |
| **FSA employment change** | -0.17           | -0.16         |
| **Fraction of CERB applicants** | 0.23      | 0.24          |
| **Observations**        | 49,571           | 4,492         |

**NOTES:** 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. SD = standard deviation. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit.
Appendix A2: Mintel credit card offers data

We use data collected by Comperemedia for the period from 2016 to 2020. Comperemedia, a Mintel company, is an industry-leading competitive marketing intelligence agency serving the United States and Canada. Our Canadian sample comprises credit card solicitations from a panel of over 1,300 households. Figure A2.1 plots four pieces of information. Panel (a) plots the distribution of interest rates (annual percentage rate, 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%.

summary statistics for the set of revolvers who could benefit from a mortgage deferral.

### TABLE A1.4

|                         | 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 ($)        | 1,740.75 | 766.67 | 3,248.67 | 1,879.55 | 712.33 | 4,187.22 |
| 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 |
| Number of accounts      | 5.88  | 5.00   | 2.62  | 6.30  | 6.00   | 2.84  |
| Number of cards         | 2.43  | 2.00   | 1.54  | 2.62  | 2.00   | 1.69  |
| Number 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 |       |       |       |

**NOTES:** 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. SD = standard deviation. FSA = forward sortation area. TFSA = tax-free savings account. CERB = Canada Emergency Response Benefit.
The dashed line shows the fraction of cards that have a low-rate introductory offer on new purchases. Lastly, the dotted line shows the fraction of cards that have a low-rate introductory offer on balance transfers. Panel (a) comprises 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.

**Supporting information**

Supplementary material accompanies the online version of this article.

**References**

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