

Consumer credit usage in Canada during the coronavirus pandemic

Anson T. Y. Ho

Ted Rogers School of Management, Ryerson University

Lealand Morin

Department of Economics, University of Central Florida

Harry J. Paarsch

Department of Economics, University of Central Florida

Kim P. Huynh

Currency Department, Bank of Canada

Abstract. The recent COVID-19 pandemic has devastated economies worldwide. Using detailed, monthly data from a major consumer credit reporting agency in Canada, we have examined individuals' use of credit cards and home-equity lines of credit (HELOCs). We found a dramatic leftward shift in the distribution of credit card and HELOC outstanding balances, providing evidence for a widespread reduction in credit usage. Our findings suggest that, during the COVID-19 recession, Canadian consumers were able to meet their financial needs without increasing their debt burdens. These results complement other findings concerning a decline in consumer spending and the results of government assistance programs, and imply that the economic consequences of this pandemic are very different from those in other recessions.

Résumé Recours au crédit à la consommation au Canada au cours de la pandémie de coronavirus. La récente pandémie de COVID-19 a ravagé les économies mondiales. Grâce aux données mensuelles détaillées d'une des agences d'évaluation du crédit les plus importantes du pays, nous avons examiné le recours aux cartes de crédit et aux

Corresponding author: Kim P. Huynh, khuynh@bank-banque-canada.ca

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marges de crédit hypothécaires des Canadiens. Sur les figures illustrant la distribution des soldes impayés de cartes de crédit et de marges de crédit hypothécaires, nous constatons un important déplacement vers la gauche, ce qui reflète un fléchissement généralisé du recours au crédit. Nos résultats suggèrent qu'au cours de la récession provoquée par la COVID-19, les consommateurs canadiens ont pu satisfaire leurs besoins financiers sans alourdir leurs dettes. Ces conclusions complètent d'autres observations, notamment sur la baisse des dépenses de consommation ou sur l'effet des programmes d'aide du gouvernement, et laissent entendre que les conséquences économiques de cette pandémie sont très différentes de celles observées dans d'autres types de récession.

JEL classification: C55, E21, E27, G51, H31

1. Introduction and motivation

THE 2019 NOVEL coronavirus (COVID-19) pandemic has devastated economies worldwide.¹ It has plunged the global economy into the deepest recession since the Second World War, with substantial economic uncertainty (World Bank 2020, OECD 2020b). Understanding the economic impacts of COVID-19 on households' financial health is imperative to economic policymaking. Canada, as one of the economies with the highest levels of household debt, serves as an important case study. In 2019, Canadians' household-debt-to-disposable-income ratio reached 181.2%, which was the highest among G7 countries and the third highest among G20 countries (OECD 2020a).² Elevated household indebtedness has been identified as a key vulnerability in the Canadian financial system (Cateau et al. 2015).

The pandemic has significantly affected the Canadian economy, with the unemployment rate surging from 5.6% in February 2020 to 13.7% in May 2020. The Canadian government has responded with various aid programs, as outlined in the Economic Response Plan.³ For individuals, the Canada Emergency Response Benefit (CERB) was launched on March 15, 2020, to provide a taxable benefit of \$2,000 every four weeks to employed and self-employed workers whose employment was affected by COVID-19.⁴ According to the CERB benefits report⁵ CERB has paid out about \$81.6 billion to 8.9 million

1 The full scientific name of the virus is severe acute respiratory syndrome coronavirus 2, abbreviated as SARS-CoV-2.

2 Putting these numbers into context, the household-debt-to-disposal-income ratio in the United States peaked at 143.6% in 2007 prior to the global financial crisis.

3 See www.canada.ca/en/department-finance/economic-response-plan.html.

4 CERB expired on September 27, 2020, and transitioned to a revised employment insurance program as well as the new Canada Recovery Benefit (CRB) program.

5 See www.canada.ca/en/services/benefits/ei/claims-report.html.

applicants, most of whom earned under \$47,630 in 2019.⁶ Since April 2020, financial institutions, at their discretion, have also provided loan payment deferrals to clients who self-declared to have been negatively impacted by the pandemic. The Financial Consumer Agency of Canada (2020) shows that the vast majority of the deferral requests were approved and that this accounted for a significant fraction of the outstanding loans; see Vallée (2020) and Allen et al. (2022).

Using anonymized monthly data from a major consumer credit reporting agency in Canada, we have investigated the financial positions of consumers—in terms of their outstanding loan balances relative to their pre-pandemic positions. We did so by forecasting the credit usage of consumers using our estimated law of motion for debt balances, which we identified in the period before the pandemic, and then compared our forecasts with actual credit usage during the pandemic. Through this analysis, we have established important facts about consumers' use of credit during the pandemic, without seeking to evaluate the effectiveness of any specific assistance program.

Our analysis focuses on two popular credit instruments: credit cards and home equity lines of credit (HELOCs). Both instruments provide individuals with fast and flexible access to credit. Account holders can use any credit amount within their pre-approved credit limits, and interest is charged only on the portion that is actually used.⁷ Repayment is flexible: while the minimum payment for credit cards is usually 1% to 3% of the outstanding balance, the required monthly payment on a HELOC is usually the interest accrued on the outstanding balance. Interest rates on credit cards and HELOCs, however, sit at two extremes. Credits cards provide unsecured lending with interest rates of about 20% (Mintel 2018), among the highest of all credit instruments. HELOCs, on the other hand, are secured by home equity, with interest rates of about 2.7% since the pandemic began.

We conducted our analysis using a variant of intervention analysis, developed by Box and Tiao (1975), and model the law of motion of the distribution of loan balances with a first-order Markov process.⁸ We used this framework to contrast what happened with what was predicted—interpreting the

6 The Canadian government also introduced the Canada Emergency Business Account (CEBA) to provide interest-free loans to small businesses and the Canada Emergency Wage Subsidy (CEWS) program, which allows eligible employers to receive a 75% subsidy on their employees' wages, up to \$58,700.

7 At origination, the amount borrowed through a HELOC cannot exceed 65% of the market value of the underlying residential property. Furthermore, the HELOC limit combined with the outstanding mortgage balance cannot exceed 80% of the market value.

8 Ho et al. (2020) provided a detailed description of the empirical methodology; we have applied a special case of this framework.

difference as the excess effect of the pandemic. Our framework is a flexible approach that accommodates features of the data, such as boundaries and gaps, that are otherwise problematic for standard time-series methods.

Using this framework, we have found dramatic decreases in individuals' credit card debt. Since the onset of the COVID-19 pandemic, we found a much higher proportion of consumers with credit card balances lower than \$1,000, relative to that predicted by our forecasts, and a declining proportion of consumers with credit card balances at all levels greater than \$1,000. Of consumers with loan balances in the range from \$4,000 to \$10,000, we found an astounding decline of 25% in the proportion. The decline attenuated but persisted after the economy gradually reopened since late June 2020. We have found similar patterns in HELOC usage. The proportion of consumers with HELOC balances in the range of \$5,000 to \$10,000—the category most affected—declined 15%, relative to our forecasts. The decline tapers off to categories with loan balances up to \$300,000, beyond which HELOCs are used mainly for home purchases in combined mortgage-HELOC plans; see Al-Mqbali et al. (2019).

Our results suggest that Canadian consumers were able to meet their financial needs without increasing their debt burdens. These findings complement other documented facts in Canada concerning job losses, CERB benefits and the pattern of decreases in consumer spending. Since the early stages of COVID-19, the Canadian labour market had shifted to its maximum telework capacity at 39.1% (Deng et al. 2020). Households with higher levels of education and earnings were more likely to keep their jobs and work remotely from home (Messacar et al. 2020). Low-income individuals, who were also at higher risk of unemployment and financially more vulnerable, have been significantly supported by government programs. The Bank of Canada (2020) estimates, in their Monetary Policy Report, that the CERB was able to replace a major fraction—in some cases over 100%—of wage earnings for individuals below the 2019 median income. The decline in consumption spending mainly occurred in categories not amenable to physical distancing, such as restaurants and recreational services, which is consistent with the substantial drop in credit card balances that we observed.

This paper complements a rapidly developing literature concerned with the effects of COVID-19 on consumer finance around the world. In the United States, Sandler and Ricks (2020) showed that consumers in the United States did not rely on credit card debt for financial liquidity in the early stages of the COVID-19 pandemic because the average balance decreased by about 10%. Nagypál et al. (2020) found that credit card applications declined in regions with more unemployment insurance claims. These findings regarding credit card usage are consistent with other research showing a decline in spending. Chetty et al. (2020) and Baker et al. (2020) reported that consumers reduced their overall spending and liquidity-constrained households responded rapidly

to the fiscal stimulus payments from the 2020 CARES Act.⁹ Similar effects on consumer spending are also found in Denmark and Spain; see Andersen et al. (2020) and Carvalho et al. (2020), respectively. A common finding across these studies is a significant switch in spending categories; spending decreases were stronger in more restricted sectors, which may arise because of a short-run aggregate supply shock from economic lock-downs. In addition to spending changes, consumers also increased cash holdings; see Chen et al. (2020a). Our analysis contributes to this literature by not only providing evidence of reduced credit usage in Canada but also analyzing this change across the distribution of credit usage.

Our research is also related to a long-standing literature on debt utilization in the presence of negative income shocks. Hurst and Stafford (2004), Chen et al. (2020b) and Agarwal et al. (2006) note that wealthy homeowners tend to borrow against their home equity through mortgage refinancing or HELOCs, but consumers with few assets smooth their unemployment shocks via unsecured debts. Agarwal and Qian (2017) reported that homeowners access credit cards when they experience unexpected reductions in home equity. Conversely, Ganong and Noel (2019) showed that households do not borrow more from credit cards during unemployment spells. The poorest often have no access to credit at all; see Sullivan (2008).

The remainder of the paper is organized as follows: In section 2, we describe the source of our data, a major consumer credit reporting agency in Canada. In section 3, we report our empirical results, introducing features of our empirical framework along the way. We also validate our method on a recent economic downturn—an unanticipated period of low oil prices that shocked residents of the province of Alberta, Canada, in 2015 and 2016.

2. Data from a major consumer credit reporting agency

We acquired access to anonymized consumer-credit data maintained by TransUnion[®], one of the major consumer-credit reporting agencies that operate in Canada. The data are reported monthly, which admits a fine analysis of the effects of COVID-19. Our dataset contains account-level information concerning consumers' outstanding balances, which we aggregated to the individual level. This represents the total amount owed by a consumer at the end of each month. For credit cards, it is the total credit used regardless of whether it is paid off or carried forward to the future. Henry et al. (2018) estimated that about 30% of Canadian credit card holders have positive revolving balances.

9 In the United States, the Coronavirus Aid, Relief, and Economic Security (CARES) Act provided a one-time cash payment of \$1,200 to most adults and \$500 per child and unemployment benefits of \$600 per week over an additional 13 weeks of benefits.

Various types of financial institutions are included in the dataset—ranging from chartered banks of different sizes to credit unions and credit card companies. Major loan types are included, such as mortgages, HELOCs, credit cards, automobile loans and other instalment loans.¹⁰ When cleaning the data, accounts that were in debt collection, being written off or included in consumer proposals or bankruptcy filings were excluded.¹¹ Accounts that have not been updated for 90 days (one quarter) or that had missing information concerning outstanding balance were also dropped.¹²

Our dataset is representative of most of the Canadian population. The aggregate balances held at chartered banks in our data closely match with those from the regulatory filings collected by the Bank of Canada. Using 2016 Census data, we estimated that some 93.9% of the Canadian population aged 20 and older is represented in the data from the credit reporting agency. A detailed description of our data validation is provided in appendix A. We drew a 1%, random sample from the entire set of credit card holders, a sample of 292,854 unique account holders with 12,743,957 monthly observations. For HELOCs, we drew a 5%, random sample of HELOC holders to obtain a sample of 303,400 unique account holders with a total of 13,841,400 monthly observations.

The time series of individuals' outstanding balances are reported in figure 1. The solid line in figure 1(a) depicts the mean individual credit card balances over the sample period from January 2017 to August 2020, while the dashed and dotted lines depict the inner quartiles. During the period January 2017 to January 2020, on average, the outstanding balance exhibited a year-over-year growth rate of around 2.7%. Since then, the average dropped to a new low in May 2020. The shift also appears in the median and the third quartile. A seasonal pattern exists: higher average credit card balances obtain in the fourth quarter of every year (the holiday season), and the aggregate

10 Because we analyzed only individuals' use of credit cards and HELOCs, other loan types are not considered in our dataset.

11 We focused on the outstanding balance instead of delinquent loans because the unprecedented availability of loan deferral programs allowed many consumers, who might otherwise become delinquent, to remain current on their payments. An analysis focusing on delinquency or bad debt may provide a misleading picture of consumers' financial status. Indeed, 90-day credit card delinquency decreased from 1.11% in March 2020 to 0.63% in September 2020.

12 Less than 0.1% of accounts in our sample are dropped with this restriction. The most common reason for accounts not being updated is that these accounts were inactive with zero balance. Those account may also be sold, transferred or paid off without being reported in a timely manner. Some lenders may cease reporting severely delinquent accounts that were eventually written off. Our way of handling outdated accounts is consistent with the method applied to the Consumer Credit Panel at the Federal Reserve Bank of New York (Lee and van der Klaauw 2010).

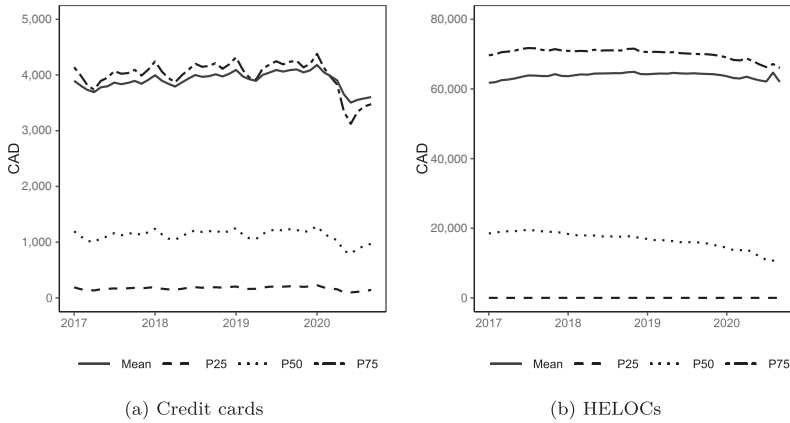


FIGURE 1 Consumers’ outstanding balances, 2017–2020

balances decrease in the first quarter every year. The seasonal pattern is more pronounced for the third quartile, indicating that much of the activity is in the upper tail. The time series of HELOC balances are depicted in figure 1b: a gradual decline in HELOC balances has occurred since the summer of 2017, but the decline was largest during the COVID-19 pandemic, with the exception of a temporary increase in July 2020.

In order to model a first-order Markov process, we assigned these balances to discrete balance categories, with one category for consumers having zero balances. Instead of using evenly-spaced bins, individual’s loan balances were organized into intervals of declining width to account for the lengthy tail of the distribution and to correspond (roughly) to typical categories of credit lines offered by banks. For credit cards, balance categories are defined in intervals of width \$250 up to \$1,500, intervals of \$500 up to \$6,000, \$1,000 up to \$10,000, \$2,000 up to \$20,000, \$5,000 up to \$30,000, one \$30,000 to \$40,000 category and a category of \$40,000 and above in the tail. We defined balance categories for HELOCs in a similar fashion, collecting those with zero balances in the first category, and we defined the next two categories to have widths of \$2,500, up to \$5,000. We then divided the next three categories with intervals \$5,000 wide, up to \$20,000, and follow those with intervals of \$10,000, up to \$50,000. Next, we used intervals of \$25,000 up to \$100,000, intervals of \$50,000 up to \$300,000, one category from \$300,000 to \$400,000 and the remaining categories with width \$200,000 up to \$800,000 followed by a category with balances of \$800,000 and above.

Any empirical framework designed to measure the impact of the COVID-19 pandemic on credit card and HELOC balances must accommodate four main features of those data: first, the distribution is highly skewed and the changes in the distribution of balances is more pronounced in the tails. In

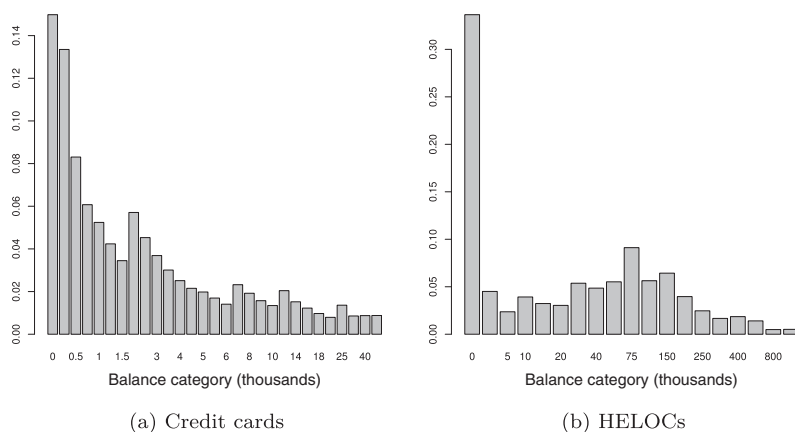


FIGURE 2 Histograms of individuals' balances

figure 1, there is little movement in the first quartile, but the third quartile hovers near the mean. During the pandemic, the third quartile of credit card balances dips below the mean. This suggests that we must use an empirical framework that focuses on the distribution, rather than the mean.

Second, a substantial fraction (over 10%) of individuals in the sample have zero balances. The case of credit cards is depicted in figure 2(a) using data from January 2017 to January 2020. Compare this to the histogram for HELOCs, in figure 2b: more than 30% of these credit lines have balances of zero, which is nearly double the proportion for credit cards.

Third, from month to month, considerable dependence exists over time; for example, if an account had a zero balance at the end of last month, then it is very likely (in general over 50% of the time) to have a zero balance at the end of this month. Figure 3 depicts the joint empirical distribution of period $(t - 1)$ (denoted by “Past”) and period t (denoted by “Current”), using data from January 2017 to January 2020. Panel 3(a) depicts the conditional histogram of current balance categories for credit cards, and panel 3(b) depicts that for HELOCs. Most of the transition probability mass is on the diagonal elements, indicating even stronger dependence on past values for credit lines of all sizes.

Fourth, not every consumer is observed in every period of the sample: consumers sometimes have gaps in their data.¹³ This would complicate the analysis of the data were we to use standard panel-data techniques. Our

13 Although none of consumers in our nation-wide sample have time gaps, there exists roughly 1% of consumers with gaps in the sample drawn from the province of Alberta. This fraction of consumers is consistent with the notion that a small subset of people have migrated both in and out of Alberta during the sample period. Our econometric technique allows for this possibility.

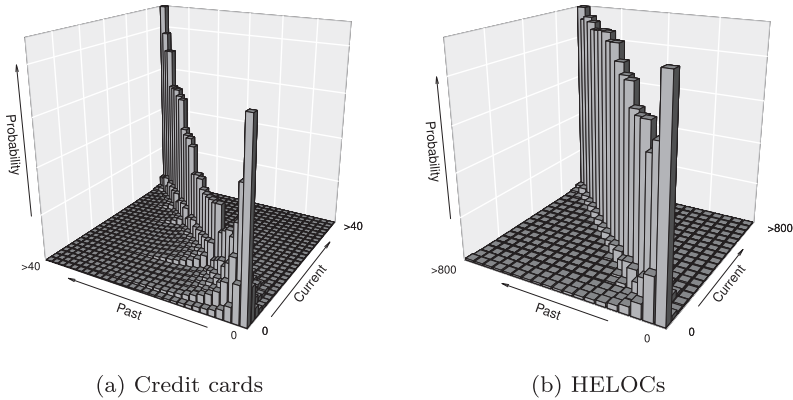


FIGURE 3 Conditional histograms of individuals' balances

framework is robust to this feature of the data: we can calculate estimates of the relevant transition matrices using a large sample of pairs of consecutive balances—whether or not the observations are recorded for all consumers every month.

3. Empirical results

Borrowing from the demography literature in which excess deaths are a measure of the effect of, say, a pandemic, we introduce the term “excess balances” for the notion that balances have increased, relative to previous experience, as a result of the pandemic; see Statistics Canada (2020). In the analysis that follows, we investigate excess balances from a number of perspectives. In the first, we compare the histograms of loan balances that occurred in 2020 against those in previous years. Because seasonality is observed in the aggregates series, we first compare histograms during the pandemic with the histograms from the same months of the previous three years. To make this comparison, we develop a statistic to measure any changes in the distributions. Next, we use this statistic to develop a graphical framework within which to view the changes in terms of the proportion of consumers in each balance category.

The analysis of histograms is only an approximation of the change, however, because it ignores any growth in balances year-over-year. For this reason, we apply an empirical framework to estimate transition matrices to describe the law of motion of the vector of proportions of consumers in each balance category. Using this information to condition on the state before the pandemic, a more precise measurement of the counterfactual distribution can be obtained. With this set of forecasted distributions as a benchmark, we can then re-evaluate changes in the distributions of balances to measure changes in the high-balance categories more accurately than before—in a way that

captures the notion of excess balances. These complement the results from analyzing histograms alone, which we discuss next.

3.1. Comparisons of histograms

Let $\tilde{p}_{k,T+\ell}$ denote the observed vector of proportions of consumers with a balance in category k at time $(T + \ell)$, which is ℓ months after some reference period T before the pandemic. Similarly, $\hat{p}_{k,T+\ell}$ denotes the observed vector of proportions of consumers in the benchmark distribution. In terms of the analysis of histograms, $\tilde{p}_{k,T+\ell}$ is represented by the histograms for activity in 2020, while $\hat{p}_{k,T+\ell}$ is represented by the histograms calculated from the sample period from 2017 to 2019. In principle, $\hat{p}_{k,T+\ell}$ could be calculated as the forecast from any model, and the sample histogram is the first such model we consider.

As a summary measure of the difference between these histograms, we consider following the statistic:

$$100 \times \log \left(\frac{\tilde{p}_{k,T+\ell}}{\hat{p}_{k,T+\ell}} \right), \quad (1)$$

which represents the percentage difference in cell $k = 0, 1, \dots, K$ between what actually obtained during the pandemic relative to what appeared in the histograms in the sample period. This object can be plotted on the ordinate versus the various cells on the abscissa to provide the reader with a visual description of how balances (however measured) have changed relative to what would have been predicted before the pandemic struck. The statistic

$$N \sum_{k=0}^K \hat{p}_{k,T+\ell} \log \left(\frac{\tilde{p}_{k,T+\ell}}{\hat{p}_{k,T+\ell}} \right) \quad (2)$$

measures the weighted average of the percentage change in the proportion of consumers in each balance category, weighted by the proportions $\hat{p}_{k,T+\ell}$, which are prescribed under the null hypothesis that the proportions are the same in both samples. The N in the definition of the statistic normalizes the random part to have a stable limiting (asymptotic) distribution.

This statistic, first proposed by Kullback and Leibler (1951) and commonly referred to as the Kullback–Leibler divergence criterion, was built on a concept of information introduced by Shannon (1948). As shown in Belov and Armstrong (2011), for a pair of continuous distributions, a version of this statistic has a limiting (asymptotic) χ^2 distribution with one degree of freedom. Parkash and Mukesh (2013) investigated the case of discrete distributions, which corresponds to our application, and determined that the statistic has a limiting χ^2 distribution, but with K degrees of freedom—that is, the number of categories minus one. Song (2002) demonstrated that the Kullback–Leibler divergence statistic is asymptotically equivalent to the likelihood-ratio statistic for detecting a difference between distributions.

TABLE 1
Divergence from sample histograms

Month	Credit cards		HELOCs	
	Divergence	<i>p</i> -value	Divergence	<i>p</i> -value
January 2020	272.05	<0.0000e-16	662.07	<0.0000e-16
February 2020	286.49	<0.0000e-16	656.63	<0.0000e-16
March 2020	156.57	<0.0000e-16	662.56	<0.0000e-16
April 2020	3,809.09	<0.0000e-16	828.96	<0.0000e-16
May 2020	6,803.32	<0.0000e-16	1,158.38	<0.0000e-16
June 2020	4,376.69	<0.0000e-16	1,453.77	<0.0000e-16
July 2020	2,682.10	<0.0000e-16	1,706.15	<0.0000e-16
August 2020	2,289.10	<0.0000e-16	1,507.30	<0.0000e-16

As a method for discriminating between distributions, the Kullback–Leibler divergence criterion is more sensitive to small changes in proportions in categories with low probability mass, which is important for comparing skewed distributions. Using simulation methods, Ho et al. (2020) demonstrated the validity of this variant of the Kullback–Leibler divergence statistic, showing that the statistic follows the χ^2 distribution with K degrees of freedom, as expected. The asymptotic distribution obtains with sample sizes on the order of 10,000 observations, which is well within the size of our cross-section of about 300,000 consumers.¹⁴

Using histograms from the sample period as the benchmark for comparison, we calculate the statistic in equation (2). The *p*-value columns show the probability of observing a statistic more extreme from the χ^2 distribution with 28 degrees of freedom for credit cards and 18 degrees of freedom for HELOCs. From the magnitude of the divergence statistics measured in table 1, the distributions in 2020 are clearly different from those in the past. The change is apparent as early as January 2020, well before the pandemic hit Canada. During April, the first complete month of lock-down, there appears a much larger difference in the distribution of balances for credit cards. This difference expands in May, recedes slightly in June and appears to level off over July and August, with a large difference still remaining by August.

The difference in April is less pronounced for HELOCs, with gradual changes through July, again, receding slightly by August 2020. This is in contrast to the abrupt jumps noted for credit card balances. For both types of loans, there exists a large difference continuing from May that persists until August. Having detected a statistically significant change in the distributions, we document the proportional changes in each of the balance categories.

14 The Kullback–Leibler divergence statistic also permits other restrictions one might seek to impose on the data in order to reduce sampling variability. Because we have a large amount of data concerning a major portion of the Canadian population, sampling variability is not a major concern.

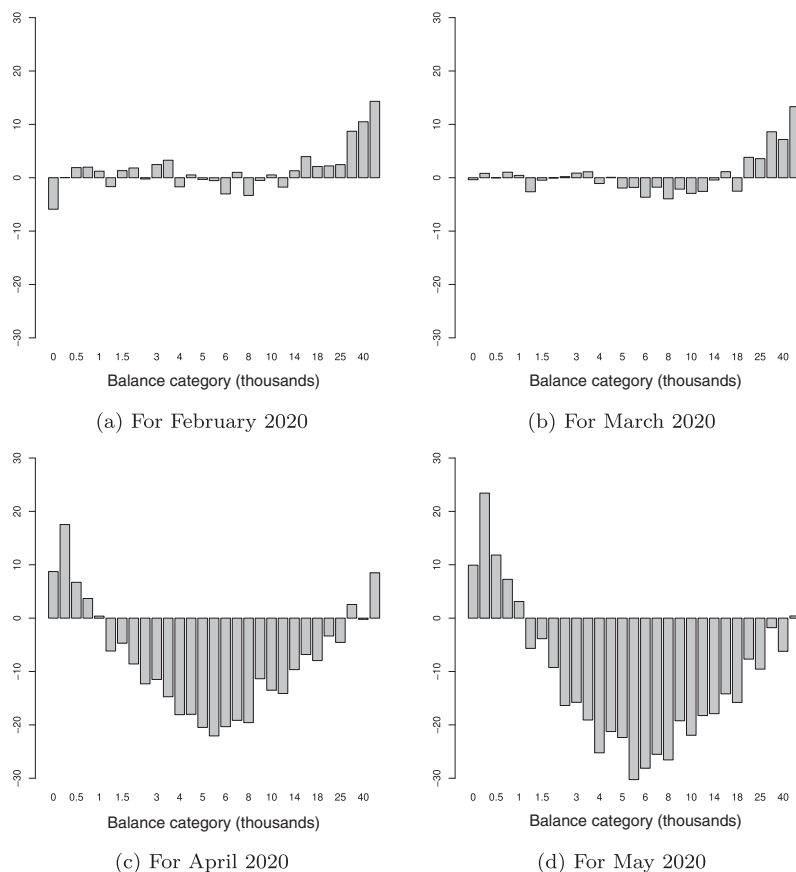


FIGURE 4 Deviations from histograms (credit cards)

3.1.1. Credit cards

The changes noted in the distributions of credit card balances are depicted in figure 4, compared with balances in the same months during the three-year sample drawn from the years 2017 to 2019. For February and March, the reduction in the proportion of zero balances, relative to the previous years, are clearly shown in the first bars on the left of each panel. This shows a 5% reduction in the proportion of consumers with a balance of zero on their credit card. On the other extreme, for balances in the tens of thousands, a substantial increase is evident for February of 2020, relative to the previous years. This pattern persists into March of 2020. The increase in the proportion of high-balance consumers was not readily apparent in the histograms shown above and explains the large values of the divergence statistic in the first quarter of 2020.

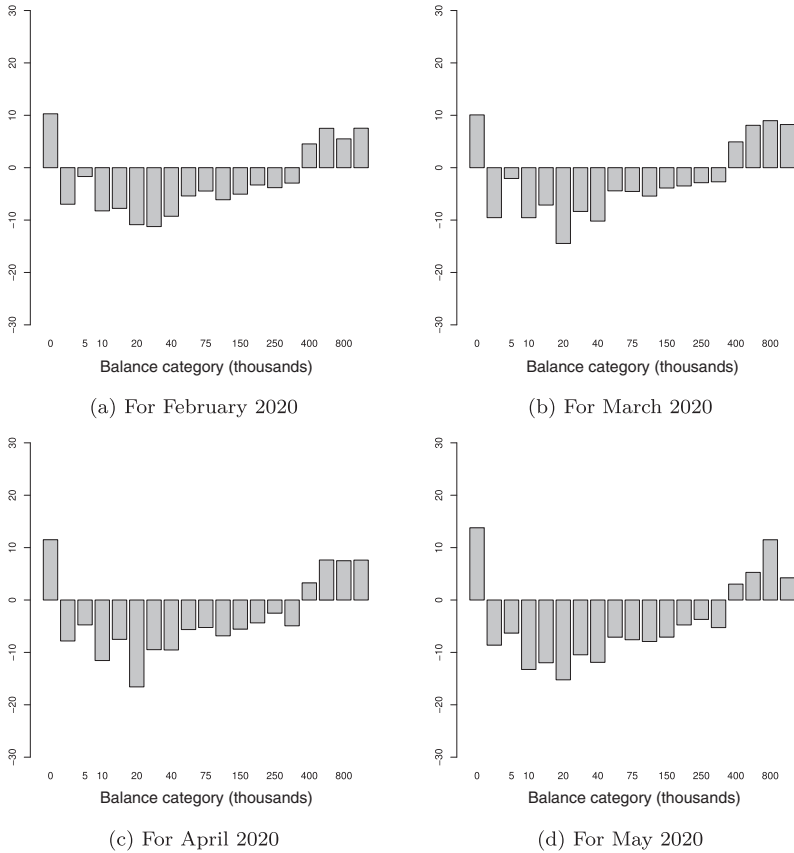


FIGURE 5 Deviations from histograms (HELOCs)

The effects of the pandemic emerged during the month of April: figure 4(c) depicts the change in the proportion of consumers in each balance category during the month of April 2020. A larger fraction of the population exists with balances below \$1,000 and a smaller fraction exists with balances between \$1,000 and \$25,000 than before. A substantial increase in the proportion of consumers with credit card balances in excess of \$40,000 also exists. In this simple comparison, the change in distributions is confounded with the rising incidence of very high balances over the previous years: a pattern that continues from February before the pandemic.

The changes noted in April 2020 persist through May and June: An increase in the proportion of consumers with credit card balances below \$1,000 and a decrease in the proportions for higher balance categories also exist. If the increase in the proportion of consumers with balances in the tens of thousands had persisted from January beyond March 2020, then the reduction in the proportion of consumers with high credit card balances may be understated for April and May.

3.1.2. Home-equity lines of credit

An investigation of home-equity lines of credit (HELOCs) exposes another source of complexity, namely, a pattern of changes in balances that continues through the months of February to May 2020 (figure 5). An increase in the proportion of HELOCs with balances of zero, a reduction in the proportions for positive balances below \$400,000, and an increase in higher balance categories occurred. From March to May, the differences from the sample histograms closely match those in February. This suggests that the month-to-month variation during the pandemic is obscured by the year-over-year changes that arise from comparing histograms measured during different years. This combination of activity makes it difficult to discern any pattern of changes connected to the COVID-19 pandemic. As in the investigation of credit card balances, the balances of HELOCs must be modelled more accurately in order to characterize adequately the changes attributable to the pandemic.

3.2. Comparisons with forecasts

Although the comparison with histograms from the sample period does account for seasonality, it does not take into account the trend of increasing balances, nor does it condition on the state of these credit markets before the pandemic. Obtaining an accurate comparison requires that we estimate a forecast of the proportions of consumers in each balance category.

How do we distinguish between dependence in the data and the effect of the pandemic on excess balances? We estimate transition matrices $\hat{\mathbf{P}}_\ell$ for each calendar month during the sample period. Because the months of the year are represented by mutually exclusive indicator variables, the transition matrices are easily concentrated out and estimated separately. Furthermore, the k^{th} rows of $\hat{\mathbf{P}}_\ell$ are also estimated separately, using only the observations with past balances in category k , which is implemented by calculating the histograms of balances across the categories in the subsequent month, using the relevant observations selected by the previous balance category.

Following this approach, we estimate these transition matrices up to the date before the pandemic—in this case, January 2020. Then, based on those estimates, we calculate the one-, two-, three-, up to the seven-month ahead forecast distributions according to the Markov model:

$$\hat{\mathbf{p}}_{T+1} = \hat{\mathbf{P}}_1 \tilde{\mathbf{p}}_T, \hat{\mathbf{p}}_{T+2} = \hat{\mathbf{P}}_2 \hat{\mathbf{P}}_1 \tilde{\mathbf{p}}_T \cdots \hat{\mathbf{p}}_{T+\ell} = \hat{\mathbf{P}}_\ell \cdots \hat{\mathbf{P}}_2 \hat{\mathbf{P}}_1 \tilde{\mathbf{p}}_T. \quad (3)$$

We then compare the distributions generated by equation (3) with what actually obtained: in our notation, $\tilde{\mathbf{p}}_{T+1}$, $\tilde{\mathbf{p}}_{T+2}$, $\tilde{\mathbf{p}}_{T+3}$, $\tilde{\mathbf{p}}_{T+4}$ and so on, using the statistic in equation (2).

The only change from equation (2) above is the estimation of the transition probability matrix, the rows of which are consistently estimated by the sample histograms. Consequently, the forecast distribution, for which the transitions

are left-multiplied several times, is also consistently estimated, assuming the correct model specification for the transition matrices. With the large sample that we have, the difference from sampling variation is minimal.

Each transition is calculated using the matrix $\hat{\mathbf{P}}_\ell$ that corresponds to the particular month. Were it not for the strong seasonality in the distribution of balances, one could use a simpler model in which the transitions are calculated using a single, fixed transition matrix throughout the year. Such a fixed transition matrix would have $28 \times 29 = 812$ parameters, with 29 categories of credit card balances in the discretized model. In contrast, the model that we estimate, with monthly transition matrices, has 12 times as many—some 9,744 parameters.

To detect whether a difference exists between the observed distributions and the forecasted ones, we perform another series of tests. In the first set of tests, we compare the benchmark with an ℓ -step-ahead forecast. We initialize the forecasts, $\hat{\mathbf{p}}_T$, with the proportion of consumers in each balance category that is observed on 1 January 2020, reflecting activity recorded during the month of December 2019.¹⁵ We then calculate a series of forecasts $\hat{\mathbf{p}}_{T+\ell}$ by left-multiplying the vector with the transition matrices for each month, $\hat{\mathbf{P}}_\ell$. The forecast for the next month ($\ell + 1$) is calculated in the same way, using the forecast from the period before: $\hat{\mathbf{p}}_{T+\ell+1} = \hat{\mathbf{P}}_{\ell+1}\hat{\mathbf{p}}_{T+\ell}$.

The results of this series of comparisons for the model are collected in table 2. As before, the statistic is the Kullback–Leibler divergence statistic, except this time, the statistic is used to compare the ℓ -step-ahead forecasted distribution with the observed sample distribution, as defined in equation (2). The p -value columns show the probability of observing a statistic more extreme from the χ^2 distribution with 28 degrees of freedom for credit cards and 18 degrees of freedom for HELOCs.

TABLE 2
Divergence from ℓ -step-ahead forecasts

Month	Credit cards		HELOCs	
	Divergence	p -value	Divergence	p -value
February 2020	44.39	2.5411e-02	25.70	1.0681e-01
March 2020	71.18	1.2710e-05	85.80	8.1259e-11
April 2020	4,436.14	<0.0000e-16	221.97	<0.0000e-16
May 2020	7,773.38	<0.0000e-16	534.41	<0.0000e-16
June 2020	5,456.78	<0.0000e-16	926.60	<0.0000e-16
July 2020	3,846.25	<0.0000e-16	1,281.55	<0.0000e-16
August 2020	3,274.21	<0.0000e-16	1,352.55	<0.0000e-16

15 Although this may be early, it avoids initializing our forecasts while the pandemic was active in Canada. Also, it allows for a few months of out-of-sample tests of the modelling framework in the months before March 2020.

The divergence statistics up to March do not wander far from those expected under the null hypothesis of no change, especially considering that they are calculated using tens of millions of observations. At the end of April, a substantial change in the distribution of credit card balances exists; this difference is even more pronounced for balances at the end of May. The divergence declines slightly from June to August, but settles at a level that suggests the distribution is still far from that forecasted from before the pandemic. For HELOCs, the change in the distribution occurs gradually; it begins to shift in April and continues through August, although the change is not as extreme as that for credit cards.

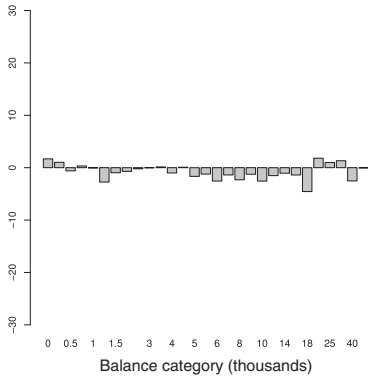
3.2.1. Credit cards

Using forecasts calculated with separate monthly transition matrices, we show the deviations in probability mass in figure 6, where each bar in the figure is provided in equation (1). In April, we find a much higher proportion of consumers with credit card balances less than \$1,000, relative to that predicted by our forecasts. The deviations from forecast with May balances are even more extreme: we find more than 20% more consumers than forecast with balances from zero to \$250. Conversely, we find a declining proportion of consumers with credit card balances at all levels greater than \$1,000, and a remarkable 25% decline in the proportion of consumers with balances in the range from \$4,000 to \$10,000. These changes persisted through July and August, even after the economy gradually reopened in late June, with a decline of roughly 20% in all balance categories above \$6,000.

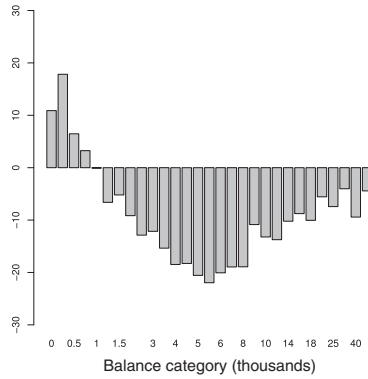
3.2.2. HELOCs

For HELOCs, smaller percentage changes exist in the distribution from forecast when compared with those for credit card balances, as shown in figure 7. The category with the greatest proportional change is represented by the fourth bars with balances between \$5,000 and \$10,000. The proportion of consumers in this category dropped by 10% in May, 13% in June, 16% in July and 15% in August. In the remaining four of the lowest six categories, balances between \$10,000 and \$20,000, in the second, third, fifth and sixth bars, the proportion decreased by about 7% in May and 10% in June, remaining in this range until August. The proportion of consumers with balances in most of the remaining categories, from \$20,000 to \$350,000, decreased by a smaller percentage, between 5 and 10%.

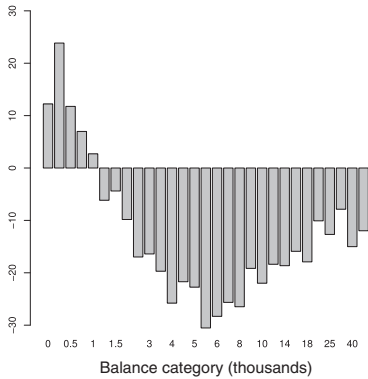
Much of the activity in the distribution of HELOC balances is concentrated in the low and high balances: many consumers paid off their HELOC loan entirely and there exists substantial variation in the highest balance categories from month to month. This suggests increased activity in the flows into and out of the HELOC market. The observed decline in HELOC balances coincides with reduced consumer spending during the lockdown period, as confirmed by the Financial Consumer Agency of Canada (2018) report, showing that 49% of HELOC holders used their accounts to pay for home



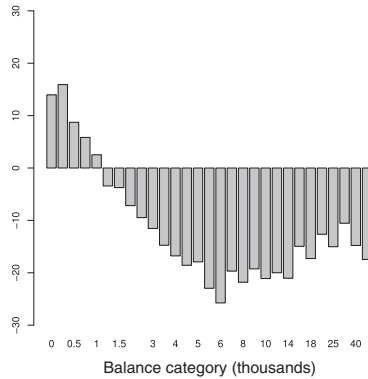
(a) For March 2020



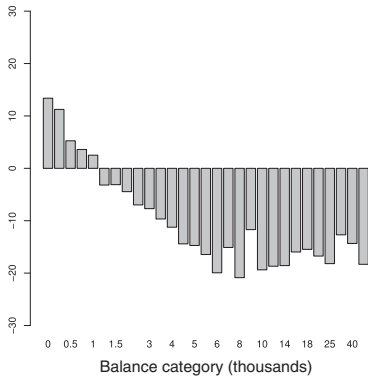
(b) For April 2020



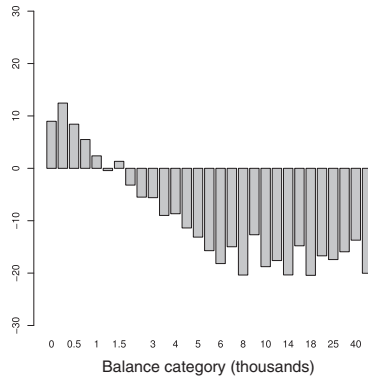
(c) For May 2020



(d) For June 2020



(e) For July 2020



(f) For August 2020

FIGURE 6 Deviations from forecasted credit card balances

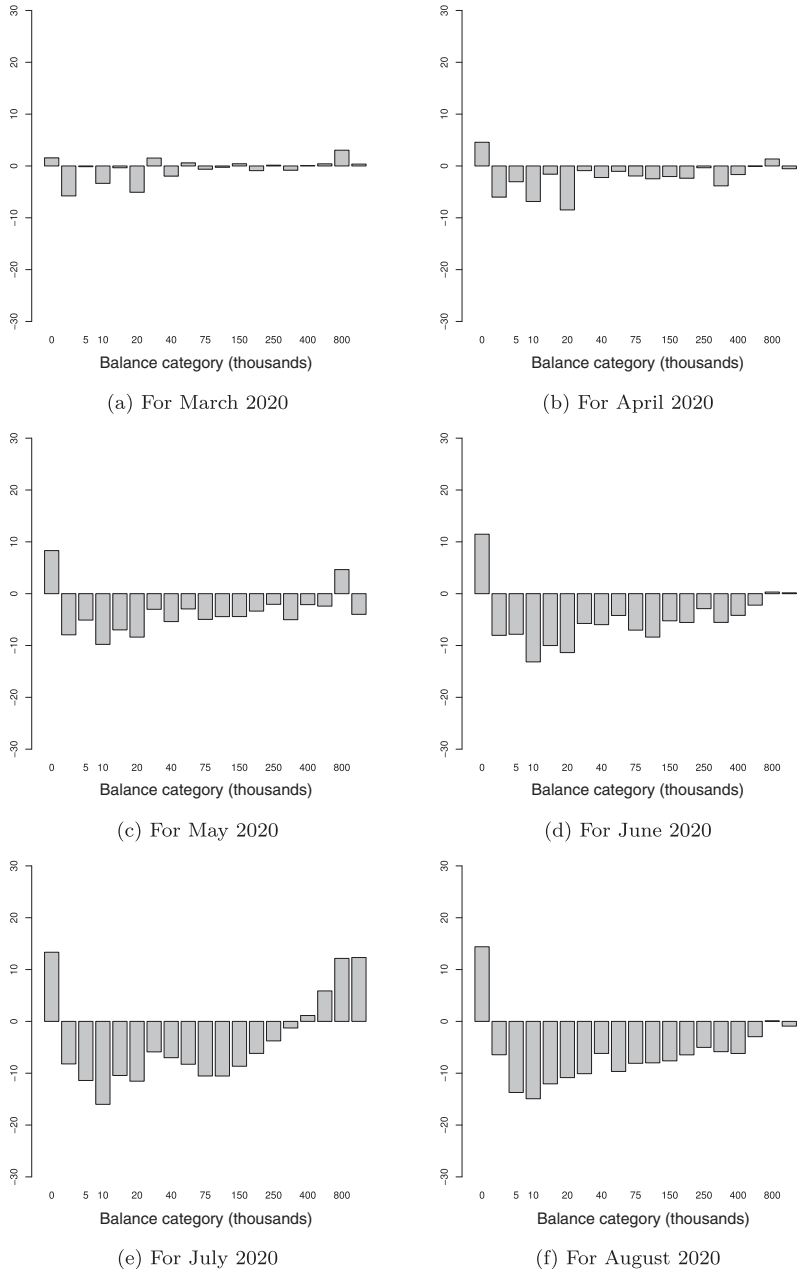


FIGURE 7 Deviations from forecasted HELOC balances

renovations, with a median amount of \$10,000. In contrast, a sharp increase in borrowing activity is observed in the three categories with balances above \$400,000 in July. This spike is due to a surge in home sales—a 30.5% increase

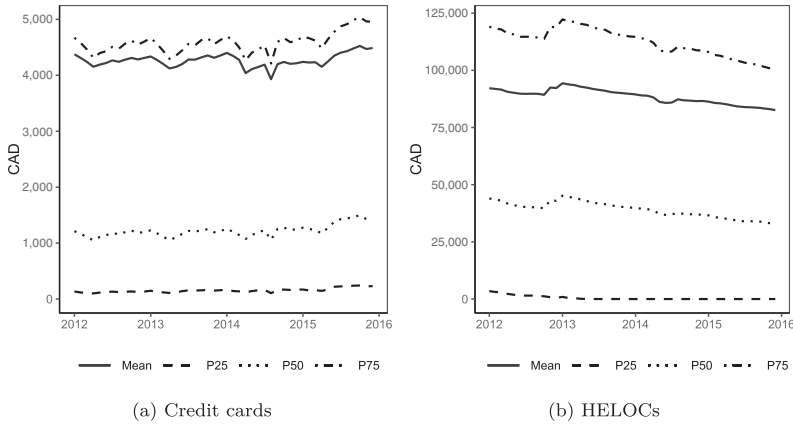


FIGURE 8 Consumers’ outstanding balances, Alberta, 2012–2016

in home sales—the highest recorded increase in the last 40 years, supported by historically low financing costs, resilient incomes for higher-earning households, and pent-up demand from delayed spring activity; see Bank of Canada (2020). This episode was short-lived, however, with decreases in all non-zero balances categories by August.

3.3. Comparison with the oil price shock in Alberta, 2014–2015

As a point of comparison, we conduct a similar analysis with a sample from the petroleum-rich province of Alberta during the oil price shock in 2015. During this episode, in late 2014 and all of 2015, oil prices declined sharply and pushed the province into a recession. In late 2014, oil prices dropped from over \$100 per barrel in July to nearly \$45 by January 2015. Prices then declined to a low of just under \$30 by the beginning of the next year, 2016. Consequently, the unemployment rate in Alberta increased from 4.2% in December 2014 to 6.4% in December 2015.

Consumers in Alberta were pushed into financial stress; a notable increase in credit card balances occurred in the province. Figure 8(a) illustrates that, following the oil price decline, individuals’ credit card balances on average increased by about 10.1% from \$4,215 at the end of 2014 to \$4,657 at the end of 2015. We use this example as a benchmark—to compare what happened during the COVID-19 pandemic. In contrast, a different scenario was unfolding in HELOC usage in Alberta over the same period. Figure 8(b) illustrates that the aggregate HELOC balances were in decline during the oil price shock.¹⁶

16 HELOC usage had already exhibited a decreasing trend since 2013 because of a policy change at the end of 2012, reducing the maximum loan-to-value ratio of HELOCs from 80% to 65%; see the Residential Mortgage Underwriting Practices and Procedures Guideline (B-20), in OSFI (2012).

To place a proper event window around the initial period of declining oil prices, we restricted the in-sample period to the year 2013. This allowed for a balanced sample size for estimating each of the monthly transition matrices. The year 2015 was reserved as the out-of-sample period over which we measure the impact of the oil price shock in Alberta, a horizon similar to that of the COVID-19 pandemic.

Our sample was drawn randomly from the years 2013 to 2015—an in-sample period of 24 months over the years 2013 to 2014. For credit cards, we drew a 10% sample in Alberta that includes 366,794 unique consumers with at least one opened credit card account, collectively the sample contains 18,286,464 monthly observations. For HELOCs, we included 40% of the HELOC holders in Alberta, which contains 330,019 unique consumers with a total of 18,427,526 monthly HELOC observations.

Loan balances were organized into the same intervals as in our analysis of the period during the COVID-19 pandemic. We estimated the transition matrix by estimating a histogram for each row, conditioning on the balance category in the previous month, using the sample period from January 2013 to December 2013. We then calculated the ℓ -step-ahead forecast of the discrete distribution for the subsequent months by applying repeated multiplication of the transition matrix, starting from the discrete distribution in December 2014. We calculated the Kullback–Leibler divergence statistic to measure the distance between the forecast probability vector and the actual one observed for each month. The test results were collected in table 3. For both credit cards and HELOCs, the distributions gradually shifted away from the distributions in December 2014. The divergence of the HELOC distribution is similar in magnitude to that during the COVID-19 pandemic. In contrast, the shift in the distribution of credit card balances was less pronounced than that during the pandemic, but still a significant divergence from the distribution at the beginning of the year.

TABLE 3Divergence from ℓ -step-ahead forecasts in Alberta, 2015

Month	Credit cards		HELOCs	
	Divergence	p -value	Divergence	p -value
January 2015	71.70	1.0733e-05	73.77	1.0296e-08
February 2015	147.90	<0.0000e-16	213.80	<0.0000e-16
March 2015	163.82	<0.0000e-16	346.98	<0.0000e-16
April 2015	308.18	<0.0000e-16	642.17	<0.0000e-16
May 2015	845.04	<0.0000e-16	959.92	<0.0000e-16
June 2015	709.63	<0.0000e-16	1,300.12	<0.0000e-16
July 2015	850.45	<0.0000e-16	1,661.28	<0.0000e-16
August 2015	748.95	<0.0000e-16	1,955.30	<0.0000e-16
September 2015	698.63	<0.0000e-16	2,257.07	<0.0000e-16
October 2015	714.21	<0.0000e-16	2,595.07	<0.0000e-16
November 2015	669.75	<0.0000e-16	3,264.34	<0.0000e-16

The difference between the forecast and observed distributions of balances for October 2015 is illustrated in figure 9(a). Each bar quantifies the percentage change in the proportion for a bin. A substantial reduction exists in the proportion of consumers with a balance of zero. Conversely, most of the categories of balances greater than \$2,000 have increased membership relative to the forecast proportions. This demonstrates a pronounced change in credit usage. It suggests that many consumers may have resorted to borrowing from credit cards to cover expenditures, while they would otherwise not do so.

In contrast, the distribution of HELOC balances moved in the opposite direction. As illustrated in figure 9(b), balances of HELOCs declined during the oil-price shock, in roughly the same proportions as observed during the COVID-19 pandemic. Our results provide further evidence that the majority of HELOC holders did not tap into their home equity to access liquidity. These findings are consistent with Financial Consumer Agency of Canada (2017) in that, from 1999 to 2010, 40% of HELOC borrowers used their accounts to pay for consumption and home renovations, 36% used their accounts for investment, and only 26% used them for debt consolidation. The oil-related economic downturn resulted in stagnant housing price growth and reduced consumer spending through HELOC usage.

Our analysis provides an appropriate yard stick with which to measure the effect of the COVID-19 pandemic on the same variables. During COVID-19, credit card balances *decreased* during the COVID-19 pandemic, to a degree roughly twice the proportion of the *increase* in indebtedness that resulted from the oil price shock. HELOC balances have declined during both COVID-19 and the Alberta price shock, suggesting that obtaining financial liquidity is not a major purpose of HELOC usage.

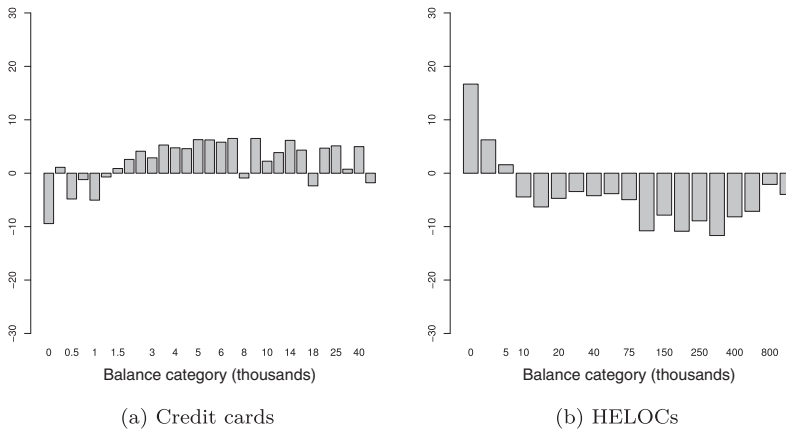


FIGURE 9 Deviations from forecasted balances in Alberta, October 2015

4. Summary and conclusions

We have presented an empirical framework to describe the law of motion of consumers' credit usage and used it to provide a plausible forecast of the distribution of credit card and HELOC balances under the counterfactual state in which the COVID-19 pandemic had not taken place. We found a significant downward shift in consumer credit usage in Canada, slashing billions of dollars off credit card and HELOC balances across the country, to a level not seen in years. This followed a long period of increasing debt levels in Canada, which has been a concern over the prospects for the Canadian economy.

The changes in financial position materialized through decreased proportions of consumers in high-balance categories. Although the percentage changes in balance categories were lower for HELOCs than for credit cards, the dollar values of the changes are measured in thousands and tens of thousands. That we found a leftward shift in the distribution of HELOC loan balances demonstrates that the reduction in borrowing is not restricted to high-interest, credit card debt: the changes that we documented are more widespread than typically perceived. Finally, the two types of accounts are typically used differently by consumers. Credit card usage represents both monthly expenditures and borrowing because many consumers will pay off their balances soon after the statement. In contrast, HELOC loans exclusively represent debt, so the reduction of the balances of HELOC loans represents an unambiguous reduction in debt for consumers in Canada.

When compared with changes during a recent recession in Canada, the magnitude of the changes in credit card balances is nearly twice as large, except that the distributions of balances shift in the opposite direction. Instead of increasing their use of high-interest debt, consumers are paying down their balances—something not usually seen during a recession.

Appendix A: Data appendix

Given the ongoing concern surrounding delayed credit reporting during the COVID-19 pandemic (Sandler and Ricks 2020), we provide detailed comparisons of our dataset obtained from the credit reporting agency with other available data sources. Overall, we conclude that our dataset is representative of most of the Canadian population, both in the cross-section and over time.

We have validated the database from the consumer reporting agency by comparing against the regulatory filings reported by chartered banks and maintained by the Bank of Canada.¹⁷ We included this comparison because

¹⁷ Financial institutions are required to report their aggregate financial status to the Bank of Canada and OSFI. A detailed list of regulations is publicly available from www.osfi-bsif.gc.ca/Eng/Docs/dti_req.pdf. Notable items include the balance sheet, income statement, mortgage and non-mortgage loan balances and reports of new lending.

regulatory filings are required to follow specific accounting regulations to report the status of a financial institute, while credit reports are constructed to reflect individuals’ creditworthiness through their historical loan performance. Although the information is largely derived from the same sources, different reporting conventions and data processing may result in discrepancies, which our results suggest to be small.

Figure A1 depicts the monthly time series of aggregate balances from January 2017 to September 2020. In the left panel, the series collected by the Bank of Canada is shown with the solid line. The dashed line represents the analogue from the database held by the credit reporting agency. It is the sum of all credit card balances held by chartered banks for all consumers in the database. Although slightly higher than that reported by the chartered banks, the monthly changes are very similar, indicating that the database held by the credit reporting agency is representative of the population of the customers of chartered banks. The dotted line shows the aggregate credit card balances from all financial institutions in Canada, recorded in the database from the credit agency. Loan balances at institutions other than chartered banks, such as credit unions and credit card companies, account for about 12% of the total outstanding credit card balances.

For another method of data validation, we examined the Nilson Report (2020). This report contains information concerning a wider range of credit card issuers in Canada. Table A1 shows a comparison of credit card statistics between the Nilson Report and the database held by the consumer credit agency. This table shows the number of accounts and the number of those accounts that are active, in millions. The numbers of accounts are similar, with less than a 4% difference between the numbers from the Nilson Report and the credit reporting agency. This similarity holds in spite of the fact that

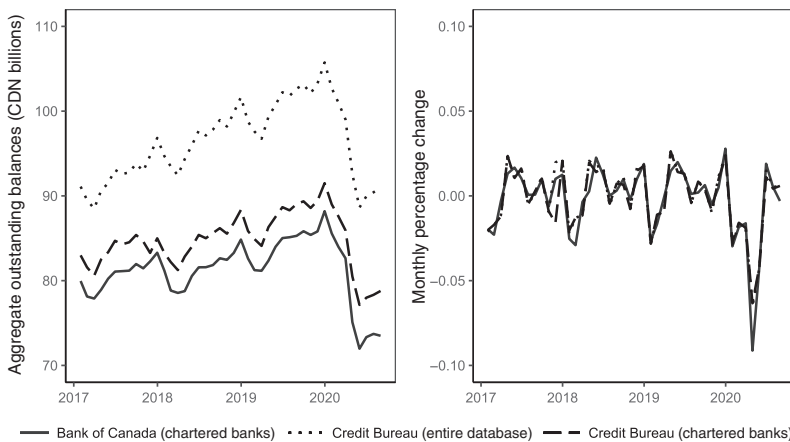
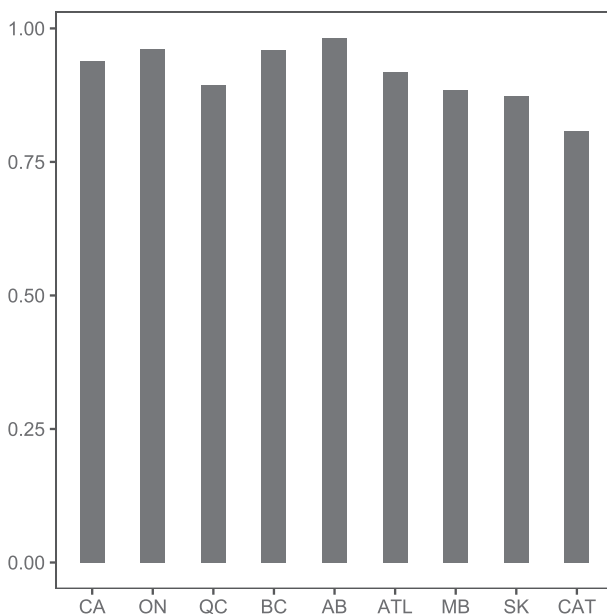


FIGURE A1 Time series of aggregate credit card balances

TABLE A1

Comparison of accounts at the credit agency with nation-wide totals in the Nilson Report

Year	Nilson Report			Credit agency		
	Accounts	Active	Balances	Accounts	Active	Balances
2019	52.9	34.4	\$102.1	51.9	35.4	\$105.5
2018	51.3	33.4	\$105.7	52.3	34.5	\$101.6

**FIGURE A2** Credit data coverage for adults in Canada, by province

the data-cleaning steps may well have been different in each set of statistics. The total balances for these accounts differ by no more than 4%.

In terms of consumer coverage, we also compared the number of credit-active consumers in the credit reporting agency with the population reported in the 2016 Canadian Census. For this comparison, we only considered the population for Canadians aged 20 and above. Figure A2 illustrates the number of individuals with any form of credit divided by the population in each province of Canada.¹⁸ The first bar shows the ratio of coverage for the entire country of Canada (CA) and it shows that 93.9% of consumers are represented in the database. The rest of the bars show the same ratio for each

¹⁸ This ratio includes not only those consumers with credit cards and HELOCs but also those with mortgages, instalment loans, other lines of credit and even telecommunication accounts.

province, ordered by population. For the provinces of Ontario (ON), British Columbia (BC) and Alberta (AB), the coverage rate is even higher than the national average. For Quebec (QC), the Atlantic provinces (ATL), Manitoba (MB) and Saskatchewan (SK), the coverage rate is slightly lower but still greater than 88%. Coverage is lowest, near 80%, for the Canadian territories (CAT), in the northern part of Canada, where the population is the lowest. Overall, we conclude that our data set correctly represents the population of the entire country.

Supporting information

Supplementary material accompanies the online version of this article.

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