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The Heterogeneous Effects of COVID-19 on Canadian Household Consumption, Debt and Savings

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Abstract

This paper develops an agent-based modelling approach to quantify the impact of COVID-19-induced economic disruptions on household debt and unplanned savings over 2020. We merge data from the Survey of Financial Security and the Survey of Household Spending to construct a representative cross-section of households who vary in their income, debt portfolios and mix of consumption expenditures. We simulate a series of individual and aggregate shocks to household income and consumption expenditures that incorporate government policies such as Canadian Emergency Response Benefit (CERB) as well as shifts in consumption expenditures across hard-to-distance goods (e.g., travel, restaurants) and easy-to-distance goods (e.g., groceries). Differential impact on household incomes resulting from unemployment and reduced hours play an important role in driving household debt and savings. We highlight two other important channels. First, income replacement programs (notably CERB) only partially replace lost income for unemployed, previously middle-income households—which drives a rise in borrowing, particularly for those with mortgages. Second, upper-income households have relatively larger expenditures on hard-to-distance goods and so experience larger declines in consumption expenditures. This contributes to the high savings observed during March and April.

Bank topics: Coronavirus disease (COVID-19); Business fluctuations and cycles; Financial stability
JEL codes: E21, E24, G51

1. Introduction

The direct and indirect economic impacts of COVID have resulted in unprecedented declines in employment, hours worked and income. Despite unprecedented increases in government transfers to households and firms, many have expressed concerns regarding the implications of these economic disruptions for household finances (e.g., Siddall 2020). Conversely, others have pointed to the significant rise in household savings during the "lockdown" in March and April as the basis for a rise in consumption expenditures in the second half of 2020, due to "pent-up" demand.[1]

This paper examines the impact of the economic disruptions of COVID on household balance sheets over 2020. We focus on how COVID-induced shifts in the distribution of household income impact both the distribution of household debt as well as unplanned savings. Our analysis adopts an agent-based modelling approach, which we initialize with a distribution of households who vary by income, asset portfolios and consumption bundles, and then feed through a projected series of individual and aggregate shocks to household income and consumption over 2020.

We find substantial differences across households in the impact of the COVID shock. Part of these differences stem from the differential impact on incomes resulting from unemployment and reduced hours. Our work points to two additional channels which result in heterogeneous impacts on households. First, income-replacement programs, notably the Canada Emergency Response Benefit (CERB), replace varying amounts of lost income across households. Second, there are large differences in household expenditures on hard-to-distance goods, with higher-income households generally spending a larger share of their income on these goods. This translates into larger declines in consumption expenditures by higher-income households, which plays a significant role in the rise in savings observed during the peak of the economic disruptions in March and April.

[1] For example, the Bank of Canada statement https://www.bankofcanada.ca/2020/07/fad-press-release-2020-07-15/ and Export Development Canada's commentary https://www.edc.ca/en/weekly-commentary/covid-pent-up-demand.html/ as well as the U.S. Federal Reserve Beige Book for October https://www.federalreserve.gov/monetarypolicy/beigebook202010.htm/ all express this view.

Our analysis begins with the construction of a representative cross-section of Canadian households for which we have detailed data on consumption, income and balance sheets. Since there is no such available dataset, we merge data from two different household surveys: the Survey of Financial Security (SFS) (Statistics Canada, 2016) and the Survey of Household Spending (SHS) (Statistics Canada, 2017). Specifically, we use common variables to impute household consumption expenditures for the SFS. In this exercise, we allocate household expenditures into three categories: essentials/easy-to-distance, luxuries/hard-to-distance (such as travel), and shelter. In addition, we use data from the Labour Force Survey (LFS) (Statistics Canada, 2020) to guide and discipline the evolution of shocks to employment and income.

The cross-section of households we construct serves as the starting point for our agent-based simulation. In our simulation, we feed through a series of shocks to household income over 2020 and early 2021. To capture the impact of COVID and social distancing restrictions on consumption expenditures, we impose a data-driven decline in household spending on hard-to-distance consumption goods (such as dining and travel) and an increase on essentials (such as groceries). We also include key policy responses to the crisis, as the simulation allows for mortgage deferrals as well as new transfer programs such as CERB.

Our simulation sheds new light on the heterogeneous impact of COVID on household finances. As with most recessions, the adverse effects of large declines in incomes is concentrated among a small number of workers (e.g., see Guvenen et al. (2014)). The COVID crisis follows this pattern, although the pace and scope of job losses dwarf recent recessions. Moreover, the introduction of CERB has impacted the distribution of earnings. Our simulations suggest that some lower-income earners will see their income increase as CERB *more* than replaces lost income. In contrast, CERB only partially replaces the income loss of many middle- and upper-income earners.

Although the percentage change in spending on hard-to-distance consumption is common across households, we find that it results in a heterogeneous impact on household gross expenditures. We show that on average, higher-income households have higher expenditure shares on hard-to-distance consumption goods. This results in a proportionately larger decline in expenditures for higher-income households due to the different weights in their consumption bundle.

The larger decline in spending for higher-income earners plays a key role in the dynamics of unplanned savings. Our simulation points to a substantial rise in unplanned savings over April and May, roughly 45% of the size of aggregate monthly consumption expenditures. This rise in savings is particularly pronounced among middle-aged and older homeowners for whom the fall in consumption is large relative to their cash flow. We find that the top quintile account for over half of the total rise in saving.

Our simulations also point to a rise in the number of households with high debt payments relative to income. This is largely driven by middle-income households who experience a spell of unemployment and for whom CERB only partially replaces their lost income. This group is a mix of renters and homeowners with mortgages. Our simulations also point to a small group – largely comprised of renters – for whom access to credit could become an issue once CERB ends.

A key policy question is whether the end of the six-month mortgage deferral window will see a jump in mortgage defaults. Based on a gradual recovery in employment in the fall of 2020, our simulations point to modest upward pressure on mortgage delinquencies. This can partially be accounted for by the high job-finding probability for households with mortgages.

Our paper illustrates how the interplay between income shocks, income support programs such as CERB and unprecedented restrictions on consumption of hard-to-distance goods is resulting in heterogeneous effects on household balance sheets. Our simulation findings appear broadly consistent with Achou et al. (2020), who surveyed roughly 3,000 Quebec households in May 2020 on how COVID has impacted household finances. Consistent with our simulations, they find that higher-income households were more likely to see expenditures decline in April 2020, with some evidence pointing to restaurants and transportation as key areas of decline. They also report that CERB applicants had lower incomes than non-applicants.

Similar to recent empirical work by Cox et al. (2020), who examine the impact of the pandemic on U.S. households, we find that government transfer programs such as

CERB have significantly supported the finances of lower-income households.[2] Hacioglu et al. (2020) use data on household accounts from a U.K. fintech company and find that nearly half of the decline in aggregate consumption can be accounted for by the top quartile of earners. They also find that government policies to support income have largely replaced income losses for the bottom quartile, who also reduced consumption expenditures the least. We differ from these papers in both our Canadian focus and our model-based approach that links household consumption portfolios, the severity of income shocks, and the evolution of savings and debt over time. Our analysis points to differences across households in expenditures on hard-to-distance goods as well as differential income replacement as key factors in the heterogeneous declines in consumption (and rise in savings) across income groups.

Our paper is also related to a growing literature on the resiliency of household finances in the face of unanticipated income declines. Bilyk et al. (2020) draw on the SFS to find that, since roughly one fifth of Canadian households with mortgages can make only up to two months of mortgage payments using liquid assets, mortgage deferrals and income-support policies are playing an important role in supporting financial stability. Our work differs in modelling and quantifying the impact of shocks to income, consumption expenditures and government policies on the build-up of debt and savings across households.[3]

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[2] Bourquin et al. (2020) consider U.K. households along similar lines.

[3] The limited amount of liquid assets available to many households has been well documented. For the U.S., see https://www.federalreserve.gov/econres/notes/feds-notes/assessing-families-liquid-savings-using-the-survey-of-consumer-finances-20181119.htm/ as well as https://www.brookings.edu/blog/up-front/2020/03/26/the-middle-class-is-not-ready-for-the-looming-recession/. An example of this for Canada is https://www.policyalternatives.ca/sites/default/files/uploads/publications/2020/03/Rent%20is%20due%20soon%20FINAL.pdf. For European countries, see https://voxeu.org/article/finances-european-households-through-pandemic/.

2. Methodology for Consumption and Income Simulation

This model is designed to roll forward COVID-shocked consumption and income scenarios across a representative panel of Canadian households. We draw on survey data to construct a balance sheet for each household in our panel, as well as a household-level consumption function which takes income (and employment status), demographics and mortgage information into account. Employment status follows an exogenous process dependent on age and education status.

2.1 Pandemic Consumption and Imputation

Our analysis of household consumption builds on the SHS. Our interest in the impact of COVID on consumption leads us to incorporate two key elements into our analysis of household consumption:

- Effects of social distancing and regulations which govern consumption of different goods
- Differences across goods in how easy it is for households to reduce spending, as some goods are essential (e.g., food) while other goods (e.g., travel) may be viewed as a luxury

We divide non-shelter goods along these two dimensions to create household-level estimates of consumption expenditures. In addition, for each household, we allocate spending on housing and shelter to a separate category (e.g., property tax).

This leads us to construct three categories for consumption spending for each household:

- Essentials and easy-to-distance (ETD): goods which households must continue to consume (e.g., groceries, medications) or are easy to consume during social/physical distancing (e.g., deliverable electronic goods).
- Luxuries, discretionary and hard-to-distance (HTD): goods for which spending is often reduced when income is reduced (e.g., jewellery) and goods for which regulations, sensible risk aversion or guidelines prevent or reduce consumption (e.g., overseas travel, drinks at bars).

- Shelter: rent payments, property taxes, key maintenance and so on (but not including mortgages, which are part of our debt dynamics modelling).

Some SHS spending categories do not correspond directly to our classification. Thus, in some cases we allocate spending partially across categories. For example, while we categorize air travel as luxury/HTD, we split electronic goods, clothing and subcategories of transport spending between essential/ETD and luxury/HTD. To better capture shifts in consumption due to social distancing, we allocate some items, such as communication equipment, to the essential/ETD category. Our full breakdown is listed in the Appendix.

To overcome the absence of information on household assets or debt in the SHS, we use the SFS. To merge the surveys, we use a multiple imputation by chained equations (MICE) (van Buuren and Groothuis-Oudshoorn (2011)) procedure to impute the consumption of households in the SFS. This imputation uses variables common to both surveys, notably income, key demographics (age, education, location, household type and members) and size of mortgage payments for mortgagors to predict household expenditures. Using the flexible non-linear random forest machine-learning algorithm, we impute the distribution of conditional consumption onto the SFS.[4] Key to this procedure is that the distribution of conditional consumption is random after the matched variables are taken into account – with the wealth of similar information between the surveys, we believe this is sufficiently met. This creates a sample of households with a full balance sheet and flows of income and consumption, which we can micro-simulate.

There are significant differences in expenditure shares on goods across households. While high-income households account for a larger share of consumption expenditures, their share of total expenditures on hard-to-distance/non-essential items is relatively larger (see Table 1). For example, while the top 20% of households (by income) accounted for 25% of expenditures on easy-to-distance/essential goods such as groceries, they accounted for 31% of expenditures on hard-to-distance goods such as

[4] We also incorporate several pre- and post-MICE modifications, importantly to correct differences between the SHS and SFS income distributions for low-income households, which we explain in the Appendix.

air travel and restaurants. This pattern of consumption expenditures plays an important role in our simulations, as it results in different impacts on consumption expenditures across households from COVID-necessitated restrictions on travel and hard-to-distance consumption.

Table 1: Expenditure Shares by Income Quintile

Income Quintile	Share of Total Consumption	Share of Expenditures on Easy to Distance/ Essential Consumption	Share of Expenditures on Hard to Distance/ Non-essential Consumption	Share of Expenditures on Shelter
Bottom 20	16%	15%	14%	20%
20-40	18%	17%	15%	20%
40-60	19%	19%	18%	20%
60-80	21%	23%	23%	19%
Top 20	25%	25%	31%	20%

Note: Cross-section of households based on SFS and SHS.

The combination of information in the SHS and the SFS provides a more in-depth profile of household balance sheets. Table 2 provides some key summary statistics of Canadian wealth, debt and income distribution by income quintiles. For comparison, note that CERB payments during the crisis are approximately $2,000 per month. There is a significant proportion of households with low liquid assets even in the middle of the income distribution. This is despite the broad definition of liquid assets we employ, which includes cash, deposits, stocks, tax-free savings accounts, bonds and mutual funds. The data also provides information on household balances across different types of debt, which include mortgages, auto loans, student loans, as well as credit card debt. We see that a high proportion of households have these debts across the distribution, which are more prominent among high-income households. Few high-income households rent, and the levels of rent among those who rent does not rise as fast as mortgage payments do with income. Line-of-credit debt in Canada is associated with higher income (due to eligibility for personal credit lines) and with the presence of a mortgage (due to the common home equity line of credit). However, the proportion holding unsecured debt is more similar across incomes.

In addition to balances, the SFS provides information on a household's mortgage payment and interest rate. We use this information to retrieve the mortgage term length, under the assumption that no refinancing will occur in the future. For all other debt categories that have information only on balances, we construct an amortization schedule by assuming a fixed term and rate (see Appendix).

Table 2: Wealth and Debt Distribution by Income Quintile

Item	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Mean monthly income	1,551	3,222	4,757	6,907	13,166
Liquid assets <$1000	40%	27%	21%	12%	6%
Mean positive liquid assets	26,055	44,509	49,643	75,721	180,397
Proportion with auto debt	9%	20%	31%	44%	43%
Mean auto debt	15,627	15,982	18,910	22,372	26,114
Proportion renting	67%	44%	31%	18%	8%
Mean rent (monthly)	794	1,039	1,122	1,251	1,401
Proportion with mortgage	11%	23%	30%	54%	60%
Mean mortgage payment (monthly)	1,055	1,001	1,109	1,319	1,753
Proportion with line-of-credit debt	7%	16%	21%	30%	35%
Mean LOC balance	31,010	24,555	31,239	35,228	64,387
Proportion with unsecured debt	40%	45%	51%	53%	47%
Mean unsecured debt	10,083	11,129	13,091	14,906	18,950

Note: Cross-section of households based on SFS and SHS. Figures are in 2016 CAD.

2.2 Projecting the Build-up of Financial Vulnerabilities and Savings

2.2.1 Simulation

Our agent-based simulation is based on the premise that short-term household consumption baskets are sticky.[5] In addition, we introduce household-specific changes in household consumption expenditure in response to job loss. In our simulations, we assume that (non-shelter) consumption expenditures decline by 10% for unemployed households relative to their (COVID-shocked) bundle (Christelis et al. (2015)). Given a path for consumption and income, the evolution of household savings (or borrowing) follows from the household budget constraint.

We parameterize the time-varying and category-specific shocks to the consumption of essentials/ETD and luxury/HTD using a range of data sources. For the March-to-June period, we target estimates of aggregate consumption expenditures based on internal Bank data, primarily breakdowns of high-frequency Visa and Interac payments reports, as well as internal Bank forecasts and publicly available reports from RBC.[6] After the initial shock, we impose a recovery path based on a sustained relaxation of social distancing rules. However, our baseline assumes that consumption will not fully recover to pre-COVID levels by the end of 2020 due to continued social/physical distancing.

The path for average consumption per household is plotted in Figure 1. There are three key take-aways from Figure 1. First, our baseline scenario incorporates a large decline in HTD consumption in March and April, followed by a sustained but gradual recovery until October. There is not a full recovery: HTD consumption remains 10% below pre-pandemic levels over November 2020 to February 2021. Second, the ETD category sees a modest increase of roughly 3% over the April-to-October period, primarily due to increased grocery and alcohol spending. Third, we assume that housing expenditures are constant over the next year.

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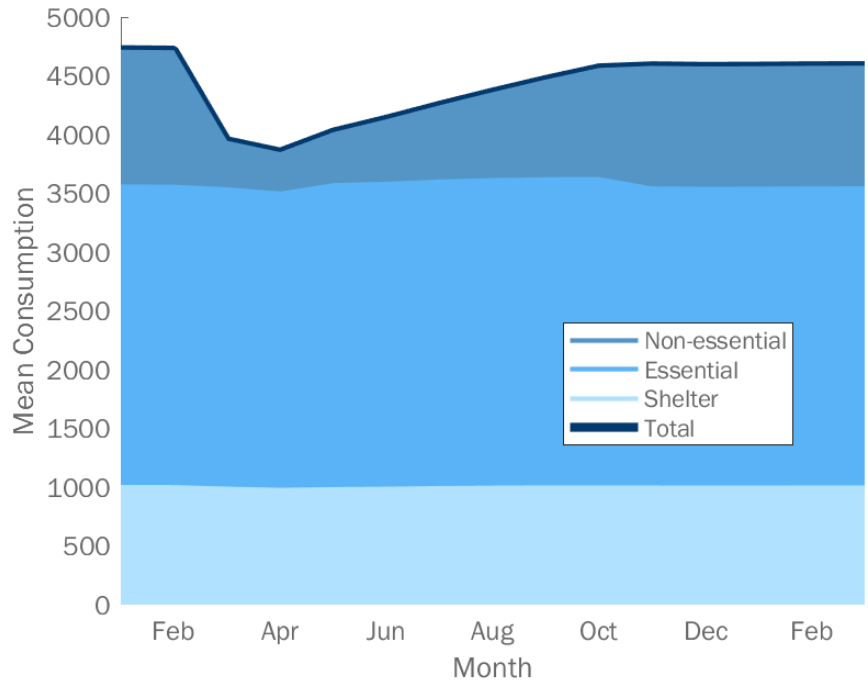
[5] That is, costly to adjust for the household, either due to monetary costs or preferences.

[6] See https://thoughtleadership.rbc.com/covid-consumer-spending-tracker/.

Figure 1: Baseline Consumption Scenario



Note: This figure plots the path of mean consumption and its subcategories over the simulation period. Consumption categories in the SHS are here broken down into three categories: essential, non-essential, and shelter. Detailed definitions found in text.

2.2.2 Income Shocks

We use the LFS to guide our parameterization of household incomes over the simulation. Our simulation features shifts in household income due to unemployment, reduced hours worked as well as changes in government transfer programs, notably CERB. Given the disruptions caused by COVID, we introduce a third employment state: *COVID-reduced hours* (in addition to employment and unemployment).

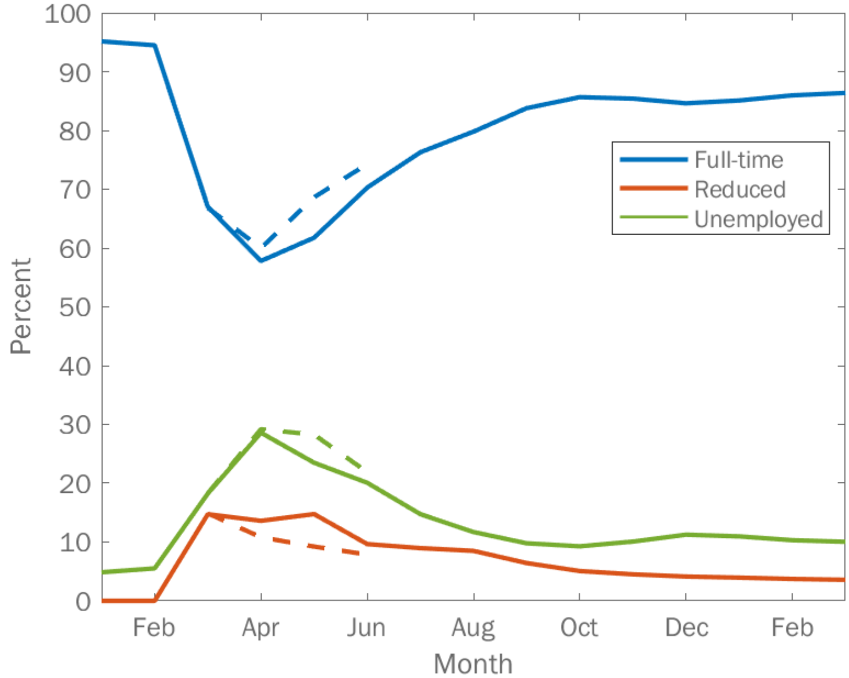
For the March-to-June period, we target a path for aggregate employment and reduced hours. To do so, we first construct COVID-adjusted employment measures from the LFS that are consistent with the employment states in our framework. A respondent is fully employed if she reports being employed, non-absent and working hours above 50% of her usual hours. We categorize two classes of workers into the reduced hours category. First, workers who report being employed but whose actual working hours fall below 50% of their usual hours. Second, workers who report being absent from work but are receiving compensation from their employer. Finally, we adjust our definition of unemployment to account for COVID-related non-participation and absences. This recognizes that the severe lockdowns depressed job-finding rates to such low levels that laid-off workers may have been discouraged from actively looking for jobs during this period. As such, we broaden the standard definition of unemployment to include (1) workers displaced between March and June who report being out of the labour force but would like to work and (2) workers who report being absent from work without pay.

Figure 2 compares our calibrated sequence of employment, reduced hours and unemployment rates (solid) with the LFS measures (dashed) that we target in our baseline simulation. Note that we assume that the reduced hours and unemployment rates remain elevated at 5% and 10% respectively until 2021.

Reduced hours play a significant role in our baseline simulation, rising slightly earlier than unemployment and implying a partial reduction in the income profile of some of those impacted by this crisis. Although this scenario assumes no second wave of infections, employment and consumption remain below pre-COVID levels throughout the simulation horizon.

To incorporate the heterogeneous risk of unemployment across the distribution, we estimate age- and education-conditional month-to-month employment status transition matrices for households based upon the cross-sectional information in the LFS. To identify these matrices we make several assumptions, including that the job finding is zero during the initial COVID shock months of March and April (which is close to the actual data). As the LFS (and SHS) provide household income while the LFS public-use files report individual income, we assume that income shocks within households are perfectly correlated, i.e., that in households with two (or more) workers, both become unemployed or employed.

Figure 2: Baseline Sequence of Employment, Reduced Hours and Unemployment

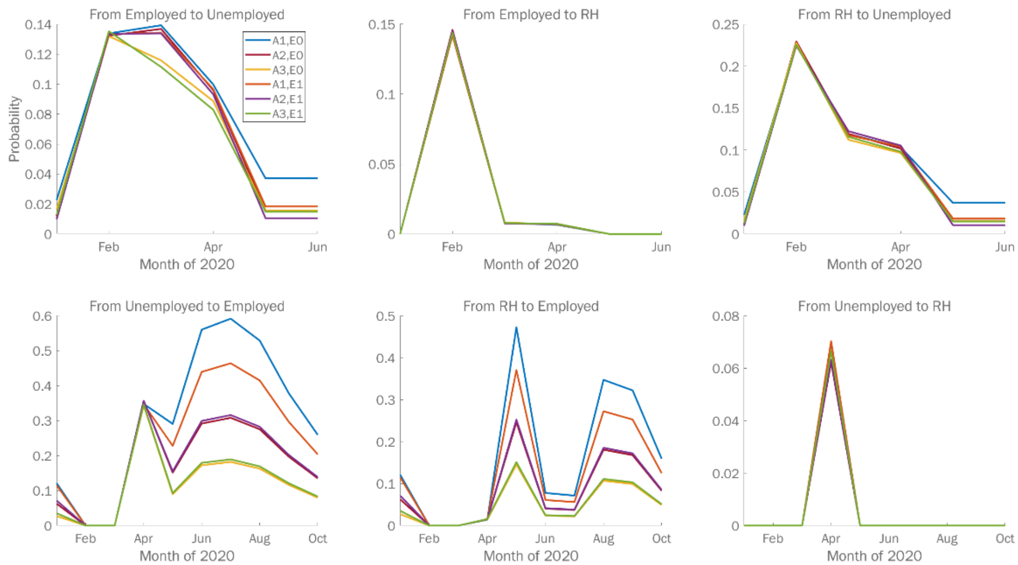


Note: This figure plots the simulated path of employment, reduced hours and unemployment rates in the simulation together with comparable measures computed from the latest available LFS data (dashed).

During the simulation, we assume that if an unemployed household becomes employed on full hours, they return to their pre-COVID income. This simplifies the simulation and is consistent with our focus of examining the impact of COVID rather than developing a fundamental model of the labour market. Our projected employment process imposes demographic-conditional job losses and finding rates estimated using 2019 data, which are uniformly scaled to match our employment and hours targets. Unemployed households receive CERB income (per adult member) or (probabilistically) an employment subsidy if in reduced-hours status.[7]

[7] For a more detailed discussion of the initial impact of COVID on Canadian labour markets, see Lemieux et al (2020).

Figure 3: Employment Flows — Transitions Probabilities



Note: The figure shows estimated transitions to match unemployment and reduced hours rates in the LFS. Note different months in the top and bottom row. 'A' indicates age group ('1' under 40, '2' 40-55 and '3' 55+), while 'E' indicates no degree (0) or degree (1).

In the initial phase of the crisis, the estimated transition paths into unemployment are broadly similar across age and education groups. This reflects the sudden and proportionally similar rise in unemployment in the LFS across age and education groups. Thereafter, in order to sustain the data's continued higher unemployment among the young and low-educated, their flow into unemployment remains higher for longer, while the older and more educated revert to lower transition probabilities into unemployment. Transitions into our defined state of "reduced hours" are only in the first phase of the crisis and are again not heterogeneous after estimation, due to relatively equal rises in the presence of this category in the data; also, reduced hours does not increase further after the initial increase. Finding rates are initially set to zero for identification purposes, and after the economy is in "recovery phase" the rescaled probabilities from 2019 data of finding a job are used; hence the young and low educated have a relatively higher chance of finding a job (partly offset by their higher chance of losing a job in 2019 used in the recovery phase).

2.2.3 Evolution of Household Net Worth: Savings and Debt Dynamics

With our agent-based modelling approach, the change in household debt (savings) is determined from the budget constraint. We use the 2016 SFS to construct the initial distribution of debt across households. Our simulation also incorporates the option for households to defer mortgage payments.

Unemployed households can defer their mortgage payments between March and August. Deferred interest payments increase the balance and imply that mortgagors who defer face higher mortgage payments post deferral. We specify the level of liquid assets and loan-to-value ratio (LTV) required for a mortgagor to qualify for a deferral so that 15% of mortgagors defer, and 20% of those who defer have an LTV of less than 50%.

The SFS provides detailed snapshot information on households' portfolios, so we track changes in net worth over the simulation period using the budget constraint. Specifically, we track households' liquid savings net of their total line-of-credit balance B. We initialize B with the household's reported liquid savings (cash; non-registered mutual funds, other investments, bonds, stocks and shares; tax-free savings account) net of their line-of-credit balance. Thus, we impose that agents first tap into their liquid savings (if $B > 0$) before drawing on their lines of credit to finance any shortfall in their income

$$B_{i.t+1} - B_{it} = Y_{it} - C_{it} - \sum_j DS_{it}^j$$

where

$j \in \{Mortgage, Auto, Line\ of\ Credt, Credit\ Card, Installment, Student, Other\}$.

For households with $B < 0$, a new amortization schedule for a loan with a 15-year term and interest rate equal to $i^{Mortgage} + 3\%$ is generated each period to determine $DS^{Line\ of\ Credit}$.

In each period, households with income (Y) less than the sum of their consumption (C) and debt service obligations from debt type j (D^j) increase their debt. In contrast, households for whom income is more than enough to cover consumption and debt payments will increase their liquid savings. Key assumptions in this exercise are the absence of new loan issuances, credit limits and default options.

3. Heterogeneous Impact on Households: Increased Savings and Financial Vulnerabilities

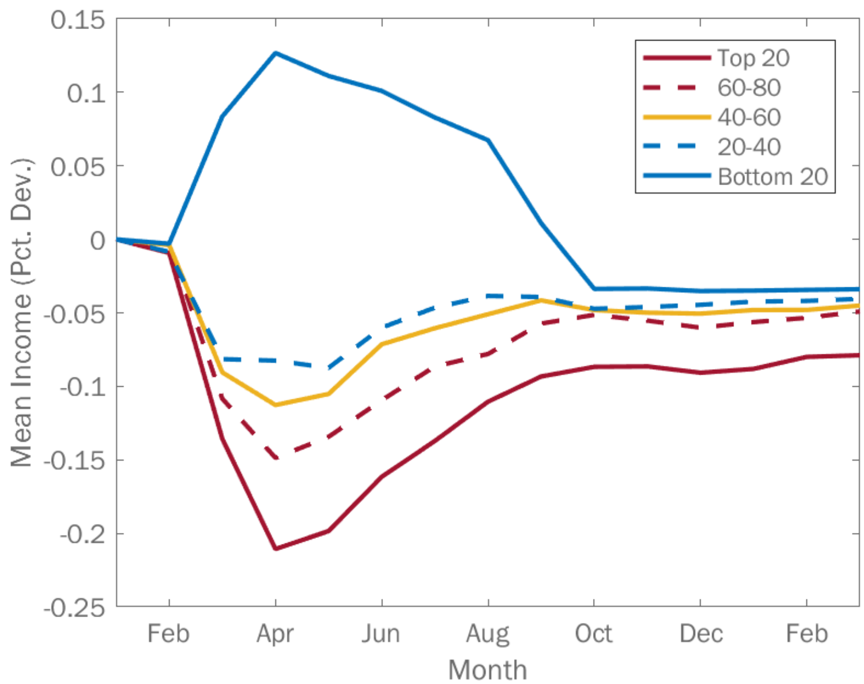
Our simulation provides interesting insights into the **heterogeneous** impact of COVID on Canadian household finances. Our analysis delivers three key messages:

1. Some lower-income households see a rise in earnings due to CERB, replacing more than 100% of lost income.
2. Household savings are projected to rise during the lockdown period. Although income transfers contribute to higher savings of some lower-income households, the majority of the rise in savings is accumulated by higher-income households who see large declines in consumption due to restrictions on hard-to-distance consumption.
3. Some households see a rise in debt, which results in an increase in the number of borrowers with high (above 40%) debt service ratios (DSRs). The majority of the increase in debt is concentrated among middle and upper homeowners with a mortgage for whom CERB only partially replaces lost income.

3.1 Heterogeneous Impact on Household Income

The combination of the rise in unemployment and a substantial fiscal response leads to very different impacts on household income. One way of illustrating these differences is to examine the path of income for households grouped by quintiles of pre-crisis income. As Figure 4 shows, the bottom 20% of earners (on average) experience a temporary rise in income due to CERB exceeding their pre-pandemic earnings. As the CERB pays a flat dollar amount, the fall in average income for higher-income quintile groups is larger due to a smaller replacement rate.

Figure 4: Shifts in Household Income by Quintile of Pre-COVID Income



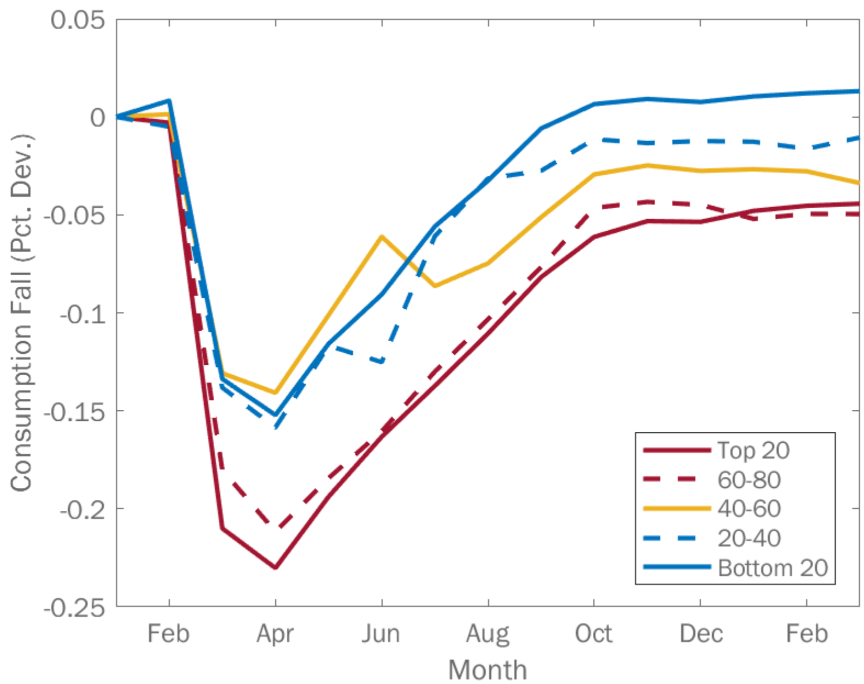
Note: This figure plots the percent deviation of simulated average household income from its pre-crisis levels among households that report to be employed in the SFS. The initial sample is first divided into quintiles of initial household income and the plotted series describes the simulated path of income once the employment shocks and accompanying CERB transfers are introduced.

3.2 Heterogeneous Build-up of Savings

The restrictions on consumption lead to a rise in savings, roughly 45% of pre-crisis monthly consumption. Somewhat surprisingly given the larger decline in income experienced by higher-income households, over 50% of the change in total savings is accounted for by the top 20% of earners, who are disproportionately older (middle-aged and above) homeowners.

This somewhat paradoxical result is driven by two factors. First, the expenditure share of higher-income households on hard-to-distance goods and services such as air travel and restaurants is higher (see Table 1). This implies a relatively larger decline in their consumption expenditures during the shutdown, as shown in Figure 5. Among the top 20% of income earners, consumption falls by 23% during the depth of the crisis, while the bottom quintile experiences a fall of 15%. Since a larger share of aggregate consumption is attributable to top earners, their consumption decline also accounts for a larger share of aggregate consumption decline. During the depth of the crisis (March to May), around 35% of the total decline in consumption is attributable to the top quintile of earners, while the bottom quintile accounts for only 12%.

Figure 5: Consumption Drop by Income Quintile

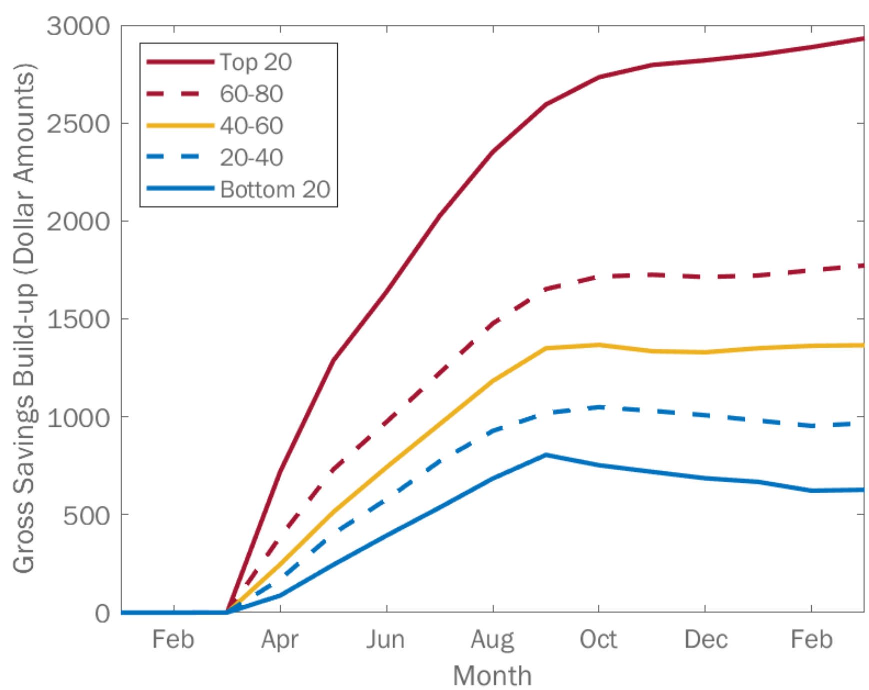


Note: This figure plots the percent deviation of simulated consumption from its pre-crisis levels among households that report to be employed in the SFS. The initial sample is first divided into quintiles of initial household income. Starting from the imputed consumption levels from the SHS, we apply the path of consumption adjustments shown in Figure 1. While each subcategory of consumption (essential, non-essential, shelter) is subject to the same path of adjustment factors, the varying paths of consumption drop across income quintiles reflect heterogeneous consumption bundles across income groups, as reflected in Table 1.

Second, since (by definition) higher-earning households account for a large share of income and expenditures, this translates into this group driving much of the unanticipated savings that resulted from the COVID restrictions on hard-to-distance consumption. The consumption fall is softer for the bottom 20% (pre-crisis) income group due to more of this group being supported by CERB than the 20-40% income group, while the top earners experience a more persistent reduction in consumption than lower earners.

This decomposition holds both when we condition on the distribution of realized income in our simulation and when considering the savings build-up (by pre-COVID income) versus a no-crisis counterfactual. In this counterfactual, we remove the non-crisis savings and debt trends by simulating a pre-crisis income and consumption scenario. As shown in Figure 6, the increase in average savings per group is larger for the top 20% of earners than for the other quintiles. Although the rise for the bottom 20% of earners is smaller, as a proportion of mean income it is a large increase in savings relative to the low level of pre-crisis savings. Figure 6 also highlights that much of the rise in savings happens during the "shutdown" period that spans March to June.

Figure 6: Gross Savings by Pre-COVID Earnings Quintiles



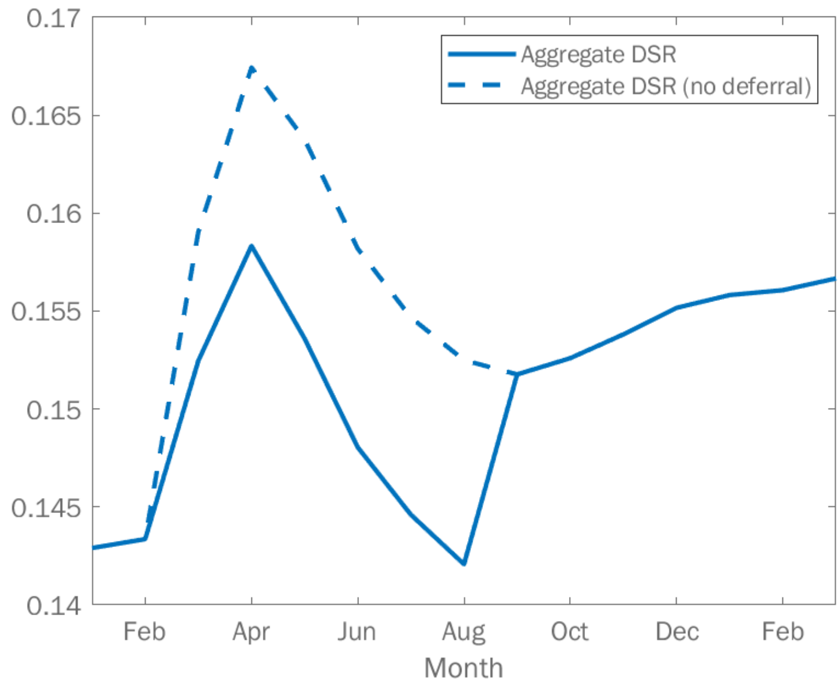
Note: This figure plots the simulated build-up of gross savings in dollar amounts among households that report to be employed in the SFS. The initial sample is first divided into quintiles of initial household income. For each group and time period, we condition on households that have positive period savings and report group averages. Reported values are net of savings that would have been accumulated under a no-crisis scenario in order to isolate savings build-up attributable to the COVID crisis.

3.3 Debt Rises for Some Households, Which Drives an Increase in Financially Vulnerable

This rise in debt drives an increase in the fraction of households with high DSR who are classified as financially vulnerable. Importantly, the increase in “highly indebted” households is not driven by the lowest-income households, but rather by middle-income households who experience only a partial replacement of income lost due to the economic disruptions.

A common measure of financial vulnerability is the ratio of debt payments to income, the DSR. Figure 7 plots the DSR for households in our simulation with mortgage deferrals (solid line) and without deferrals. The jump in the DSR in our simulation is driven by the fall in average income due to the fall in employment. The recovery in employment drives a rise in income that pushes down the DSR after April until the end of mortgage deferrals in August. After deferrals end, the aggregate DSR begins to rise as households resume mortgage payments and face additional debt accumulated over the crisis. At the end of the simulation period, aggregate DSR is 1.4 pp higher relative to its pre-crisis levels. Under a scenario where there are no mortgage deferrals, the DSR rises more rapidly but converges to the same level as in the baseline scenario after September 2020. This implies that insofar as DSR is concerned, mortgage deferrals provide only a temporary reprieve.

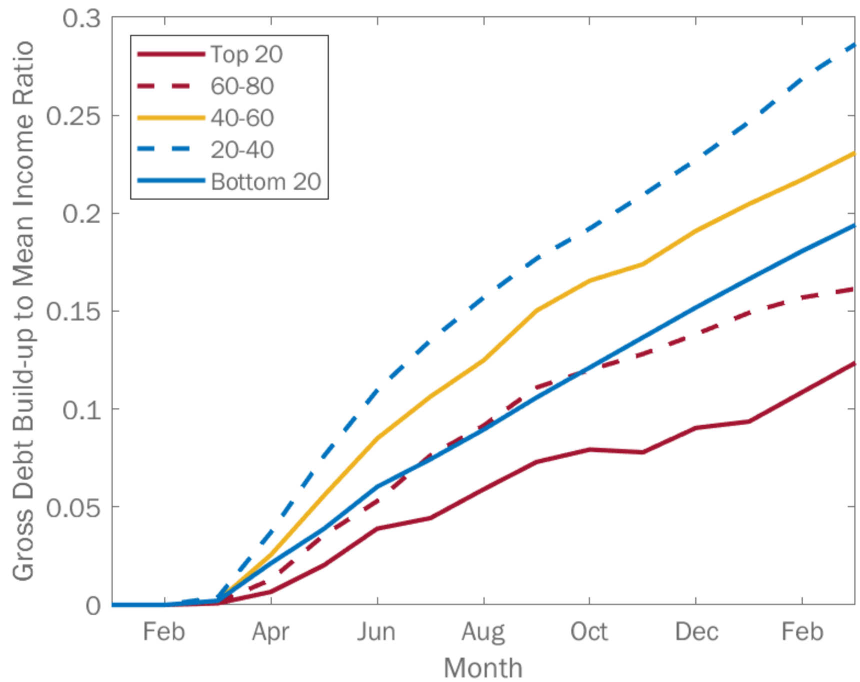
Figure 7: Aggregate Debt Service Ratio



Note: This figure plots the aggregate DSR, which is calculated as total monthly debt payments divided by total monthly income. The dashed lines represent a counterfactual path of DSR under a scenario without a mortgage-deferral option.

To decompose the debt build-up, we group households by their pre-COVID earnings quintiles. We divide the change in debt by mean income in each quintile to highlight the shift in debt relative to income. Figure 8 shows that the largest increases in debt to income come from middle-income households (i.e., the 20-40 and the 40-60 income quintiles). This reflects two forces. The first is the pattern of income replacement, where middle-income groups see only partial replacement of lost income. Second, some middle-income households have relatively large (compared to income) mortgage or rent payments and modest expenditure shares on hard-to-distance consumption goods. This results in smaller declines in expenditures than income, which in turn drives a rise in debt for these households. These households often have significant unused credit lines (and access to deferrals), so we see a rise in indebtedness and not a lot of delinquencies. After CERB expires (assumed to be in September), the debt-to-income of the bottom 20% starts to catch up with other groups.

Figure 8: Gross Increase by Pre-COVID Earnings Quintiles (Employed Households Who Borrow Only)



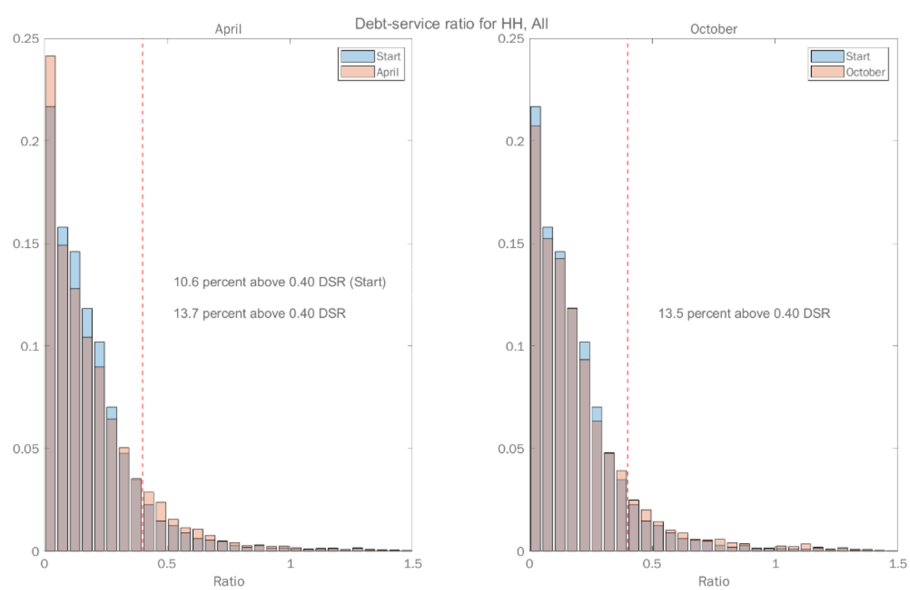
Note: This figure plots the simulated build-up of debt when the initial sample of employed households in the SFS are grouped into quintiles of income. Debt build-up is expressed as the ratio of total debt to total pre-crisis monthly income of the relevant group. In order to isolate the effect of the crisis, we subtract any debt build-up that would have occurred in a counterfactual no-crisis scenario.

While informative, the average DSR does not necessarily provide information on which types of households become financially vulnerable due to high debt. We use our simulation to look behind the average and understand the demographics of borrowers with high DSRs.

We follow previous work (e.g., Faruqui (2008)) and define a borrower as financially vulnerable if their debt service ratio exceeds 40% of their income. In Figure 9 we plot the DSR distribution pre-COVID, in April and in October. In our simulations, there is a significant and sustained rise in the fraction of households with high debt service ratios. The fraction of households with DSR above 40% rises by roughly 3 pp by April. Importantly, this rise in financially vulnerable households persists through late 2020 despite the bounceback in employment in our simulations.

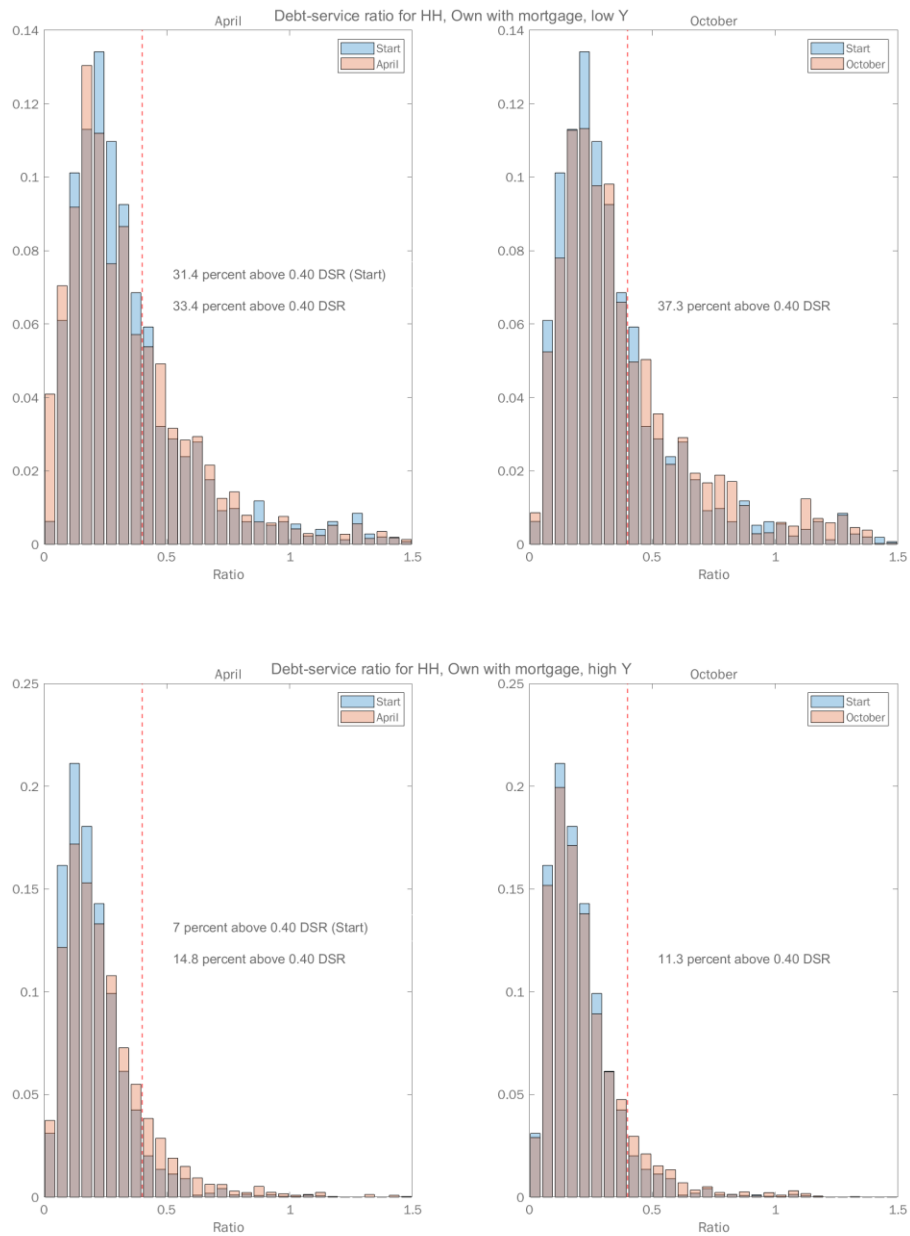
This rise in financial vulnerability is primarily attributable to renters and homeowners with mortgages. Figures 10 and 11 show an interesting pattern that emerges when we further decompose these households by income. Mortgagors with low income experience a small increase in financial vulnerability at the onset of the crisis (2 pp rise from 31% to 33%), owing to the introduction of CERB payments. In contrast, the fraction of high-income mortgagors with high DSR more than doubles (from 7% to 15%), given that they are less likely to receive CERB and, conditional on receipt, receive a lower replacement rate. However, this pattern reverses by October. Once CERB is terminated, low-income mortgagors experience a sustained rise in financial vulnerability, while high-income mortgagors recover. Meanwhile, renters also exhibit heterogeneity in financial vulnerability across income groups. While both low- and high-income renters experience an increase in the fraction with high DSR, this effect is larger and more persistent for low-income renters.

Figure 9: Distribution of DSR, All Households



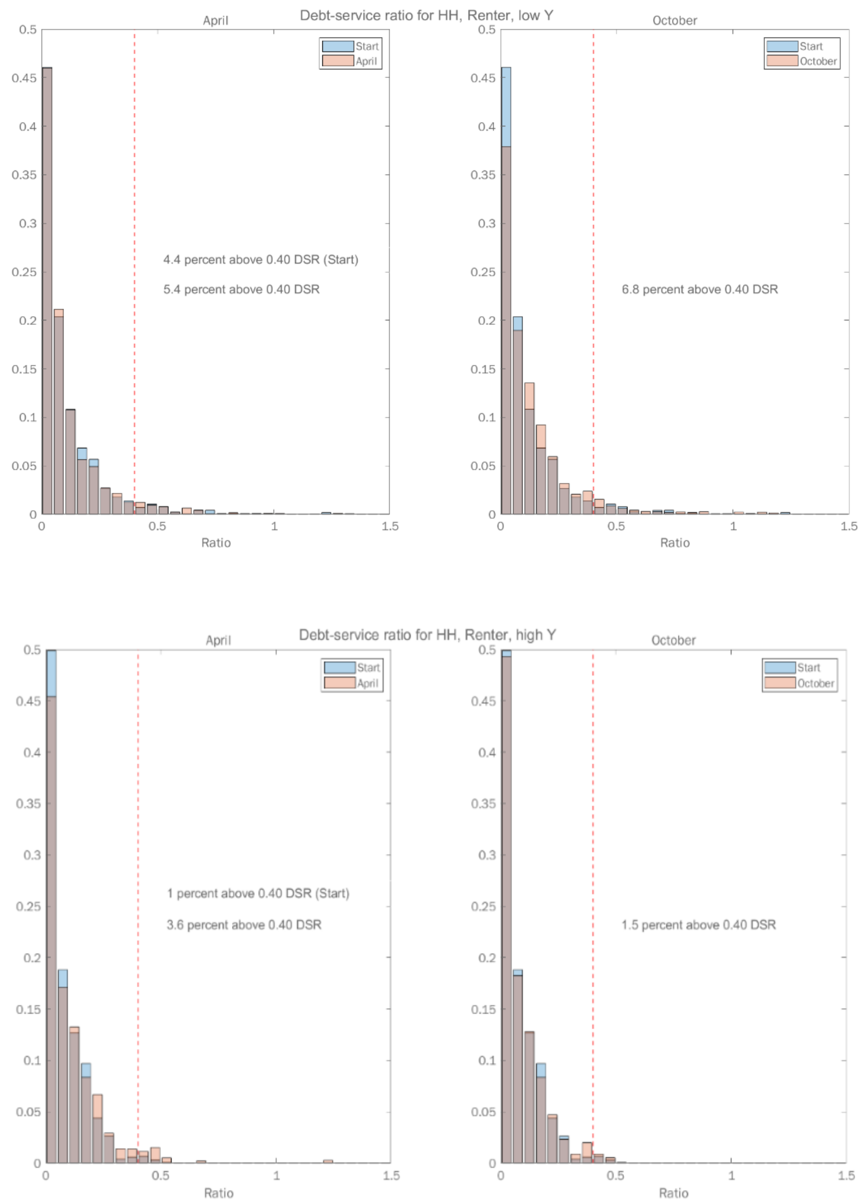
Note: This figure compares the distribution of DSR across households prior to the crisis with the simulated distribution in April and October. We consider a household to be financially vulnerable if DSR is above 0.40.

Figure 10: Distribution of DSR, Homeowners with Mortgages



Note: This figure compares the pre-crisis distribution of DSR across homeowners with a mortgage with the simulated distribution in April and October. Households are classified as either below or above median based on their reported income in the SFS, which serves as our starting point for the simulation.

Figure 11: Distribution of DSR, Renters



Note: This figure compares the pre-crisis distribution of DSR across renters with the simulated distribution in April and October. Households are classified as either below or above median based on their reported income in the SFS, which serves as our starting point for the simulation.

4. Recovery Dynamics: Mortgage Deferral Cliffs and Pent-up Demand

The early stages of the COVID crisis have seen substantial debate over the risk of a rise in mortgage defaults after the "mortgage deferral cliff" (e.g., Siddall 2020) as well as the potential for a significant bounceback in consumption expenditure due to "pent-up demand" after the relaxation of social distancing restrictions (e.g., Deloitte 2020). As we discuss below, our approach points to a modest rise in mortgage defaults as deferrals end, rather than a "cliff."

The uniqueness of the COVID shock – at least in recent history – leaves us with little direct empirical evidence to assess the impact of the build-up of unplanned savings by some households on consumption. Instead, we draw on estimates of the marginal propensity to consume from lottery winnings from Fagereng et al. (2019) for households with different levels of income and liquid wealth. We find that these estimates imply a modest bounceback in consumption in late 2020 and early 2021, although the rise in debt for some households implies a longer-term drag on consumption.

4.1 Mortgage Deferrals: A Modest Slope, Not a Cliff

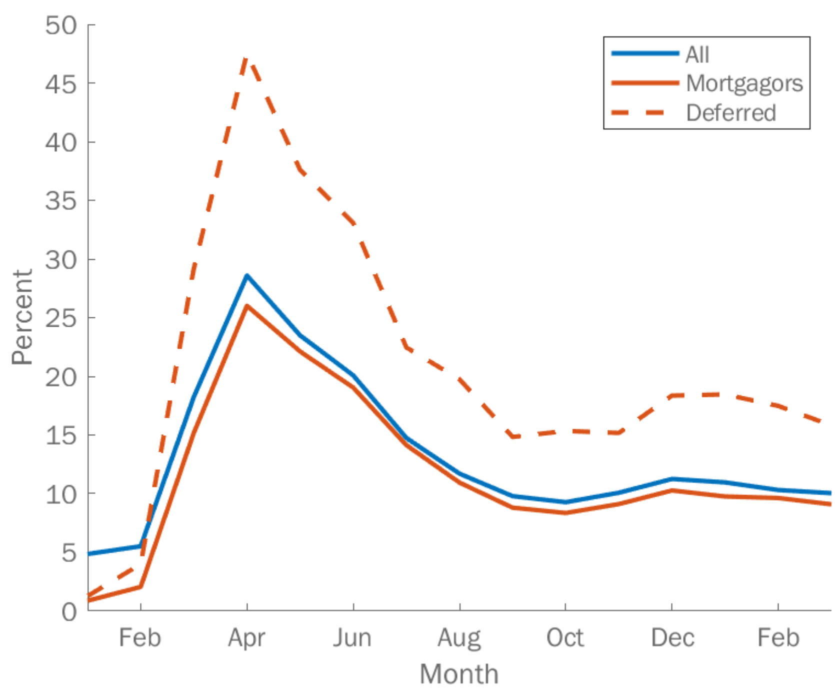
The likelihood of a "mortgage deferral cliff" occurring after the mortgage deferral window closes depends on the incidence of the so-called double trigger. The first trigger involves the persistence of elevated levels of unemployment, rendering mortgagors with limited income unable to resume payments on their mortgages. The second involves low (or negative) levels of home equity among those who defer mortgages, which may be exacerbated if home prices decline. Using our simulation procedure combined with LTV and wealth information from the SFS, we can understand whether the incidence of these triggers should be a cause for concern.

Figure 12 plots the unemployment rate of all mortgagors as well as mortgagors who elect to defer payments during the six-month window. By construction, mortgage deferrers comprise agents with low liquid wealth and high LTV. Since job loss results in a reduction of savings, especially if debt service obligations are high, the unemployed are more likely to select into mortgage deferrals. However, as long as the rate of joblessness recovers as the crisis subsides, the fraction of mortgagors who will be unable to pay will remain manageable. Figure 12 shows that by early 2021, the unemployment rate of mortgagors who defer would have dropped to 15% despite reaching a peak of close to 50% in April 2020. This implies that most mortgagors who defer should be able to resume payments given the resumption of employment.

Table 3, on the other hand, shows that the fraction of unemployed households with excessively high LTVs (above 80%) remains low, even among the jobless with low savings. This holds true even in a scenario where house prices decline by 10%.

Our approach thus predicts a low incidence of double triggers. While we do not explicitly model default, this exercise suggests a modest increase in mortgage defaults.

Figure 12: Unemployment Rate of Mortgagors



Note: This figure plots the simulated path of unemployment rate for all households, all mortgagors, and mortgagors who defer. Recall that in our framework, mortgage deferrals are triggered by low liquid wealth and high LTV. Since the incidence of unemployment affects both metrics, agents that defer their mortgages are also those with a higher incidence of unemployment.

Table 3: Loan-to-value Ratios of Mortgagors

Percent of Mortgagors with >0.80 LTV by August	Unemployed	Unemployed + Deferred Mortgage
Baseline	1.3	0.19
House price decline (10%)	2.3	0.50

Note: LTV is calculated as the ratio of debt on principal residence and the value of the principal residence.

4.2 Consumption Dynamics: Impact of Unplanned Savings and Higher Debt

The unprecedented scope and magnitude of the COVID shock and its heterogeneous impact on household balance sheets have resulted in debate over near-term consumption dynamics. In part, this reflects the opposing effects of potential pent-up demand following the unplanned accumulation of savings by some households versus the potential depressing effect on aggregate consumption due to "debt drag" as households whose debt rose as a result of the crisis begin making higher debt payments.

Given the lack of direct historical evidence, we tackle the question of near-term consumption dynamics by assuming that the rise in debt for some households and savings for others has been unplanned and unanticipated. For households with savings, we treat the rise in savings as akin to lottery winnings. This allows us to draw on estimates of the varying impact of lottery winnings by household income and liquid asset positions. For households who see a rise in debt, we assume that spending adjusts dollar for dollar with the necessary rise in debt payments implied by higher debt.

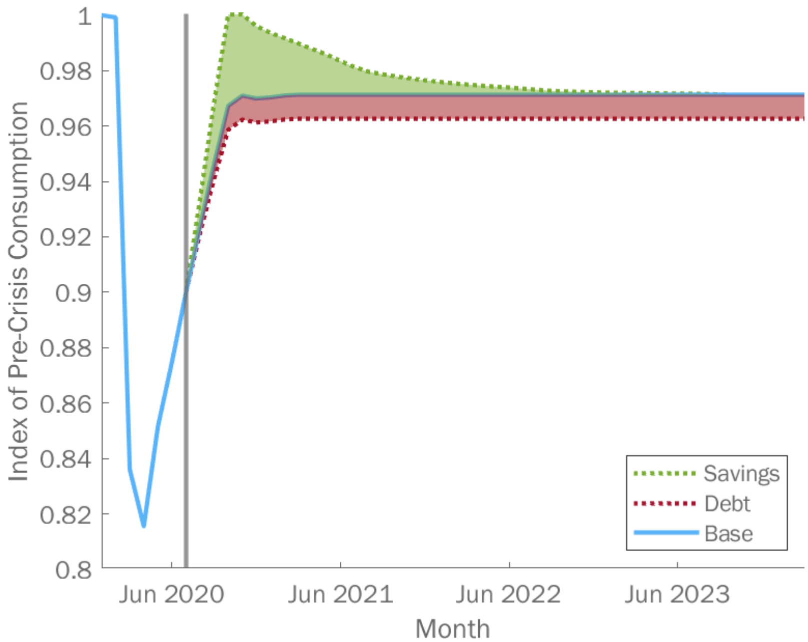
Our thought experiment assumes households stochastically shift from our baseline scenario consumption pattern to a "recovery" state over September to December of 2020. When a household whose debt has risen (e.g., due to a mortgage deferral) switches to recovery mode, they adjust their consumption to reflect the higher monthly debt payments. We construct these debt payments by imposing an amortization period of 15 years[8] at the current level of mortgage interest rates. The implied drag on consumption from this higher debt burden is the shaded gap in Figure 13 between the red and the blue lines, as the blue line is our baseline path of aggregate monthly consumption. This downwards drag is approximately 0.8% of pre-crisis monthly consumption, and due to the lengthy amortisation period, this drag persists for more than the next decade.

We find a larger initial but less persistent rise in consumption due to the rise in savings. We assume that households with unanticipated savings that switch to the recovery state treat the excess savings resulting from COVID-19 as if they were unexpected lottery winnings. Specifically, we draw on the estimates of Fagereng et al. (2019), who used data on Norwegian Lottery winners to identify how the propensity to consume depends on the size of winnings and the household's liquid wealth. This gives large variation across households in the amount of unplanned savings spent; Fagereng et al. (2019) found that small lottery winnings are spent quickly while large prizes are not, and households with low liquid assets spend a larger fraction of their winnings (see Table 4).

Given the large rise in savings predicted by our baseline model, it is not surprising that we find that the pent-up demand channel is initially much larger than the debt drag channel. As can be seen from the green shaded area in Figure 13, the peak effect of the rise in savings is approximately 3% of aggregate consumption versus the 0.8% drag from households whose debt rose as a result of the crisis. However, the rise in expenditures due to unplanned savings dissipates rapidly over 2021, and by the end of 2021 the debt drag channel is slightly larger.

[8] Increasing (reducing) the amortization period reduces (increases) the level of drag on consumption but increases (decreases) the horizon which it affects.

Figure 13: Impact of Higher Savings and Debt on Consumption



Note: This figure plots the simulated dynamics of consumption when accounting for (1) the potential spending of unanticipated savings accumulated by households during the crisis and (2) the additional debt service obligations resulting from debt build-up. We show these in green and red respectively.

Table 4: Lottery Spending Proportion by Liquid Deposits and Prize Size

	Magnitude of Prize			
Quartiles Liquid Deposits	0-3300	3300-8243	8243-13799	13799+
Bottom 20	1.047	0.745	0.720	0.490
25-50	0.762	0.640	0.559	0.437
50-75	0.663	0.546	0.390	0.386
Top 25	0.354	0.325	0.242	0.216

Note: From Fagereng et al. (2019); prize values converted to 2016 CAD.

While this exercise points to substantial scope for pent-up demand, it is worth emphasizing several caveats that follow for our agent-based modelling approach. First, we abstract from both the potential for a shift in household behaviour towards increased precautionary savings (which would dampen the near-term rise in expenditures) and households increasing their borrowing to finance the purchase of durables. Moreover, our estimates here do not incorporate how household spending could be impacted by shifts in their willingness to substitute easy-to-distance for harder-to-distance goods over time.

5. Conclusion

The impact of COVID-19 on the Canadian economy, much like in other nations, is heterogeneous and severe. The combination of government-mandated closures of parts of the economy and voluntary social distancing by some consumers has dramatically shifted consumption expenditures. To capture the impact of this shock on labour markets, we incorporate COVID-related hours reduction, a separation of goods into categories with different social/physical distancing characteristics and discretionary/essential status, and major policy interventions (e.g., CERB, mortgage deferrals) into a scenario analysis.

We find that the lowest quintile of earners are cushioned by the widespread CERB payments of $500. Combined with their relatively large expenditures on easy-to-distance essentials, their consumption expenditures decline modestly. However, low- to middle-earning households see a faster and larger increase in debt than the bottom quintile, as their committed spending and rent/mortgage payments are not fully covered by CERB if they lose jobs or experience a large reduction in income. While we do not consider overall fiscal effects, the end of CERB threatens a rise in debt among households with pre-crisis low earnings.

High earners and older households face a different path – with relatively large expenditures on hard-to-distance/luxuries, they see a larger decline in consumption expenditures during the lockdown in March and April. As a result, they see higher saving. If this “excess” saving created by a lack of spending opportunities is treated like an unexpected windfall similar to lottery winnings after the economic reopening begins, this extra spending by the wealthy will cause a substantial upside to future consumption – but not all of the savings will be spent. Due to the relatively small size of excess savings by individual households, the spending proportion is expected to be high (over 70%), but this effect is countered by the need for households who have accumulated debt to begin paying back that debt. While overall debt does not rise much (mostly from consumption reductions leading to debt paying off), the concentration of debt increases, as does the number of high-debt households.

Our work points to several key directions for future research. First, the substitution between hard-to-distance and easy-to-distance goods is extremely important in determining the future consumption path, particularly including income and wealth effects due to the prominence of high-earning households in these patterns. Second, the fiscal programs have had substantial effects limiting debt rises and, in a loose sense, vulnerabilities among low-earning households. However, we identify that low to middle earners may be a concern for policymakers. Lastly, our modelling is a simple simulation that does not include household expectations, risk aversion or smoothing desires, except implicitly from the use of the survey data. We hope that future work can build upon our insights with these mechanisms.

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Appendix

Consumption Categorization Details

The table depicts the weight of each consumption sub-section in our analysis from the Survey of Household Spending.

Shelter	Essentials + Easy Distance	Luxuries or Hard Distance	Variable Name	Name
	0.25	0.75	CL001_C	Clothing and accessories
	1		ED002_C	Education
	1		HC001_C	Health care
		1	HF002_C	Household furnishings
	0.5	0.5	HE001_C	Household equipment
1			HE020	Services related to household furnishings and equipment
	1		HO001_C	Household operations
		1	CC001_C	Child care
		1	HO002	Domestic and other custodial services (excluding child care)
	1		HO003_C	Pet expenses
			HO006	Veterinarian and other services
	1		ME001_C	Miscellaneous expenditures
	0.5	0.5	PC001_C	Personal care
	0.5	0.5	RE010_C	Computer equipment and supplies
	0.5	0.5	RE016_C	Photographic goods and services
	0.5	0.5	RE022	Collectors' items
	0.5	0.5	RE040_C	Home entertainment equipment and services
	1		RE067	Television and satellite radio services
		1	RE070	Use of recreation facilities
		1	RE074	Package trips
		1	RV001_C	Recreational vehicles and associated services
	1		RO001_C	Reading materials and other printed matter

1			SH003	Rented principal residence
		0	SH011	Mortgage paid on the principal residence
1			SH012	Repairs and maintenance of owned principal residence
1			SH991	Condominium fees, property taxes and school taxes for owned principal residence
1			SH015	Homeowners’ property insurance for owned principal residence
			SH016	Other expenditures for owned principal residence
1			SH992	All other expenses for the principal residence
1			SH019	Premiums for mortgage-related insurance for owned principal residence
1			SH030	Water, fuel and electricity for principal accommodation
		0	SH042	Mortgage paid on secondary residences
1			SH044	Property insurance for owned secondary residences
1			SH046	Other expenses for owned secondary residences
1			SH060	Communication and home security services, satellite radio and Internet for owned secondary residences
1			SH061	Property and school taxes, water and sewage charges for owned secondary residences
1			SH062	Electricity and fuel for owned secondary residences
1			SH047	Other owned properties
		1	SH050	Accommodation away from home
		0	TR004	Purchase of vehicles
		1	TR008	Accessories for vehicles
	1		TR010	Fees for leased vehicles
		1	TR020_C	Rented vehicles

	1		TR031	Vehicle registration fees
	1		TR032	Vehicle insurance premiums for owned and leased vehicles
	1		TR033	Tires, batteries, and other parts and supplies for vehicles
	1		TR034	Maintenance and repairs of vehicles
	1		TR035	Vehicle security and communication services
	0.5	0.5	TR038	Parking costs
	0.5	0.5	TR039	Driver's licences and tests, and driving lessons
	0.2	0.8	TR050	Public transportation
	1		FD003	Food from stores
	0.2	0.8	FD990	Food from restaurants
	1		CS001_D	Communications - Diary
			CS010	Postal, courier and other communication services
		1	CC001_D	Child care - Diary
	1		HO004	Pet food
	0.5	0.5	HO005	Purchase of pets and pet-related goods
	1		HO010	Household cleaning supplies and equipment
	1		HO014	Paper, plastic and foil supplies
	1		HO018_D	Garden supplies and services - Diary
	1		HO022	Other household supplies
		1	HF002_D	Household furnishings - Diary
	0.5	0.5	HE001_D	Household equipment - Diary
1			HE016	Maintenance and repairs of household furnishings and equipment
	0.25	0.75	CL001_D	Clothing and accessories - Diary
		1	TR020_D	Rented vehicles - Diary
	1		TR030_D	Vehicle operations - Diary
	0.5	0.5	TR036	Gas and other fuels
	0.5	0.5	TR037	Other vehicle services

1		HC001_D	Health care - Diary
0.5	0.5	PC002	Personal care products
		RE001_D	Recreation - Diary
0.5	0.5	RE002_D	Recreation equipment and related services - Diary
1		RE040_D	Home entertainment equipment and services - Diary
0	1	RE060_D	Recreation services - Diary
0	1	RV001_D	Recreational vehicles and associated services - Diary
0		RV010_D	Operation of recreational vehicles - Diary
1		RO001_D	Reading materials and other printed matter - Diary
1		ED002_D	Education - Diary
1		TA001	Tobacco products and alcoholic beverages
1		GC001	Games of chance
1		ME001_D	Miscellaneous expenditures - Diary

Debt Interest and Term Assumptions

The table shows the assumed interest rate and term length for debt categories for which the SFS does not provide any information.

Debt Category	Interest Rate (Annual)	Term (Years)
Lines of Credit	Mortgage rate + 3%	15
Credit Card	15%	13
Installment	15%	2
Vehicle	2%	3
Student	1%	10
Other	8%	7