A framework to assess vulnerabilities arising from household indebtedness using microdata

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I. Introduction

Over the last decade, significant increases in house prices, sustained income growth, record low interest rates, favourable financial conditions and financial innovations have all contributed to raising the level of indebtedness of Canadian households. The household debt-to-income ratio increased from 110% in early 2000 to approximately 127% at the beginning of the crisis,[2] before reaching 148% by the third quarter of 2010. In comparison, over the period between 1990 and 2000, the debt-to-income ratio increased from 90% to 110%. The period after 2000 coincided with rapid growth in household debt in other OECD countries as well (OECD 2010). The rapid increase in household indebtedness over the last decade has raised concerns in many countries regarding the deterioration of the resilience of households to negative shocks. It has also motivated many central banks to develop stress indicators for the household sector and closely monitor the evolution of households' financial obligations.

Changes in household debt-service costs as a share of income – i.e., the debt-service ratio, or DSR – are a measure of changing risk associated with household debt. An increase in the DSR could have a negative effect on both the real economy and the financial system. It might, in fact, translate into a decline in consumer spending, undermining economic growth (depending on the nature of the shock). For example, if the average DSR ratio increases subsequent to an interest rate hike, in the short run this would imply that less funds are available for spending. On the contrary, if this increase is driven by a rise in the level of household loans, this would boost household spending, in the short run, by relaxing the household income constraint. However, a higher DSR would imply that households are more vulnerable to negative shocks to income or to interest rates, making household balance sheets more precarious and having negative fallout on financial institutions. Since household debt constitutes a large part of the loan portfolio of Canadian banks, it is important to monitor and anticipate changes to household vulnerability as a function of developments in macroeconomic conditions.

While aggregate data provide an indication of average shifts in household debt positions, such variations frequently obscure vulnerabilities that only a review of the microdata can reveal. The availability of microdata for this type of review has assisted the Bank of Canada

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I thank Pierre Duguay, Pierre St-Amant and Paul Masson for their helpful comments. Special thanks go to Allan Crawford, who continuously contributed to the development of the methodology and the framework and strongly supported this project. My thanks also go to the participants at the Canadian Economics Association conference in May 2010 and to the participants at the Irving Fisher Committee conference where this paper was presented in August 2010.

[2] Average for 2007.

in developing an analytical framework for assessing risk in the household sector.[3] While aggregate approaches allow us to conduct these exercises in terms of averages, they do not permit us to assess the impact of alternative shocks on the distribution by income group, nor to determine the proportion of households that are vulnerable. Our work will thus complement previous efforts and inform us of the extent to which shocks to the interest rate, indebtedness, and income could lead to deterioration in the financial situation of Canadian households.

Microdata have been used by the Bank of Canada to examine the evolution of the distribution of the DSR since 2006. The novelty of our work lies in the development of a framework for using these microdata to evaluate the incidence of potential shocks (interest rate, indebtedness, income, etc.) on the distribution of the DSR and on households' payment defaults.

The purpose of this article is to present the analytical framework developed at the Bank of Canada to stress test household balance sheets using microdata. To assess the impact of changes in macroeconomic conditions on household vulnerabilities, it is necessary to understand how these changes will affect the DSR distribution going forward.

$$\text{DSR distribution} = F(\text{Income, Debt, Interest rates, Other household factors}) \qquad (1)$$

As presented in equation (1), at every period, the DSR distribution will be a function of the distribution of income, debt, interest rates and some other structural factors that relate to household individual behaviour (amortization period, individual risk premium, debt structure, debt accumulation dynamics, etc.). This framework provides an internally consistent way to project this distribution over time according to a macro scenario and assess the impact of the projected path of the distribution on the resilience of the household sector.

The DSR distribution covers all households in the sample. However, given that every household will have a specific value for its DSR that relates to its own income, debt, interest rates and some other household specific factors, it is necessary to determine how the assumptions set in the macro scenario will affect each household in a specific way. To perform the whole exercise, there are three complementary steps (Table 1) that need to be conducted (Djoudad 2010, p. 57). Each of these steps is discussed after providing some general comments in section 2.

Table 1

Steps in the stress-testing exercise

Step 1	**Step 2**	**Step 3**
Establish the key assumptions for the macro scenario: – Growth in aggregate credit and income – Interest rate path	Calculate the implications of the macro scenario for the distribution of the household debt-service ratio	Estimate the impact of adverse shocks on bank loan portfolios

3 Data are from the Canadian Financial Monitor (CFM) survey of approximately 12,000 households per year conducted by Ipsos Reid. The survey was launched in 1999.

II. General framework

The Statistics Canada aggregate DSR takes into account only interest payments. When calculating the DSR using microdata, principal repayments on all instalment loans are included. In order to calculate the DSR from microdata, we estimate the following three major elements: the interest rates paid, household income and the outstanding balance of household debt.

To calculate the micro DSR, we use the following formula:

$$DSR = \frac{\sum Payments}{Gross\ income} = \frac{\sum(Principal\ repayment + interest\ repayment)}{Gross\ income} \quad (2)$$

In the microdata used, there are five types of loans: credit card loans, personal loans, personal lines of credit, vehicle loans, and mortgage loans. The following information is available for all loans other than credit card loans:

– loan payments;

– interest rate paid on the loan;

– term of the loan (in years);[4] and

– the outstanding balance of the loan.

Changes in the DSR have been used at the Bank of Canada to assess variations in households' financial health. In issues of the *Financial System Review*,[5] the distribution of the DSR calculated using microdata helped to evaluate how risks related to financial obligations are distributed across households. All things being equal, households with a higher DSR will have more difficulty in meeting their financial obligations. Accordingly, the higher the household debt load, the greater the sensitivity of this household to any negative shock (such as illness, loss of a job, divorce, etc.).

In the model, changes in the interest rates affect the amount of interest payments and have no impact on the principal repayments that must be made by the households. Therefore, interest payments must be distinguished from repayments of principal.

Assume that the variable PC represents a household's total annual loan payments, SC is its current credit balance, and ir, the applicable interest rate. The amount of the principal repayments due is:

Principal = PC - Interest = PC - (SC * ir). (3)

Over the simulation period, principal payments are set as a constant share of the credit balance. In fact, this proportion may vary over time. However, over a short period of time, we believe that this assumption cannot significantly affect the results:

Share_Principal = (Principal/SC). (4)

At every period, a household is required to make the following payment:

PC = SC * (Share_Principal + ir). (5)

Future payments and the dynamics of the DSR will be determined by the simulated profile of changes in household income and debt, as well as interest rates.

[4] 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, and variable-rate loans. But we do not have any information on maturity dates.

[5] See all issues of the *Financial System Review* published since December 2007.

II.1 Missing data

For each household we have the information on the balances and interest rates for each loan held. To calculate the payments carried out by each household and to evaluate its DSR, it is necessary to incorporate the information relative to each of the loans. For example, the questionnaire gives the possibility to the household to list up to eight different mortgages. For each mortgage, the household must then provide information on the balance, the term, the interest rate paid, etc. But some households will only report part of the information requested. It is then difficult to carry out simulations of the DSR for these households given that some required information is missing. In fact, with the information provided, it may be difficult to break the payments into the share related to interest payments and that relating to principal repayment. Consequently, we were faced with two choices: either to exclude these households from our simulations, with the risk of biasing the composition of the sample, or to keep them in the sample and then make additional assumptions for the missing information. We believe that making reasonable supplementary assumptions for missing data would bias the results less than omitting these observations.[6]

Whenever the information on the interest rate for a specific loan is missing, we choose to assign to that household and for that specific loan the average interest rate calculated for all households belonging to the same income group and related to the same type of loans. For example, if we do not have information on the interest rate paid on its personal loans, we assign the average interest rate paid on personal loans by all households in the same income class to which the household belongs. If it is the information related to the outstanding balance of a loan that is missing, we assume that it is more appropriate to maintain a constant level of the payments carried out by the household for this loan, rather than to substitute any value which could be very different from the level of the balance actually held by the household. Thus, if a household states that it is paying $200 per month for a personal loan, but omits to indicate the balance on its loan, we assume, over the entire simulation, that the payments on this loan remain unchanged. Finally, when information on the term of the mortgage is missing, we consider that the mortgage is at a variable rate.

II.2 Macro scenario

In Step 1 of the exercise, we set the key assumptions of the macro scenario. For example, in the December 2009 issue of the FSR (pp. 23–24), the Bank conducted a stress test to evaluate the likely impact of a sharp and significant rise in interest rates and risk premiums. In the December 2010 issue of the FSR (p. 21), the Bank’s stress test objective was to assess the potential impact of an increase in the unemployment rate. In both cases, these scenarios have to be completed by assuming coherent paths for growth of aggregate household debt and its components, as well as income (and interest rate path when necessary). It is important to maintain consistency between the paths for different macro variables. For example, we might want to assess the impact on households’ balance sheets of a sudden and significant increase in interest rates (stress scenario). Or on the contrary, we may want to determine how current market expectations on interest rates would affect households’ financial position while assuming a specific path for credit and income growth. As indicated in Table 1, these assumptions relate to growth of aggregate credit and income, unemployment and interest rate paths for the overnight rate as well as for all the mortgage terms available in the database. Once the aggregate assumptions are set, Step 2 consists of exploring how this macro scenario will affect every household in the sample.

[6] Missing data occur in around 1–2% of the households.

III. Interest rates, income and debt dynamics

The purpose of this section is to show, for every household, how interest rates, income and debt evolve in the model (Step 2 in Table 1). CFM data are not panel data. The CFM is essentially a cross-sectional database and most households are not in the sample for more than several years. This is not sufficient to allow us to use the raw microdata to estimate econometric equations that relate growth in debt to income, interest rates and other economic variables. Given that the time series information does not refer to the same households we use pseudo-panel techniques.[7]

III.1 Interest rate dynamics

All consumer[8] lending, except for credit cards, is assumed to be at variable rates. Each household pays an effective rate that is equal to the banks' prime rate plus an individual risk premium. We compute the premium for each household in the sample using the latest actual data. Any movement in the overnight rate directly affects the banks' prime rate. The new effective rate is calculated for each household by adding the individual risk premium, determined in advance, to the prime rate.

We can assume that the individual risk premium remains unchanged over time or, alternatively, varies with the economic conditions in the stress-test scenario. However, as a simplifying assumption we may suppose that the individual risk premiums will follow analogous paths for all households. For example, in the December 2010 issue of the FSR (p. 22), it was assumed that the risk premiums were decreasing over the simulation horizon. Similarly, we assume full passthrough of variations in the overnight rate to variable-rate mortgages.

Table 2

Distribution of mortgages between variable and fixed interest rate terms (%)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Fixed	91.58	92.12	89.35	81.00	78.55	74.59	70.77	73.96	76.50	75.26
Variable	8.42	7.88	10.65	19.00	21.45	25.41	29.23	26.01	23.50	24.74

For mortgage lending, there are two categories of term loans: variable-rate mortgages and fixed-rate mortgages. Table 2 presents the distribution of mortgage loans between variable and fixed interest rate loans by term for the period between 1999 and 2008. Two key points are worth highlighting: firstly, fixed interest rate loans represented the vast majority of mortgage loans over the last decade. Secondly, while in 1999, fixed interest rate mortgages represented 91.6% of all mortgages, in 2008, this proportion had decreased to 75.3%, indicating a shift toward variable-rate mortgages. This shift was fuelled by the significant gap that emerged between the overnight rate and fixed term mortgage rates. This gap rendered variable mortgage rates more attractive than fixed interest maturities in an environment where policy rates were low, compared to historical levels. Variable mortgage rates are linked to the overnight rate.

[7] For more details on building the pseudo-panel data used, please refer to Appendix 1.

[8] Consumer debt excludes mortgage debt.

Table 3 reports the distribution of fixed interest rate mortgages by maturity term. These data show that the 5-year fixed mortgage term is the most popular one. It has accounted for an average of 60% of all fixed mortgage terms over the last ten years. In the most recent years, the second most popular term is the 10+-year term, followed by the 3- to 4-year term. These three terms accounted for more than 80% of all fixed term mortgages over the last decade. A simulation exercise could take into account dynamic changes to the proportion of fixed versus variable and the proportion of fixed term mortgages by maturity according to changes in the macroeconomic conditions.

Table 3

Distribution of fixed interest mortgages by mortgage term (%)

	6 months	1 y	2 y	3-4 y	5 y	7 y	10+ y	Others	Total
1999	2.1	7.1	4.6	13.0	58.8	4.3	8.3	1.8	100
2000	2.4	6.8	4.2	12.2	58.4	4.1	10.1	1.9	100
2001	1.6	6.3	4.0	10.5	61.6	4.3	9.7	2.0	100
2002	1.5	6.6	3.4	13.0	60.6	4.7	8.3	1.8	100
2003	0.8	4.8	2.8	16.3	60.2	4.7	8.7	1.7	100
2004	1.0	7.0	3.2	14.9	58.1	4.9	8.8	2.2	100
2005	0.9	5.8	4.2	14.2	58.3	4.4	10.7	1.4	100
2006	0.9	4.8	3.5	12.7	60.2	5.5	9.9	2.4	100
2007	0.8	2.6	2.3	8.6	56.7	4.9	19.5	4.6	100
2008	0.7	2.0	1.9	8.3	53.1	5.4	22.7	5.9	100
Average	1.3	5.8	3.6	12.8	59.2	4.6	10.5	2.2	100

The CFM survey provides the maturity term of the fixed mortgage loan; however we do not have the information on when the mortgage is due for renewal. Accordingly, in the applied exercise we will be assuming that, for each fixed term mortgage, a given proportion of households will renew their mortgage every year. This proportion of households will be equal to the inverse of the term to maturity. For example, 20% (1/5 = 0.2) of households with a 5-year term would renew their mortgage each year (5% per quarter).

In summary, we assume full and immediate passthrough to variable-rate debt and slow passthrough to the stock of fixed-rate mortgages.

III.2 Income growth dynamics

Income is the second variable required to plot the projected evolution of the DSR. Household income is divided into four income classes (for details, see Djoudad 2009). The following equation represents the distribution of income growth for a particular class:

$$\text{Income} \sim N\left(r_j, \sigma_j\right) \quad j = 1, 2, 3, 4 \tag{6}$$

where:

j: household income class;

rj: average income growth of households in class *j*;

σj: estimated standard deviation of income growth for households in class *j* (see Djoudad 2009).

Table 4

Estimated standard deviation of income growth by income class (σ)

Income group	Less than $32,500	$32,500–57,499	$57,500–84,999	$85,000 and above
Standard deviation	0.04	0.03	0.025	0.006

In Table 4, we report the estimated standard deviations of income growth for each of the four income classes. Income growth is assumed to be heterogeneous within each class – that is, the simulated distribution of income growth across households is consistent with the standard deviation reported in Table 4. Between classes, the average growth may be assumed to be identical or different, although overall growth must be consistent with the aggregate scenario set in Step 1. For example, we may assume that a shock to income has a greater impact on income growth for households in the lowest income classes (1 and 2) relative to the households in the highest income classes (3 and 4). Note however that since the survey constrains us to define income classes in nominal terms, there will be a shift over time of households toward higher income categories.

III.3 Debt growth dynamics

One of the assumptions that have to be made in Step 1 relates to the dynamics of aggregate debt growth. This assumption should detail the respective paths considered in the macro scenario for growth in consumer and mortgage debt. We cannot assume that all households will experience equal debt growth. Therefore, we have to determine how aggregate debt growth will be distributed among all households according to each household's specific socio-economic characteristics. Debt growth is assumed to be heterogeneous across households.

In our sample, there are two types of households, in regard to home ownership. The first category of households does not yet own a house or have a mortgage. Some of the households in this category will buy a house and enter into the mortgage market during the simulation exercise. They will be called first-time homebuyers. Households in the second category already have a mortgage. In the treatment of debt growth, a specific distinction is made between first-time homebuyers, who have yet to contract mortgage debt, and all others.

III.3.1 First-time homebuyers

Over recent years, home ownership has increased significantly in Canada. This indicates that first-time homebuyers have been, over that period, an important contributor to the growth of mortgage credit. The Canadian Association of Accredited Mortgage Professionals (CAAMP 2010) reports that approximately 50% of all new mortgages in 2009 were the result of first-time homebuyers. Another survey report, from Canada Mortgage and Housing Corporation (CMHC 2010), estimates that approximately 43% of all households that bought a house in 2009 were first-time homebuyers. The dynamics of mortgages for first-time homebuyers are different from those of other mortgage holders.

To be eligible for being a first-time homebuyer, we identify households in the data set that have neither a mortgage debt nor a house. The value of the house this household can afford is related to the amount of its liquid savings and a maximum DSR that is randomly attributed. The DSR value allocated to this household is drawn from a random distribution whose average is consistent with observed data.

This feature tracks how household balance sheets change, for first-time homebuyers, both on the asset side and on the liability side. It also allows us to assess the impact of changes in house prices on the household balance sheet. If a crisis occurs, households that had liquidity but bought houses cannot use that liquidity for loan payments since it was used for the downpayment. However, households may have other assets that could be valued at market prices.

III.3.2 Other households

Using the pseudo-panel data set, we are able to estimate equations for the growth of household debt as a function of income, household wealth, house prices and interest rates. Housing wealth is defined as the difference between the value of the house and the amount of the mortgage.

We estimate the following equations for growth in total household debt and mortgage debt:

$$\Delta TC_t = c_{11} + \alpha_{11}\Delta r_t + \alpha_{12}\Delta i_t + \alpha_{31}(1 + hp_t)HW_{t-1}I_0 + \lambda_1(c_{11} + \alpha_{11}\Delta r_t + \alpha_{12}\Delta i_t + \alpha_{31}(1 + hp_t)HW_{t-1}I_0)\mathrm{D40} + \varepsilon_1 \quad (7)$$

$$\Delta MC_t = c_{12} + \alpha_{12}\Delta r_t + \alpha_{22}\Delta i_t + \alpha_{32}(1 + hp_t)HW_{t-1} + \lambda_2(c_{12} + \alpha_{12}\Delta r_t + \alpha_{22}\Delta i_t + \alpha_{32}(1 + hp_t)HW_{t-1})\mathrm{D40} + \varepsilon_2 \quad (8)$$

where:

t: time;

Δ: first-difference operator;

ΔTC and ΔMC: are respectively growth of total household debt and mortgage debt;

i: interest rate;

r: logarithm of household income;

hp: house price growth;

I_0: 1 for homeowners, 0 otherwise;

HW: logarithm of housing wealth;

D40: 1 if the household has a DSR level equal to or above 40%, 0 otherwise.

We consider equations (7) and (8) to be the reduced-form equations of demand and supply for household debt. Consequently, it would be difficult to formulate precise expectations regarding the signs of the coefficients.

The inclusion of λ_1 and λ_2 in both equations indicates a non-linearity in the growth of household debt for households with a DSR level at or above the 40% threshold, given that banks' decision to extend additional credit is influenced by the household's initial level of the DSR. There is a DSR threshold over which a household becomes more financially vulnerable. Financial institutions generally use a DSR threshold of 40%. Djoudad and Traclet (2007) use this industry threshold to sort financially vulnerable households in the CFM sample. Accordingly, we expect this parameter to be negative suggesting that growth of household debt will be lower for households with a DSR equal to or greater than 40%.

The purpose of these equations is to provide parameter estimates for the determinants of debt growth. When combined with the household specific path for income growth and assumptions for interest rates and property values (i.e., the explanatory variables in the equations), they allow us to simulate the distribution of debt growth across households.

The dynamics of debt growth follow the dynamics implied by equations (7) and (8). For each household in the sample, given its simulated income growth (see section II.2), changes in the overnight rate, its housing wealth and its current level of DSR, we calculate the corresponding growth in total credit and mortgage credit implied by these two equations. The mean of the distribution of growth implied by equations (7) and (8) is adjusted to comply with the aggregate assumptions from Step 1 using equations (9) and (10). We maintain the distribution of credit growth but shift the overall mean by a constant, for all households. Future extensions to this framework may integrate the determinants of credit growth which would endogenously affect individual credit growth. However, for current purposes, we allow for heterogeneity and non-linearity in the debt growth dynamics by linking the distribution of credit growth to economic factors.

$$\Delta C_t = \frac{\left(\Sigma(1 + \Delta C_{it}) w_i C_{it-1} - \Sigma w_i C_{it-1}\right)}{\Sigma w_i C_{it-1}} \quad (9)$$

$$\Delta C_{1it} = (AG - \Delta C_t) + \Delta C_{it} \quad (10)$$

With:

t: time;

i: household;

C: consumer or mortgage debt;

ΔC_{it}: individual growth of consumer and mortgage debt implied by equations (7) and (8);

ΔC_{1it}: adjusted individual growth of consumer and mortgage debt consistent with equations (7) and (8) and the aggregate scenario;

AG: assumed aggregate growth (adjusted for the first-time homebuyers).

Equations (9) and (10) will ensure that total growth of credit, in the simulation exercise, is consistent with aggregate assumptions set in Step 1. Debt growth (consumer and mortgage) for every household is adjusted so that the average growth across all households is equal to the assumptions set in Step 1.

III.3.3 Estimation and result

Table 5

Estimation results[a]

Variables	Total household credit equation	Mortgage credit equation
Constant	0.005	0.0155
Δ interest rate	-0.0266	-0.0538
Δ log of income	0.8030	0.5282
Δ log of housing wealth	0.0007	0.001
λ	-0.2163	-0.3367
$\bar{R}^2$	0.15	0.37

a. All coefficients are significant at the 1% level.

Results of the estimations are presented in Table 5. We use the method of weighted least squares with a corrected covariance matrix. All equations are estimated with debt, income, and housing wealth in first differences. We also added the lagged value of housing wealth (the difference between the property value and the mortgage debt), in levels, with a home ownership variable to the two debt equations. In both cases, the housing wealth variable is significant. This indicates the importance not only of the growth in house prices, but also of the level of wealth. In order to avoid problems of simultaneity, this variable was lagged. The results indicate a negative and significant relationship between growth in debt and changes to the interest rate. The relationship is positive and significant for income. This result obtains for both equations. Finally, as to mortgage and total debt, their growth is also positively related to growth in property values and the level of housing wealth owned by the household. Finally, as expected λ is negative for both equations indicating that growth in debt will be reduced for households with a DSR equal to or greater than 40%. For example, everything else being equal, growth in mortgage debt will be 34% lower for a household with a DSR above the 40% threshold, compared to the same household with a DSR below 40%. Similarly, growth in total household debt will be reduced by 22% for a household with a DSR equal to or above 40%, compared to a similar household with a DSR below 40%.

The change in debt will not be identical across households since the model permits the growth of each household's debt to depend on household specific income and housing wealth according to empirical relationships (equations 7 and 8).

III.4 DSR calculations

Finally, the simulated DSR for every household and for each period is calculated using the household specific changes in income and debt and the assumed path for interest rates. This information is combined to construct the simulated distribution of the DSR.

IV. Household vulnerabilities and risk

In order to assess the vulnerabilities stemming from the household sector, we need to define a metric that will help us in quantifying the changes to the vulnerabilities in our simulation exercises. In our analysis, we will use two metrics.

IV.1 Vulnerable households

Vulnerable households are defined as those for which the DSR is equal to or greater than the 40% threshold. This measure is consistent with industry benchmarks and empirical results (Dey et al. 2008). Dey et al. suggest that the DSR level beyond which there is a qualitative and significant increase in a household's propensity to be delinquent on mortgage debt is consistent with 40%.

IV.2 Change in the aggregate probability of default given a negative employment shock

The change in the proportion of vulnerable households is, to a certain extent, an indication on how vulnerability levels change, rather than a direct measure of potential losses if a shock materializes. To address the latter issue, we examine the effect of a significant negative shock to employment on the probability of default on loan payments.

Since defaults will be affected by households' balance sheets (liabilities and assets) as well as their income and interest rates, this measure represents a more integrated view of the resilience of households to negative shocks. Interestingly, default rates allow us to directly quantify potential bank losses.[9] In the December 2010 issue of the FSR, the Bank of Canada

[9] When complemented with some other information.

calculated the effect of a severe negative shock to employment on the loan portfolios of banks. This approach provides a more direct indication of how risks are transmitted from households to the financial system than the measure based on the 40% threshold.

If a negative employment shock occurs, households that are affected will lose their income coming from employment. In our framework, the loss of jobs is distributed randomly among households with employment income. Thus, retirees, students, etc. will not be affected by this negative income shock. Once households are affected by an unemployment shock, there are two sources of funds that may be readily available to them to make loan payments: employment insurance income if they are qualified and proceeds of the sale of their liquid assets and part of their mutual funds if they have any. Liquid funds include all funds in chequing and savings accounts, term deposits, government bonds, GICs,[10] etc. “If a broader range of assets were used, then the second-round effects would also need to be considered in the model.” Djoudad (2010, p. 61). In fact, severe stress situations may trigger asset fire sales from households that would potentially have feedback effects on aggregate variables like house prices. To take fully into account the dynamic of the shocks, a broader model is needed.

Empirical data suggest that only a proportion of households qualify to receive unemployment benefits, once they become unemployed. CFM data show that in 2010, almost half of households were double income earners. We assume that if a double income household is hit by an unemployment shock, the household keeps half of its income plus the unemployment benefits (if any) for the other half.

In our empirical exercise, we assume that only part of the liquid funds available to the households is used to service the debt, while the other portion is directed toward household expenses. If a household is not able to meet its financial obligations (servicing its debt), over the course of its unemployment spell, for at least three consecutive months, this household will be deemed insolvent. Default on any unsecured outstanding debt will then be considered a loss to financial institutions.

Our simulations assume that the duration of unemployment varies among households and follows a chi-squared distribution. Duration of unemployment is a critical factor in assessing whether a household will become insolvent. The longer the duration of unemployment, the bigger is the stock of liquid assets needed to continue making loan repayments. Consistent with historical evidence, the higher the unemployment rate, the longer is the assumed average period of unemployment.

IV.3 The implementation of an unemployment shock

Now that we have discussed the framework driving a negative employment shock, we will proceed in this section by presenting the technical steps used to implement it in our model.

In order to perform this simulation, we need the following information for every household:

i. income level;

ii. working status;

iii. total loan payments;

iv. liquid assets (and other assets if taken into account in the exercise);

v. household weights.

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[10] GIC: guaranteed investment certificate.

In the survey, each participant is attributed a population weight. In order to perform the simulations, we first rebuild the population distribution. We use the weights to match the distribution of the population. All calculations are based on the distribution of the population and not on the sample distribution. For example, if the survey attributes an eight (x_a) to household (A), there will be x_a identical households in the generated sample. The number of households in the new sample will be equal to the summation of all weights. This feature is important in the simulations to avoid any bias toward any specific representative household.

V. Numerical example

To illustrate the capabilities of the framework, we will use 2008 CFM data to simulate the impact of various shocks on the distribution of the debt-service ratio and, therefore, the probability of default for households.

V.1 DSR distribution for 2008

Figure: 1 : DSR distribution for 2008

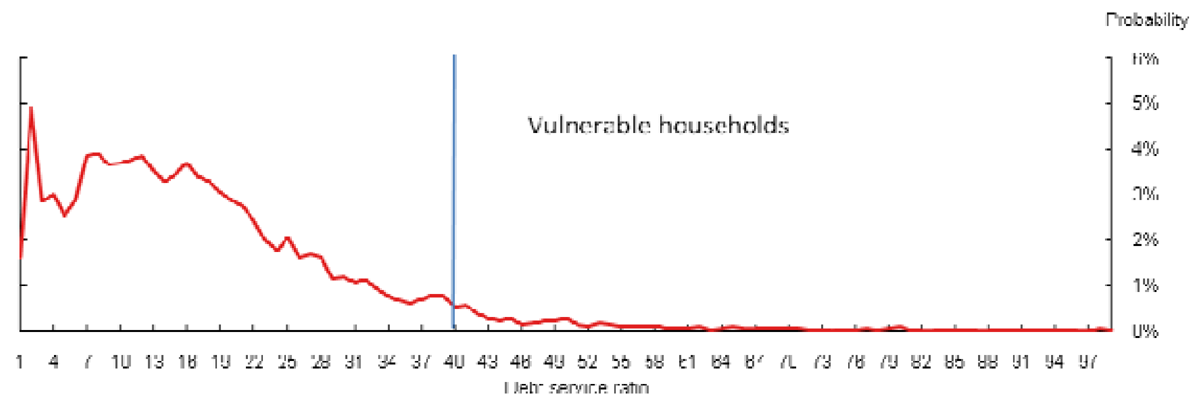

Figure 1 presents the DSR distribution for 2008. As reported in Table 6, in 2008, the proportion of vulnerable households was 5.70% while the proportion of debt owed by these households was 10.63%. Also, 60% of the households that were in the sample had some type of debt (credit card, consumer loans, mortgages), of which 70% had a mortgage.

Table 6

Vulnerable households and debt owed[11]

Period	Proportion of households with a DSR equal to or greater than 40%	Proportion of debt owed by households with a DSR equal to or greater than 40%
2008	5.70%	10.63%

[11] All calculations refer only to households with debt.

The actual DSR distribution for 2008 represents a starting point for the following simulations. The evolution of the distribution over the simulation horizon is determined using an assumed macro scenario and the methodology described in previous sections.

V.2 Interest rates scenario

Since there are eight different interest rate terms across mortgage loans of different maturities, we must assume a specific path for each of these terms. However, because these paths are not determined independently of each other, we use the following formula to generate the mortgage rate for each maturity:

$$i_{yt} = ovn_t + risk\ premium_{yt} + term\ premium_{yt} \qquad (11)$$

t: period;

y: maturity term;

i_{yt}: mortgage rate for maturity *y* at period *t;*

ovn_t: overnight rate or policy rate;

$risk\ premium_{yt}$: aggregate risk premium;

$term\ premium_{yt}$: aggregate term premium.

Depending on the characteristics of the assumed stress test, we can suppose any level of risk and term premium in the exercise.

Table 7

Interest rates for fixed term mortgages over the simulation periods (%)

Period	6 months	1 y	2 y	3-4 y	5 y	7 y	10+ y	Overnight rate
1	3.46	3.24	3.24	3.91	4.25	6.24	4.95	0.25
2	3.71	3.49	3.49	4.16	4.50	6.49	5.20	0.50
3	3.96	3.74	3.74	4.41	4.75	6.74	5.45	0.75
4	4.21	3.99	3.99	4.66	5.00	6.99	5.70	1.00
5	4.46	4.24	4.24	4.91	5.25	7.24	5.95	1.25
6	4.71	4.49	4.49	5.16	5.50	7.49	6.20	1.50
7	4.46	4.24	4.24	4.91	5.25	7.24	5.95	1.75
8	5.21	4.99	4.99	5.66	6.00	7.99	6.70	2.50
9	5.46	5.24	5.24	5.91	6.25	8.24	6.95	2.75
10	6.21	5.99	5.99	6.66	7.00	8.99	7.70	3.50
11	6.96	6.74	6.74	7.41	7.75	9.74	8.45	4.25
12	7.71	7.49	7.49	8.16	8.50	10.49	9.20	5.00

Table 7 reports the assumed mortgage rates for maturities available in CFM data. We suppose that over the simulation periods (each period is a quarter), the overnight rate will increase from 25 bps to 500 bps. At the starting point and consistent with what happened during the crisis, both the risk premium and the term premium were at elevated levels (in 2008) while the policy rate was at its effective lower band. Over the course of the simulations, it is assumed that both the risk premium and the term premium will fall to 350 bps, as economic conditions improve. At the same time, the policy rate will increase to 500 bps in quarter 12. Indeed, different scenarios can be assumed for different components (overnight rate, term and risk premiums) but the assumptions must all be consistent with the macro stress scenario chosen (debt and income growth).

V.3 Assumptions for the debt-to-income ratio

In this scenario, we assume that consumer debt will rise at an average of 8% per year while mortgage debt will increase at 7.5%. Income will rise at an average of 4% over the same horizon. According to these assumptions, debt-to-income will continue to increase. We also assume that interest rates will evolve according to Table 7. Rising interest rates and rapidly increasing indebtedness may be seen as unlikely, since higher interest rates should cause the debt increase to slow over the simulation period. However, the purpose of this illustration is to expose the capabilities of the methodology and to assess the build up of vulnerabilities consistent with a tail event scenario rather than presenting the most likely scenario.

V.4 Simulation results

Table 8

Results of the simulations (%)

	Assuming that debt-to-income ratio is constant and interest rates are increasing (Scenario 1)			Assuming that both debt-to-income ratio and interest rates are increasing (Scenario 2)		
	Average DSR	Proportion of households with a DSR equal to or greater than 40%	Proportion of debt owed by households with a DSR equal to or greater than 40%	Average DSR	Proportion of households with a DSR equal to or greater than 40%	Proportion of debt owed by households with a DSR equal to or greater than 40%
Base year	16.9	5.7	10.6	16.9	5.7	10.6
Q1	16.3	4.9	9.4	17.0	5.7	10.7
Q2	16.3	4.9	9.1	16.4	5.0	9.5
Q3	16.2	4.8	8.9	16.5	5.0	9.4
Q4	16.2	4.8	8.7	16.6	5.1	9.4
Q5	16.2	4.9	8.9	16.7	5.3	9.5
Q6	16.3	4.9	9.1	16.9	5.4	9.6
Q7	16.3	5.0	9.1	17.1	5.7	10.1
Q8	16.5	5.1	9.4	17.2	6.0	10.7
Q9	16.5	5.3	9.6	17.6	6.4	11.1
Q10	16.7	5.4	9.9	17.8	6.6	11.5
Q11	16.9	5.7	10.4	18.2	7.0	12.4
Q12	17.2	6.1	11.0	18.6	7.6	13.4

Table 8 reports vulnerabilities for every period considered in the simulations. Let us first maintain debt-to-income constant. In this scenario, we isolate the specific impact of interest rates on the DSR distribution. With the increase in interest rates as stated in Table 7, the average DSR would increase to 17.2% in twelve quarters from 16.9% at the beginning of the simulations. The initial decrease in the average DSR is due to the impact of lower interest rates for consumer debt and households rolling over their mortgage debt. The proportion of households with a debt equal to or greater than 40% as well as the proportion of debt these households owe respectively increase to 6.1% and 11.0% after twelve quarters, from their respective levels of 5.7% and 10.6% in the base year.

However, if we assume that debt-to-income will continue to grow as described above, the average DSR will increase to 18.6% at the end of the simulation from 16.9% at the starting point and the percentage of vulnerable households as well as the proportion of debt they owe will increase to 7.6% and 13.4% from their respective levels of 5.7% and 10.6% at the start of the simulations.

V.5 Impact of a negative employment shock on the probability of default for households

In this section, we introduce an explicit negative shock to employment at different periods (quarters 1 and 12) and we assess how the risks change over the medium term. The risk depends on the vulnerability levels (Table 8) and the size of the shock. Everything else held constant, the risk increases over time if vulnerability increases.

Given the simulation results for the DSR obtained in the previous section, we calibrate the unemployment shock program by adjusting key assumptions to replicate the default rate on household loans, at the base year. The calibration is done by adjusting the proportion of liquidity that can be used by households to service their debt payments. Recall that liquid funds available to unemployed households will include unemployment benefit (if any), liquid assets (chequing and savings accounts, term deposits, government bonds, GICs, etc.), and a proportion of mutual funds. For example, in the present simulation, the proportion of mutual funds used for payments was adjusted to replicate the level of default[12] on household loans that was observed in 2008 (0.36%), given the unemployment rate of 6.1% and an average unemployment spell equal to approximately 15 weeks.

Once the unemployment program has been calibrated at the starting point, a shock is performed by changing the level of the unemployment rate from 6.1% to 11% and increasing the average duration of unemployment from 15 weeks in 2008 to 25 weeks twelve quarters later, using as input data on payment obligations from the DSR simulations. The results suggest that the default rate, on total loans, would increase from 0.36% at the base year to 1.2% at period 12 of the simulation, should Scenario 2 materialize.

The objective of this section is to obtain default rates on household loans under the stress scenario. Given these default rates, assumptions on loss given default and the level of unsecured debt that the households owe, we calculate the magnitude of the losses to banks on their household portfolio. We then compare the level of these losses to Tier1 capital (or any other measure that is appropriate) and evaluate whether financial institutions remain well capitalized after the shock.

[12] Default is defined as loans for which payments are in arrears for 90 days and more.

VI. Conclusion

In this paper we have presented a framework for using microdata to assess potential risks stemming from household indebtedness. These microdata have been an important complement to aggregate data. At the Bank of Canada, we have been using these data for several years now and reporting the results in our *Financial System Review*.

In this paper we have presented the general concept surrounding the methodology used to exploit the microdata. The examples offered are illustrative of the capabilities that this framework offers. All assumptions used are intended to calibrate the model and may be changed according to various needs and objectives. They should not be seen as a limitation to the method. This framework is in continuous development. For example, future work may introduce more behavioural assumptions for households, consistent with economic theory or economic priors. One important development would be to substitute the random draws for income by a household specific income that depends on its socio-economic characteristics.

Appendix 1:
Building pseudo-panel data

The building of this data set is necessary given the non-panel nature of the data set. To allow us to perform data series analysis, we construct a new data set where each observation consists of a grouping of households belonging to the same characteristic group. For example, we can build two groups of households that relate to the employment status of the households (working or not). The first group will have all the households that have a job. The second group will contain all other households. For each of these two groups, we can determine the amount of credit, income, wealth, etc. This approach will reduce the number of observations in the database into two main observations. If we add the area of residence (inside or outside a region) to the employment status (working or not working), we will then have a grouping of four criteria (two for employment and two for residence). The transformed database will then contain four representative household categories for each year. The most attractive feature of this method is that we can compare the data for each group of representative households across time and compute growth rates and estimate parameters in equations (7) and (8).

This approach has been presented in different papers and according to Biao (2007), Dargay and Vythoulkas (1999) were the first to use it. Subsequently, it was taken up by Dargay (2002), Bourguignon et al. (2004), Navarro (2006), and Biao (2007), among others. While this approach is an interesting complement to the cross section analysis of data, it raises a number of questions and challenges such as the choice of the characteristics that are used to group the data.

For this study, we define clusters of households based on the following criteria:

- Age groups: 18–24 years, 25–34 years, 35–49 years, and 50 years and over.
- Labour market status: households are divided into two categories: those who receive income from a working activity, and those whose income is from other sources, such as students, retirees, unemployed, etc.
- Education: on the one hand are those who completed up to 13 years of schooling, and on the other are those with a university degree.
- Status as owner or tenant.
- Those with a DSR equal to or above 40 and those with a DSR below 40.
- Given that the dynamics of the economy in Alberta have been different compared to the rest of Canada over the last decade, whether the household lives in Alberta or outside Alberta has been added as a criterion.

The combined groups add up to 128 categories. For each household group considered, we compute weighted averages for each category of borrowing (credit cards, secured and unsecured personal lines of credit, car loans, other loans, and mortgages), income, house values, and the DSR.

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