A framework for assessing household indebtedness using microdata

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Abstract

We present a formal framework for using microdata to assess the impact of various economic shocks on the distribution of the debt-service-ratio for the household sector. In this framework, we use Ipsos Reid Canadian Financial Monitor survey (CFM) data to construct the current DSR distribution for households. We simulate changes in the distribution using a macro scenario describing the evolution of some aggregate variables, and micro behavioural relationships. For example, to simulate credit growth for individual households, we use cross-sectional data to estimate debt-growth equations as a function of household income, interest rates, and housing prices. We also use simulated distributions to measure vulnerabilities in the household sector. Finally, we present a combined methodology where changes in the probability of default on loans, for households, are used as a metric to evaluate the quantitative impact of negative employment shocks on the resilience of households.

JEL classification: C15, C31, D14, E51
Bank classification: Econometric and statistical methods; Financial stability

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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. Household debt–to-income increased from 110 per cent in early 2000 to approximately 146 per cent by the first quarter of 2010. In comparison, over the period between 1990 and 2000, debt-to-income increased from 90 per cent to 110 per cent. This period coincided with rapid growth in household debt in other OECD countries as well (OECD's Factbook 2010). This 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 developp 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 economy and the financial system. It might, in fact, translate into a decline in consumer spending, undermining economic growth. In addition, a higher DSR would make households more vulnerable to negative shocks to income or interest rates, making household balance sheets more precarious and having negative fallout on financial institutions.

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 in developing an analytical framework for assessing risk in the household sector.[1] 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

[1] 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.

of the extent to which shocks to the interest rate, indebtedness, and income could lead to a deterioration in the financial situation of Canadian households.

Microdata have been used by the Bank to examine the evolution of the distribution of 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' payments defaults.

To the extent that 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. The purpose of this article is to present the analytical framework developed at the Bank of Canada to stress test household balance sheet using microdata.

We examine the DSR distribution to evaluate the build up of the vulnerabilities in the household sector. Therefore, to assess the impact of changes in the macroeconomic conditions on the household vulnerabilities, it is necessary to understand how these changes will affect the DSR distribution going forward.

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

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 relate to 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 of the household in a specific way. To perform the whole exercise, there are three complementary steps (Table 1) that need to be accomplished Djoudad (2010, 57).

Table 1: Steps in the stress-testing exercise

Step1	Step1	Step1
Establish the key assumptions for the macro scenario: – Growth in aggregate – 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

II. General framework

The Statistics Canada aggregate DSR takes into account only interest payments. When calculating the DSR using microdata, principal repayments, on all installment 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:

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

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

- payments are available on a weekly, biweekly or monthly basis (normalized to a monthly frequency);
- interest rate paid on the loan;
- term of mortgage loans (in years)[2] and;

[2] 6 months, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, and variable-rate mortgage loans. But we do not have any information on its maturity date.

- 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*,[3] the distribution of the DSR, 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 diffculty 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, the impact of interest rates changes affect the amount of interest payments and have no impact on the proportion of 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:

$$\text{(3)} \qquad \text{Principal} = PC - \text{Interest} = PC - (SC * ir).$$

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:

$$\text{(4)} \qquad \text{Share\_Principal} = (\text{Principal}/SC).$$

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

$$\text{(5)} \qquad PC = SC*(\text{Share\_Principal} + ir).$$

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.

[3] See the five issues of the *Financial System Review* published from December 2007 to December 2009.

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 reasonnable supplementary assumptions for missing data would bias the results less than omitting these observations[4].

Whenever the information on interest rate for a specific loan is missing, we chose 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 the level of the payments carried out by the household for this loan unchanged, 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. Consequently, the values of the DSR obtained during these simulations may constitute a lower limit. Finally, when information on the term of the mortgage is missing, we consider that the mortgage is at variable rate.

[4] Missing data represent around 1-2% of the information.

In step 1 of the exercise, we set the key assumptions of the macro scenario. As indicated in Table 1, these assumptions relate to growth of aggregate credit and income, 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 explianing how this macro scenario will affcet every household in the sample.

II.2 Transmission of interest rates shocks

All consumers' 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 this latter 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 will suppose that the individual risk premiums will remain constant. Similarly, we pass variations in the overnight rate on to variable-rate mortgages.

Table 2: **Distribution of mortgages between variables 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 points are worth highlighting: firstly, fixed interest rate loans represented the vast majority of mortgage loans over the last decade. Secondly, while in 2000, fixed interest rate mortgages represented 91.6% of all mortgages, in 2008, this proportion decreased to 75.3%, suggesting 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.

Table 3 reports the distribution of fixed interest rates mortgages by maturity term. This 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 years term. These three terms accounted for more than 80% of all fixed term mortgages over the last decade. A simulation exercise could change the proportion of fixed versus variable and the proportion of fixed term mortgages by maturity according to changes in the macro economic 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 its mortgage every year. This proportion of households will be equal to the inverse of the term to maturity. For example, for a 5-year term, 20 per cent (1/5 = 0.2) of households would renew their mortgage each year (5 per cent per quarter).

III. Income and debt dynamics

The purpose of this section is to show, for every household, how income and debt evolve in the model (Step 2).

CFM data that is available to us is not a panel data. It is essentially a cross-sectional database and only a small proportion of households is in fact in the sample for more than one year. This is not sufficient to allow us to estimate econometric equations that relate growth in debt to income, interest rates and other economic variables, given that the times series information do not refer to the same households.

III.1 Building pseudo-panel data

The building of this dataset become necessary given the nature of the observations we have. 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 to the employment characteristics, the area of residence (province or a city), we will then have a grouping of four criteria (two for employment and two for residence). The transformed database will then contain four representative households 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.

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 do the grouping of the data.

Finally, the results depend on the choice of characteristics to define the groups of consumers. For this study, we define clusters of household based on the following criteria:

- Age groups: 18–24 years, 25–34 years, 35–49 years, and 50 years and over.
- Labor 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, the 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 of owner or tenant.
- Those with a DSR equal or above 40 and with a DSR below 40.
- Given that the dynamic of the economy in Alberta has been different compared to the rest of Canada over the last decade, the criteria about whether the household leaves in Alberta or outside Alberta has been added.

The combined groups add 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.

III.2 Income growth dynamics

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

$$\text{(6)} \qquad \mathrm{Income} \sim \mathrm{N}(\mathrm{r_j}, \sigma_\mathrm{j}) \quad \mathrm{j} = 1,2,3,4,5$$

where

j = household income class

r_j = 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 34 999 $**	**32500$ - 57499$**	**60000$ – 84999$**	**Above 85000 $**
Standard deviation	0.04	0.03	0.025	0.006

In Table 4, we report the estimted standard deviations of income growth for each of the five classes (income class 4 and 5 are merged). Income growth is assumed to be heterogeneous within each class. Between classes, the average growth may be assumed to be identical or different, although overall growth must be consistent with the aggregate scenario. 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, 4, and 5). Note however that given that we are using nominal class, there will be a shift over time of low income households toward higher income categories.

III.3 Debt growth equations

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:

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

$$\Delta MC_t = c_{12} + \alpha_{12}\Delta r_t + \alpha_{22}\Delta i_t + \alpha_{32}(1 + hp_t)HW_{t-1} + \lambda_1(c_{12} + \alpha_{12}\Delta r_t + \alpha_{22}\Delta i_t + \alpha_{32}(1 + hp_t)HW_{t-1}) + \varepsilon_2 \quad (8)$$

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 values;

I_0: 1 if the household has a mortgage, 0 otherwise;

HW: logarithm of housing wealth;

D40: dummy variable indicating whether the household has a DSR variable below, equal or above 40% threshold.

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. In fact, these results from the structural equations are for both supply and demand.

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, they allow us to estimate the distribution of debt growth.

The inclusion of λ in both equations indicates a shift in the growth of household debt for households with a DSR level at or above the 40% threshold, given that banks' decision to extend credit is influenced by the level of DSR that the household is currently faced with. There is a DSR threshold over which a household is 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 or above 40%.

The dynamics of debt growth follow the dynamics implied by equations (7) and (8). For each household in the sample, given its income growth, changes in the overnight rate, its housing wealth and its level of DSR, we calculate the corresponding growth in total credit and mortgage credit implied by these two equations. The distribution of growth implied by equations (7) and (8) is adjusted to comply with the aggregate assumptions using equations (9) and (10):

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

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

With:

t: time;

i: household;

Δ : first-difference operator;

C: is consumer or mortgage debt;

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

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

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

According to equations (9) and (10), the 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.3.1 Estimation and results

Table 5: Estimations 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
$\bar{R}^2$ (%)	15	37

a. All coefficients are significant at 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 homeownership variable to the two debt equations. In both cases, the housing wealth variable is significant. This indicates the importance of not only 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 all 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 or above 40%. For example, everything being equal, growth in mortgage debt will be 34% lower for a household with a DSR equal or above 40%, compared to the same households with a DSR below 40%. Similarly, growth in total household debt will be reduced by 22% for a household with a DSR equal or above 40%, compared to a similar household with a DSR below 40%.

The change in debt will not be identical across households since it permits the growth of each household's debt to depend on specific household income and housing wealt according to empirical relationships (equations 7 and 8). We must though distinguish between first-time homebuyers, who did not have neither a house nor a mortgage previously, and other households that already have a mortgage or a house.

III.3.2 First-time homebuyers

Over recent years, home ownership has increased significantly. This indicates that first-time homebuyers have been, over that period, an important contributor to the growth of mortgage credit. CAAMP (2010) reports that approximately 50% of all 2009 mortgages were the result of first-time homebuyers. Another survey report from 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 not similar to those that describe the other households and formalized by equations (7) and (8).

Once the growth of debt is calculated for all households that already have a consumer or a mortgage loan, the proportion of debt that is devoted to first-time homebuyers is randomly spread across the eligible households.

To be eligible for being a first-time homebuyer, the household should 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 sheet changes, for first-time homebuyers, both on the asset side as well as 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 their liquidity since it was used for the downpayment. However, households will have other assets that will be valued at market prices.

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 distrbituion 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 analysis, we will be using two metrics.

IV.1 Vulnerable households

These households are defined as those for which the DSR is equal to or greater than the 40% threshold. In a paper Dey et al. (2008) compare CFM and Statistic Canada's Survey of Financial Security (SFS) databases for 2005 (the latest SFS available was 2005). They conclude that both sets of data are broadly comparable. Then using SFS data, the authors estimated the probabilitiy of mortgage debt delinquency and its changes with respect to DSR. They then identified a DSR level above which they find a significant increase in the probability of mortgage debt delinquency. The exercise was performed for years going from 1999 to 2006 of the *CFM* survey. The average DSR threshold over this period was approximately 44%. This result suggests that the DSR level beyond which there is a qualitative and a significant increase in the 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.

An alternative measure of household vulnerability is the probability of default on loan payments given a negative employment shock. It is a test of the sensitivity of households to adverse employment shocks. Since defaults will be affected by households' balance sheet (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 employment shocks.[5] Interestingly, this measure allows us to quantify directly potential bank losses. In the June 2009 issue of the FSR, the Bank of Canada calculated the effect of a severe negative shock to employment on the loan portfolios

[5] See the June 2009 issue of the FSR, pp. 21–23, for an example.

of banks. This approach provides a more direct indication than the measure based on the 40% threshold of how risks are transmitted from households to the financial system.

If a negative employment shock occurs, households that are affected will lose their income coming from employment. In our framework, the loss of jobs among households in the population is random. However, we assume that non-employed households are precluded from this shock. For example, 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; employment insurance income if they are qualified and liquidity funds (and liquidated assets) if they have any. Liquid funds include all funds in chequing and savings accounts, term deposits, government bonds, GICs, 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, 61).

Empirical data available to us suggest that only a proportion of households would be qualified to receive employment insurance benefits, when they become unemployed. In our empirical exercise we will assume that just half of the liquid funds available to the households will be used to service the debt, while the other half is directed toward household expenses. If a household is not able to face 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. Its unsecured outstanding debt will then be considered as a loss to financial institutions. Our simulations assume that the duration of unemployment varies among households. In the model, we assume that the duration of unemployment will follow a chi-squared distribution. The unemployment rate is calculated as follows:

$$(11) \qquad U_t = \frac{\sum_i Number\ of\ weeks\ unemployed\ per\ individual_i}{\sum_i Total\ number\ of\ weeks\ \ in\ the\ labour\ force_i}$$

With:

i: individuals in the labour force over year period;

The average spell of unemployment is a critical factor in assessing whether a household will become insolvent. Consistent with historical evidence, the higher the unemployment rate, the longer the average period of unemployment will be.

Accordingly, the probability of default (PD) will be equal to:

$$PD_t = \frac{\sum_i Household\ that\ defaulted\ on\ any\ loan\ for\ more\ than\ three\ months_i}{Total\ number\ of\ households} \quad (12)$$

If the calculations for the number of unemployed households are done as deviations from the base year, calculations for the probability of default should also be considered as deviations as well.

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.

In the survey, each participant has a weight to construct the distribution for the population. 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 done on the distribution of the population and not on the sample distribution. This feature is important in the simulations. However, if the survey does not contain any weight, this step is skipped

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 debt-service-ratio and, therefore, the probability of default for households.

V.1 DSR distribution for 2008

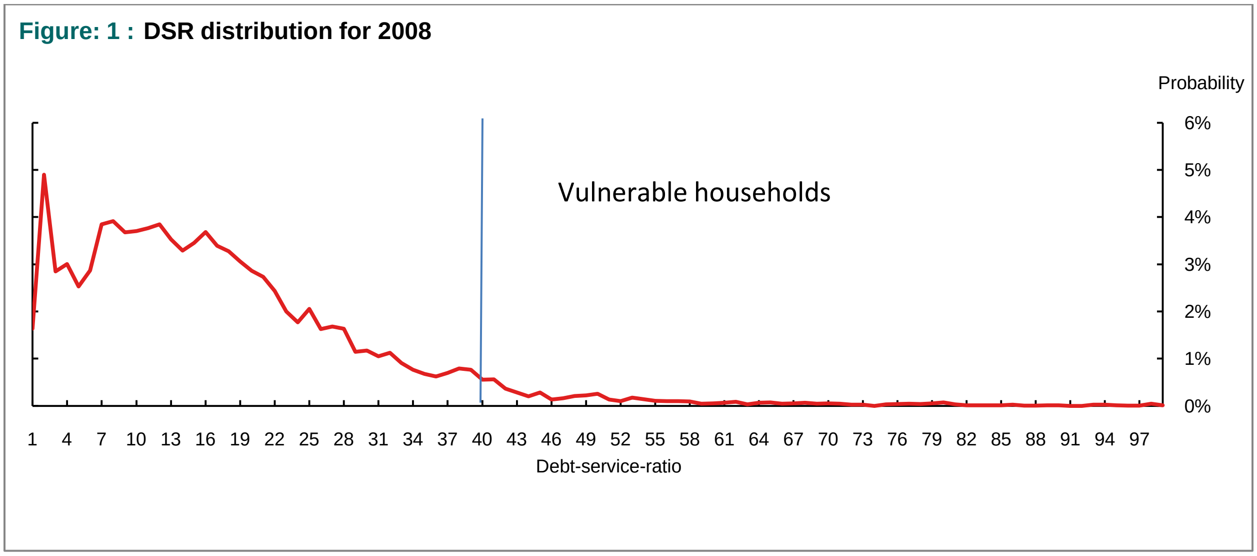

Figure 1 presents the DSR distribution for 2008. As reported in Table 6, in 2008, the proportion of vulnerable households was 5.70% while the proportion of debt owed by these households mounted to 10.63%. In 2008, 60% of the households that were in the sample had a debt of any form (credit card, consumer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

Table 6: Vulnerable households and debt owed[6]

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

The DSR distribution for 2008 represents a starting point for our simulations. Going forward, let us assume the following macro scenario and assess its impact on the DSR distribution.

V.2 Interest rates scenario

Since there are 9 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 deteremined independantly of each other, we use the following formula to generate the mortgage rate for each of them.

$$i_{yt} = ovn_t + risk\ premium_{yt} + term\ premium_{yt} \tag{13}$$

[6] All calucaluations refer only to households with debt.

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.

We can suppose any level of risk and term premium in the exercise. Let us assume that, at every maturity and at each period, mortgage rate will be calculated according to equation 13.

Table 7: **Distribution of fixed interest mortgages by mortgage term (%)**

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 period, the overnight rate will increase from 25 bps to 500 bps, which represents a significant increase. However, both the risk premium and the term premium will remain at their historical averages before increasing significantly after the fourth quarter. Different scenarios can be assumed for all the components (overnight rate, term and risk premium) consistent with the macro stress environment chosen.

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

In this scenario, we assume that both total household and consumer debt will continue to rise at an average of 8% per year and mortgage debt will increase at 7.5 percent. Income will rise at an average of 4% over the same horizon. According to these assumptions, debt-to-income will continue to increase. In fact, different assumptions can be assumed. We also assume that interest rates will evolve according to Table 7. Rising interest rates and 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 the exercise is to expose the capabilities of the methodology rather than presenting realistic assumptions.

V.4 Simulation results

Table 8 reports vulnerabilities for every period considered in the simulations. Let us first maintain debt-over-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 augment to 15.4% in twelve quarters from 16.9% at the beginning of the simulations. The 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 or above 40% as well as the proportion of debt these households owe respectively decrease to 9.9% and 4.9% after twelve quarters, from their respective levels of 10.6% and 5.7% in period 1.

However, if we assume that debt-over-income will continue to grow as described in the previous section, the average DSR will increase to 17.6% 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 7.2% and 14.5% from their respective levels of 5.7% and 10.6% at the starting of the simulations.

Table 8: Results of the simulations for scenario 1 and scenario 2 (%)

	Assuming that debt-over-income ratio is constant			Assuming that both debt-over-income ratio and interest rates are increasing		
	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	14.2	3.9	7.9	14.3	4.1	8.2
Q2	14.2	3.9	7.8	14.5	4.2	8.2
Q3	14.2	3.8	7.6	14.6	4.2	8.2
Q4	14.2	3.7	7.3	14.8	4.3	8.3
Q5	14.2	3.8	7.5	15.0	4.5	8.6
Q6	14.2	3.8	7.5	15.2	4.7	8.9
Q7	14.3	3.7	7.5	15.4	4.9	9.3
Q8	14.5	3.8	7.7	15.8	5.4	10.4
Q9	14.6	4.0	7.8	16.1	5.7	11.0
Q10	14.8	4.2	8.4	16.5	6.1	12.0
Q11	15.1	4.5	9.0	17.0	6.6	13.3
Q12	15.4	4.9	9.9	17.6	7.2	14.5

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 and we will assess how the risks change over the medium term. We assume that the unemployment rate will increase by the same percentage at the beginning and the end of the simulations and then calculate how the probability of being insolvent will change from one period to the other, given the changes in the DSR distribution.

For example, we first simulate the DSR distribution according to the previous scenario. We restrict our employment shock to combined the shocks (interest rate and debt-over-income), because it is the most stressful one. Then, we extract at period 1 and 12 the data series needed to perform a negative employment shock (see previous sections for details). Both simulations (period 1 and 12) are performed assuming a 10% unemployment rate and 20 weeks for the average unemployment duration. The results are reported in Table 9. Results suggest that the probability of insolvency would increase from 1.0% to 1.15% at the end of the simulations, should scenario 2 materialize. This measure shows by how much the resilience of the household sector would change in reaction to the realization of the assumptions contained the previous scenario.

Table 9: Impact of a 10% unemployment shock with a 20 weeks average duration

Period (quarters)	1	12
Probability of default (%)	1.00	1.15

These numbers can be used to calculate the losses on unsecured household debt.

VI. Conclusion

In this paper we have presented a framewok for using microdata to assess potential risks stemming from the household sector. These microdata have shown to be an important complement to agregate data. At the Bank of Canada, we have been using these data for several years now.

In this paper we have presented the general concept surrounding the methodology used to exploit the microdata. The examples offered are more 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 sophisticated behavioural assumptions for households, consistent with economic theory or economic priors. One important development would be to substitute the random draws for income by an autoregressive equation for every houshold.

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