Household Indebtedness and Delinquency: Simulations and Estimations Using Microdata

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Abstract

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Introduction

In recent years, an environment of low interest rates coupled with rapid innovations in the financial sector has contributed to the increase in indebtedness of Canadian households. In the short run, this increase has boosted consumer spending and economic growth. However, in the long run, this increase in indebtedness will to lead to increased financial obligations for Canadian households. These financial obligations are measured by the debt-service ratio (DSR), which represents the portion of income that households have to devote to servicing their debt obligations. This rising DSR, in turn, will ultimately lead to a steady deterioration of household's financial health - captured by the probability of debt delinquency. In this paper, we want to the capture the inter-linkages between household indebtedness and delinquency in some detail.

Given what rising household indebtedness may imply for the Canadian economy and its financial institutions, it is important to analyse the dynamics of household DSR and evaluate its impact on household's probability of debt delinquency. So far, simulation exercises with the aggregate DSR have been performed to evaluate the impact of interest rate and income shocks on household's financial position (*FSR* June 2007). Although the simulations based on the aggregate data are informative, they do not permit an evaluation of the impact of shocks on the distribution of household indebtedness and neither can they help us determine the proportion of financially vulnerable households. An analysis of the distribution of financially vulnerable households is key to measuring and pricing credit risk. The inter-linakages that we will uncover between household indebtedness and delinquency rate is going to be a step in the right direction.

In the first section, we discuss the *CFS* and the *SFS* - the two main datasets used in this study - and present some stylized facts. In the second section, we describe the methodology that uses the *CFM* survey data to perform the DSR simulations. In the following section, we present a model that assesses the impact of changing economic conditions on delinquency rates of Canadian households. In the final section, we offer some conclusions of our current study.

1 Empirical Observations on Household Indebtness

This section discusses the strengths and weaknesses of the two main survey datasets used in this article, identifies and defines important variables of our analysis and documents empirical facts on household indebtedness. There are two survey datasets available for analyzing household indebtedness in Canada - the Ipsos Reid's *Canadian Financial Monito*r (*CFM*) and the *Survey of Financial Security* (*SFS*) by Statistics Canada.

1.1 Data: *CFM* and *SFS*

Even though *CFM* and *SFS* are similar in focus, each has its strengths and weaknesses. Faruqui and Lai (2007) and Armstrong and Lim (2008) provide more detailed discussions on the quality comparison of the two datasets. We highlight several key differences discussed in those studies here. First of all, in terms of the coverage of information on household finances, both data-sets have a similar scope with attention to all major financial and non-financial assets and the money owing on mortgages, vehicles, credit cards, student loans and other debts. However, the *CFM* provides superior coverage of debt payments with details on credit cards, bank loans and mortgages, while the *SFS* only provides information on mortgage payments. On the other hand, there is more detailed information on privately held businesses and various pension plans in the *SFS*. The *SFS* identifies assets and debts associated with privately held businesses as well as assets in employer pension plans. In addition, the *SFS* provides a break down of total household income whereas the *CFM* only identifies total income.

Secondly, there are differences in the sample size and the survey frequency. The *CFM* samples about 12,000 households on an annual basis beginning in 1999. The *SFS* is conducted less frequently. The last two waves were in 1999 and 2005. The sample size varies between waves. About 16,000 and 5,000 households were in the sample in 1999 and 2005, respectively. Third, the survey method is different between the two datasets. The *CFM* conducts mail surveys while *SFS* surveys through phone and personal interviews. Both surveys aim to capture Canada's major demographic and geographical subgroups. One important concern of household finance survey is to capture the distribution of households over income and wealth since it is well known that income and wealth are highly concentrated among "rich" households. In addressing this issue, both the *CFM* and the *SFS* oversample high-income households. However, how they conduct oversampling is quite different. In the *CFM*, half the sample is reserved for households with income above \$60,000 and thus the other half for less than \$60,000. On the other hand, 10% to 15% of the *SFS* sample is for households with total income above \$200,000 or investment income exceeding \$50,000.

Finally, variable coding is also different between the two datasets. In the *CFM*, quantitative information on debts, assets, income and payments is coded within ranges although variables may differ in terms of the ranges in which the respondent's answer must be placed. The numbers used in this article are midpoints from the appropriate ranges.[2] On the other hand, the *SFS* provides dollar values directly as reported by respondents.

Given these issues, Faruqui and Lai (2007) conducts a quantitative study to compare *CFM* and *SFS* with respect to total debt, financial assets and non-financial assets on several dimensions of household characteristics. Even though they identify that there are differences in the methodologies of the two surveys, they mainly find that *CFM* data on debt and assets are quite comparable to those from *SFS* with some exceptions. They attribute the discrepancies to the methodological differences such as definitions of some variables.

1.2 Definition of Variables

We define main varialbes used in the analysis. Some of these variables are constructed based on the given information in each dataset. We construct them so that variables from the two datasets are as consistent as possible.

Total debt: Total household debt is the sum of balances outstanding on all forms of debt including credit cards, mortgages, personal loans, and lines of credits.

Debt payments: Annual debt service payments are the sum of all principal and interest payments on all debt.

Liquid assets: Total liquid assets include checking and saving account balances, term deposits and GIC, bonds, T-bills and other guaranteed investments, stocks and derivatives, mutual funds and precious metals.

Total assets: Total household assets are liquid assets plus registered savings plans, employer pension plans, real estates, and vehicles.

Total income: Total household income is the sum of all income of the household members.

Household head: Social and demographic characteristics of households are used in analysing indebtedness by household type. We identify households' social and demographic characteristics with that of the household head. Hence, the definition of household head has to be consistent between the two datasets. The *CFM* provides social and demographic information on two potential heads of a household, male and female, whenever both are present. The *SFS* defines a household head to be "the adult mainly responsible for the financial support of the family" implying that the highest income adult in the household is the head. We follow the definition of

2. For the highest ranges, the lowest value of each range is assigned.

the *SFS*. Unfortunately, we can not directly identify the member satisfying the *SFS* definition in a *CFM* household since data on individual member's income is not available. However, data on work status, education and age are available. We therefore proxy income using these information by designating as household head the member who is working full-time or self-employed and favour higher education where work status is equal and age data where candidates are equally well educated.

1.3 Observations on Household Indebtedness

In this section, we document and discuss basic observations on household indebtedness using the *CFM* data from 1999 to 2006. We use three indicators of indigenes: (1) the debt-service ratio (DSR), (2) the ratio of debt-service to liquid resources (DSLR), and (3) the debt-asset ratio (DAR).[3] The DSR is the ratio of all principal and interest payments to total household income. The DSLR is the ratio of all principal and interest payments (as in the DSR) to total income and liquid assets. Both the DSR and the DSLR are able to measure short-run vulnerabilities, since households can draw on income or proceeds from the sale of their liquid assets to meet their obligations in the short-run. However, frictions may prohibit the sale of non-liquid assets on short notice or at the least would require significant sacrifices in terms of sale price. Such assets are generally only available to supporting debt service in the long-run. Therefore, we measure long-run vulnerability using the DAR whose denominator includes all assets regardless of liquidity.

3. These indicators do not take into account the maturity structure of household debt. The maturity structure on assets and debt is important in assessing financial stability. Meh and Terajima (2008) document in detail maturities on the household balance sheet and consider implications for the redistributional effects of inflation.

1.3.1 Aggregates and Distributions

Figure 1 shows the aggregate DSR, DSLR and DAR from 1999 to 2006. The aggregate DSR is calculated by aggregating individual debt service and income separately, then taking their ratio. The aggregate DSLR and DAR are similarly calculated. All three series increase initially then decline after a peak in 2001 or 2002. For example, the DAR increases from 0.193 in 1999 to 0.221 in 2002 and declines to 0.172 in 2006. The changes in Figure 1 were not uniform across households. Heterogeneity among households is important, particularly since delinquency and defaults are concentrated among those with high DSR, DSLR and DAR. Figures 2, 3 and 4 give the distributions of the DSR, the DSLR and the DAR across individual households, respectively, over three separate years: 1999, 2002 and 2006. The DSR and the DSLR show a similar pattern over time. The fraction of households with zero debt payments increased. Those in middle ranges (i.e., between zero and less than 0.4) have increased between 1999 and 2002 and then decreased in 2006 contributing to the peaks observed in Figure 1.

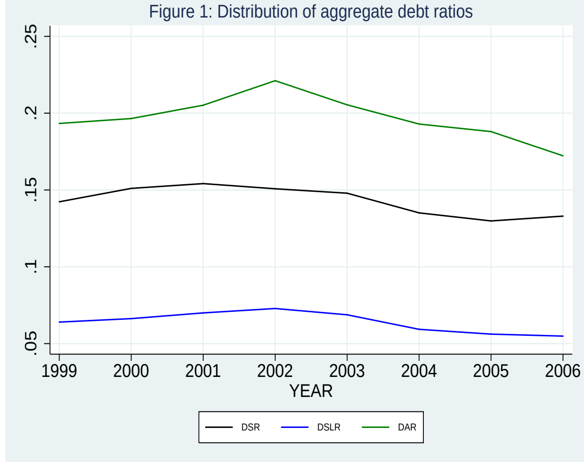


Figure 1: Distribution of aggregate debt ratios

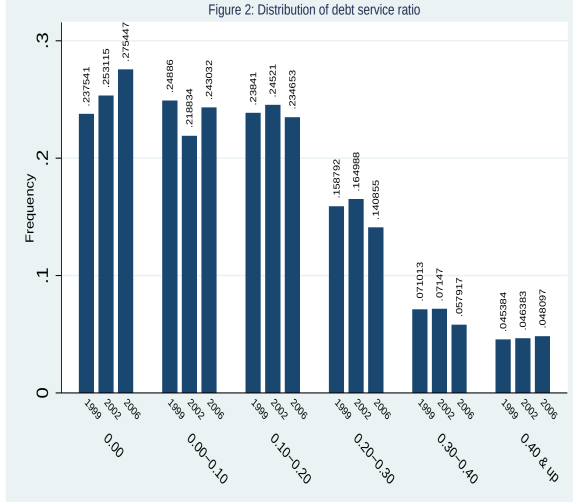


Figure 2: Distribution of debt service ratio

The increase in the fraction of households with the DSR and the DSLR above 0.4 seems trivial, however, there were changes among this group. The average DSR in this group changes from 0.607 in 1999 to 0.627 in 2002 and then to 0.629 in 2006. In addition, even though it is relatively a small fraction of households who have DSR above 0.4, the share of total debt they hold is much larger. They represent about 12% of the total debt in the economy for all three years. On the other hand, the DAR in Figures 4 shows that there is a notable increase in the higher end of the distribution with the fraction of households having the DAR of 1.5 or higher changing from 4.9%

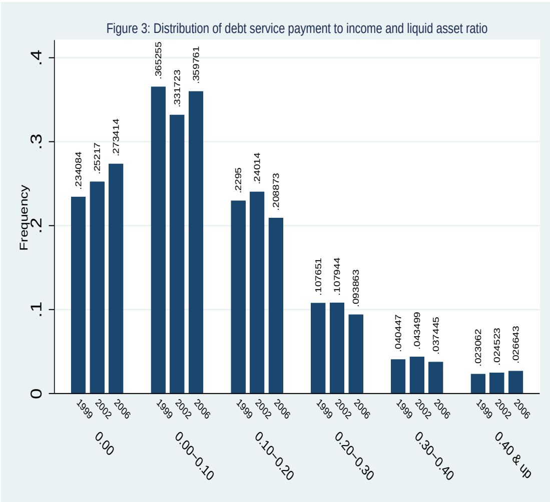


Figure 3: Distribution of debt service payment to income and liquid asset ratio

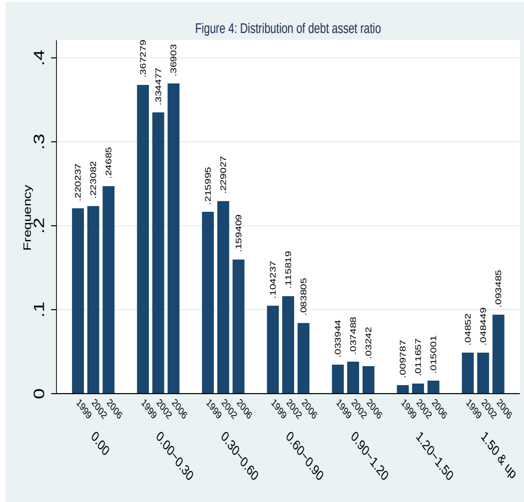


Figure 4: Distribution of debt asset ratio

in 1999 to 9.3% in 2006. The share of total debt in the economy this group holds has increased significantly from 1.73% in 1999 to 10.88% in 2006.

1.3.2 Household Characteristics

The previous section showed that a sizable and increasing share of households find themselves at the right tail of the debt ratio distributions. In order to understand further the financial stability of the household sector, we focus on these households and seek to identify their key characteristics.[4] We will focus specifically on those with DSR exceeding 0.4, a standard threshold used in the loan approval process. We also consider DAR exceeding 1.5.[5] Table 1 considers subgroups in terms of income, age, education, and occupations, and report the fraction of households in each subgroup exceeding the DSR and DAR thresholds for three years: 1999, 2002 and 2006. For example, in Table 1, the top left cell indicates that 4.63% of households in the first income quintile had DSR exceeding 0.4 in 1999.

Income Class: In Table 1, we observe for most years that as income quintile increases the fraction of high DSR households decrease. In 2006, there are about 4 times more households with high DSR among the lowest income quintile (6.36%) than that among the highest quintile (1.7%). There is an increase in the fractions for the lowest two quintile in 2006 from 2002. The table shows

4. Meh, Terajima, Chen and Carter (2008) document further the source of high debt ratios using *SFS*. They find that real estate backed debts (i.e., morgages and home-equity line of credits) are the largest element of household portfolios and that these debts have increased especially among middle-aged households.
5. Faruqui, Lai and Traclet (2006) document that the average DAR of insolvent households is around 2. We look at a lower value of 1.5 since the value calculated in their study is ex-post the bankruptcy.

Table 1: Percentage of households

Characteristics		With DSR>0.4			With DAR>1.5		
		1999	2002	2006	1999	2002	2006
Income Quintile	1st	4.63	5.40	6.36	10.69	9.65	12.14
	2nd	5.75	5.41	5.82	4.63	5.36	9.96
	3rd	4.94	4.03	4.36	2.36	2.88	9.03
	4th	2.72	2.48	2.29	0.84	1.27	6.12
	5th	0.89	2.16	1.70	0.16	0.63	3.85
Age	30 and under	4.86	5.13	5.86	11.53	12.58	21.26
	30 to 40	4.87	5.61	5.92	4.74	5.33	10.87
	40 to 50	4.87	4.24	4.24	3.66	3.07	8.73
	50 to 60	3.45	3.95	4.16	1.88	1.78	6.28
	60 and up	1.89	1.56	2.09	2.41	2.31	2.77
Educa-tion	Less than high school	3.96	3.50	4.70	5.66	4.74	8.32
	High school	4.19	4.95	4.35	4.50	4.93	10.04
	College	3.68	3.27	3.24	2.86	3.08	6.41
Occupa-tion	Worker	4.54	3.87	4.37	4.26	4.62	10.48
	Self-employed	N/A	10.14	7.57	N/A	1.23	6.50
	Not working	2.46	2.06	2.36	4.92	4.98	5.63

that more households are likely to have high DAR as income lowers. In addition, we observe an increasing trend in the fraction of households with high DAR after 2002 in all income quintiles. However, the significant increases are observed among the fourth and the fifth quintile between 2002 and 2006 from 1.27% to 6.12% in the fourth quintile and 0.63% to 3.85% in the fifth quintile. Thus, even though high income households are in general less likely to have high DAR, they are 5 to 6 times more likely so in 2006 than in 2002.

Age: Household age is also an important determinant of high DSR. It is observed from Table 1 that younger households are more likely to have high DSR. In addition, we observe an increasing trend in high DSR among age 40 and younger as well as age 50 to 60 since 2002. In the table for the DAR, we can observe that young and middle-aged households became increasingly more likely to have high DAR since 2002, but there has been no comparable increase for households with age 60 or above.

Education: Here, we look at three groups, those without a high school diploma, those with a high school diploma and those with a college degree. Households without a college degree tend to have high DSR. The difference seems to have picked up in 2006, when households without a high school diploma were about 1.5 times more likely to have high DSR than those with a college degree. The DAR observations show a similar pattern except that there are more significant increases for all education groups over the period.

Occupation: We look at three groups: full-time workers, self-employed and non-working households.[6] Occupation seems to matter. Among these three groups, more self-employed households have high DSR relative to full-time workers or non-workers. In 2006, self-employed households were about 1.7 time more likely to have high DSR than full-time workers and 3 times more likely than non-working households. However, if we compare the DSR observations to those with the DAR, a different picture emerges. Even though self-employed households are more likely to have higher DSR than worker households in all available years, workers are more likely to have high DAR than the self-employed. This implies that, while self-employed households are sensitive to short-run risks, they hold assets to back their debt. Also, it should be noted that there is an increasing trend in the fraction of high DAR among workers and self-employed, while no trend is apparent for non-workers.

2 Simulations of the DSR using microdata: methodology, assumptions, and limitations

In this section, we present and discuss the methodology used to simulate household DSR using microdata. The debt service ratio is a measure indicating financial constraints facing households. It assesses the proportion of income available to the household for discretionary expenditures. This constraint can be represented as follows:

6. For the 1999 survey, the CFM did not include ``self-employed" as a choice for work status.

$$DSR_t = \frac{\sum_i Payments_{i,\,t}}{Income_t}$$

with

- *Payments*: payments on different loans {credit cards, auto leases, personal loans, personal lines of credit, mortgages};
- *Income*: household income.

For each type of loan covered by the data, except for credit card balances, we have the following information:

- Monthly payments.
- The effective interest rate.
- The type of contract (fixed rate or variable for mortgages).
- The term of the loan (one, three, five years, etc.) for mortgages. It should be noted, however, that the data do not indicate the date on which the mortgage loan matures.
- The current balance.

At this point, we need to make certain assumptions to allow us to proceed with the simulations.

2.1 Assumptions regarding consumer lending

For purposes of our simulations, we consider that payments made on credit cards amount to 2 per cent of the current outstanding balance, corresponding to the minimum reimbursement required by the credit card companies. The household must then reimburse an amount corresponding to 24 per cent of the annual balance each year, regardless of the interest rate. All other categories of consumer lending (personal loans, personal lines of credit, and car loans) are at variable rates.

In our simulations, shocks to interest rates will affect only the amount of interest paid, not the proportion of the principal that must be reimbursed. Thus, from the information in the survey, we must estimate how much of the payment is for interest and how much for the principal.

We denote the annual reimbursements of consumer lending, which include both interest and payment of principal, with ***PC***. We have information on the current balance, **CB**, and on the interest rate paid by the household (**iv**). Thus, the payment of principal can be computed as follows:

$$\boldsymbol{Principal} = \boldsymbol{PC} - \boldsymbol{Interests} = \boldsymbol{PC} - (\boldsymbol{CB} * \boldsymbol{iv})$$

For the simulations, we assume that the portion of the principal that the consumer repays during each period, Share-of-principal-repaid = (Principal / CB), remains constant and is always proportional to the current balance (CB). Conversely, the share of interest paid will depend on assumptions regarding the interest rate. The amount of payments made will equal:

$$\boldsymbol{Payment} = \boldsymbol{SC} * (\boldsymbol{Share\text{-}of\text{-}principal\text{-}repaid} + \boldsymbol{iv})$$

Therefore, payments will be conditional on the path taken by the interest rate and on the growth of indebtedness.

2.2 The dynamics of household credit

For our simulations, we make assumptions regarding average aggregate growth in income, debt, and property values. However, we require a tool that will allow us to establish how this growth will affect each household. This is the role of the equations for credit dynamics. We estimate a model of household's credit as a function of its characteristics and macroeconomic data.

The household's employment status, level of education, place of residence, and income, along with its housing wealth and the interest rate, are all factors that influence the demand for credit. The household wishes to smooth its consumption over time by incurring loans. We estimate a demand for credit for both total household and mortgage credit.

The microdata available to us are, in general, cross-sectional survey data that do not always track the same households. This makes it difficult, if not impossible, to monitor fluctuations in the credit available to the household over time. To conduct a dynamic analysis, we need to use new methodologies and construct pseudo-panel data.

In pseudo-panel data, each observation consists of a cluster of households having similar characteristics. To illustrate, if we take employment status (working or not) for each household considered, we can construct two groups of individuals. The first contains all households earning employment income and the second all those whose income is not linked to working. Thus, in this case, regardless of the number of households in the survey, the new database will contain only two observations. If, in addition to the employment measure, we add a variable for area of residence (within or outside of each region), we will have a combination of four criteria (two for employment and two for residence). The new database will therefore contain four observations per year. The most interesting aspect of this procedure is that we can compare the data for each group across time and calculate growth rates, for example.

This approach is relatively new 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. Of course, this approach raises a number of questions and challenges. The choice of characteristics to delineate the groups of consumers is important.

For this study, our first criterion is the age groups defined as: 18-24 years, 25-34 years, 35-49 years, and 50 years and over. The second criterion describes labour market status. Households are divided into two categories: those who receive income from an activity, and those whose income is from other sources, such as students, retirees, the unemployed, etc. A third criterion is related to 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. The fourth measure describes the status of owner or tenant. Finally, in light of the fact that the dynamics of the Alberta economy have diverged from those of the rest of Canada during the years of these surveys-in terms of growth in incomes, wages, investment, property values, consumer spending, etc.-we deemed it worthwhile to differentiate between households residing in Alberta and those living elsewhere.

Most financial institutions consider that a DSR of 40 per cent represents the threshold above which a household could begin to struggle with meeting its repayment commitments. Thus, it becomes more difficult for these households to obtain loans, because financial institutions scrutinize their credit requests more closely, and they become constrained. Therefore, we consider that the debt-related behaviour of households will be affected above that threshold. We assume that the marginal effect of an increase in income on the level of indebtedness of a household whose DSR is greater than or equal to 40 per cent will be less than it would be on a household carrying less debt. Also, the marginal impact on debt of a hike in interest rates will be positively correlated with the household's level of indebtedness. Consequently, we also group households on this criterion. We created a total of 128 categories of household for each year.

For each household group considered, we compute weighted average debt for each category of borrowing (credit cards, equity lines of credit and unsecured lines of credit, car loans, other loans, and mortgages), income, house values, and the DSR.

As of the end of the 1990s, financial innovations have granted households more ready access to their housing wealth, through either mortgage refinancing or equity lines of credit, making it more available for consumption or investment. We estimate that, since the mid-2000s, a significant proportion of household consumption has been supported by the extraction of housing wealth. This is why we view housing wealth as a potential determinant of the demand for mortgages and equity lines of credit.

In addition to the preceding variables, for each household, we incorporate the value of the overnight rate on the day the survey questionnaire was completed. To the extent that the decision to incur debt depends not only on the characteristics unique to the household, but also on the interest rate, and the growth in housing prices, it is important to include these data in our analysis.

We specify equations for total household credit and mortgage credit of the form:

$$\Delta TC_t = c_{11} + \alpha_{11}\Delta r_t + \alpha_{21}\Delta I_t + \alpha_{21}(1 + hp_t)D_o HW_{t-1} + \lambda_1$$
$$(c_{11} + \alpha_{11}\Delta r_t + \alpha_{21}\Delta I_t + \alpha_{21}(1 + hp_t)I_o HW_{t-1})D_o D_{40} +$$
$$\varepsilon_{1t} \tag{1}$$

$$\Delta MC_t = c_{21} + \alpha_{21}\Delta r_t + \alpha_{22}\Delta I_t + \alpha_{23}(1 + hp_t)D_{4o} HW_{t-1} + \lambda_2$$
$$c_{21} + \alpha_{21}\Delta r_t + \alpha_{22}\Delta I_t + \alpha_{23}(1 + hp_t)D_o HW_{t-1})D_{40} + \varepsilon_{2t} \tag{2}$$

with:

t: period;

Δ: first order lag operator;

TC: total household credit;

MC: mortgage credit;

r: interest rate;

I: household income;

hp: house price growth;

HW: housing equity;

D_{40}: indicator variable for household with a DSR above 40%;

$D_{o:}$ indicator variable for owner households;

Ultimately, we consider equations (5) and (6) to be the reduced-form equations of a demand system for household credit. Consequently, it would be difficult to formulate precise expectations regarding the signs of the coefficients. In fact, these result from the structural equations for both supply and demand. However, once we know the sign, we can use it to determine whether we are on the demand or the supply equation. For example, if credit is inversely related to the interest rate and positively related to income, we may be inclined to believe that we are on the demand, rather than supply, curve for credit.

The purpose of these equations is to provide a distribution of the growth of each household's debt load, given certain assumptions on the growth of income, interest rates, and property values. These equations are of marginal use for forecasting the evolution of household indebtedness.

2.3 Estimation and results

We use the method of weighted least squares with a corrected covariance matrix. In both cases, λ_ι is significant and negative. It confirms our intuition that, on average, growth of credit is lower for households with a DSR above 40%. The significance of the coefficient related to housing wealth indicates the importance of not only the growth in housing prices, but also the level of wealth. To avoid problems of simultaneity, this variable was lagged. The results indicate a negative and significant relationship between growth of credit, in both equations, and changes in interest rates. The relationship is positive and significant for income. This result obtains for all equations. Signs related to all variables suggest that these equations are consistent with demand curves. Although some results[7] indicate that there have been some substitution among consumer credit instruments that relate to house price movements, share of components in consumer credit are kept constant over the simulation horizon. We do not think that this may impact significantly, in any way, our simulations results.

2.4 Dynamics of household income

Households are categorized according to four classes of income (see Table 5). We assume that the income of each class follows a stochastic process of the following form:

$$revenu_i \sim N(\bar{r}_i, \sigma_{r_i}) \quad i = 1, 2, 3, 4$$ [8]

The advantage of this type of approach lies in its ability to accommodate a symmetric dispersion as well as an asymmetric distribution of income growth by household group. Indeed, following a negative shock on the labour market, it is likely that growth in the revenues of households belonging to the lowest income groups (categories 1 and 2) will be more affected than growth in the incomes of households in categories 3 and 4. We can, of course, also assume an equal

7. For further details, please refer to a forthcoming working paper on this methodology.
8. The variances have been estimated using microdata; σ_1=0.04, σ_2=0.03, σ_3=0.025, σ_4=0.006.

distribution of growth across all income groups and assess its impact on the distribution of the DSR.

2.5 Proportion of households renewing their mortgage

The survey data available to us do not indicate the date on which mortgages mature. Therefore, we need to make assumptions regarding the proportion of households having to renew their mortgage each year. The CFM data contain eight different terms. For our purposes, we assume that households whose mortgages have terms of one year or less renew their loan every year. For terms exceeding one year, we assume that the proportion of households renewing will be equal to 1/ (duration of term). Thus, for a 5-year mortgage, 20 per cent (1/5 = 20%) of households will renew their mortgage each year. For 10-year terms, 10 per cent (1/10 = 10%) of households will renew each year.

We further assume that the distribution of mortgages by type (fixed vs. variable) will remain stable. We realize that this assumption is simplistic since, logically, the proportion of households with a variable-rate mortgage should decrease/increase gradually as we increase/ decrease the interest rates. However, the introduction of assumptions regarding how these proportions respond to interest rates changes would make the exercise more complicated. Finally, the distribution of mortgage holders by term (one year, two years, three years, etc.), among fixed term mortgages, also remains constant in our exercise, consistant with historical data.

2.6 Scenario of indebtedness, income, and house prices

Our objective in building these exercises is to illustrate the usefulness of the methodology in analysing the impact of risk scenarios on household financial situation. These scenarios are similar to those presented in the Review of Financial System of December 2007.

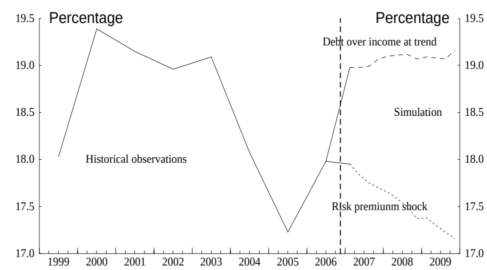
Scenario 1) Impact of higher household debt on the distribution of the DSR. In this scenario, we assume that the level of interest rates remain unchanged over the simulation horizon. We suppose that both total(8%) and mortgage (6%) credit as well as income (5%) will grow at speeds similar to those observed over the period 2000 - 2007. We also assume that house prices continue to rise at 5%. The purpose of this scenario is to asses the impact of increasing indebtedness on the distribution of the DSR assuming that monetary policy will not respond.

Scenario 2) The second scenario will assess the effect of an increase in risk premiums on the distribution of the DSR. We consider a crisis scenario in which the premiums increase to historical highs of 322 basis points, on average. This level is about 140 basis points higher than actual. Again we assume that this shock is not offset by monetary policy actions. We know that in reality this is unlikely to happen however it is useful to show the marginal effect of risk premium shock.

2.7 Results

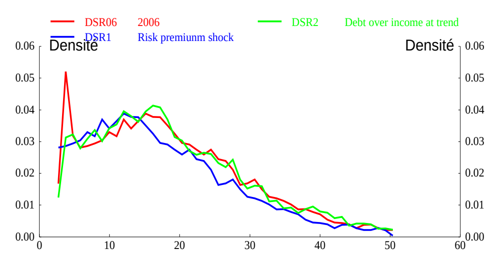
Table 2 shows the evolution of the average and the distribution of DSR for different periods. These results indicate that the DSR respond more to an increase in household debt than to an increase in interest rates. In our exercise, assuming an increase in debt over income ratio increases the DSR from 17.90 at the starting point to 19.2 twelve quarters later. The proportion of households with a DSR above 40% increases from 6.6% to 8% over the same horizon. On the other an increase in the risk premium assuming a constant debt-over-income ratio keeps the DSR and the proportion of vulnerable households barely changed over the twelve quarters horizon. This result suggest that a slowing income will likely have a more significant impact on the DSR than a proportional increase in interest rates.

Figure 5: Average debt service ratio



Source: Ipsos-Reid, Bank of Canada Calculations

Figure 6: Distribution of the DSR



Source: Ipsos-Reid, Bank of Canada Calculations

Table 2: Simulations results

		Debt to income at trend			Risk premium shock		
Quarter	Initial	Q4	Q8	Q12	Q4	Q8	Q12
Average	17.9	19.0	19.1	19.2	17.7	17.4	17.2
Proportion of Households with DSR > 40%	6.6	8.0	8.0	8.2	6.1	5.7	5.5
Proportion of debt held by Households with DSR > 40%	12.1	14.70	14.8	14.7	11.9	10.7	9.8

3 Estimations and Simulations of Probabilities of Debt Delinquency

In this section, we use the *SFS* and the *CFM* survey datasets to asses the impact of changing economic conditions on the distribution of the probability of debt delinquency for Canadian households.

Data constraints explain why we have to combine these two separate sources of information for our study. *SFS* is the only source of survey data that includes observations on the incidence of delinquency for Canadian households along with its explanatory variables identified in the literature.[9] Therefore, *SFS* can be used to estimate a household delinquency equation. However, *SFS* data are not available on a regular and frequent basis. Hence, it cannot be used to regularly track the evolution of the distribution of probability of delinquency for Canadian households. Although *CFM* contains majority of the explanatory variables of delinquency identified in the literature, it does not include the all-important observations on the incidence of delinquency. *CFM* is, however, obtained on a frequent and regular basis (annually). Hence, using the delinquency equation estimated with the *SFS* data and a common set of regressors, we plan to assign a probability of delinquency to households in the *CFM* dataset. In order to accomplish that task, we need to first describe our estimation methodology.

9. See Domowitz and Sartain (1999), Stavins (2000), Fay, Hurst and White (2002), Gross and Souleles (2002) and Pyper (2002) for reference.

3.1 Estimation methodology

A household's propensity to be delinquent can be described by:

$$di^* = Xib + ui \qquad (1)$$

where:

*di**: propensity to be delinquent (latent variable);

Xi: set of regressors;

b: set of parameters;

ui: error term.

We consider two specifications of the delinquency variable. In the first specification, the delinquency variable is mortgage payments in arrears for two months or more i.e.,

di_1 = 1, if in 2004, the household was behind two months or more on its mortgage

loan payments, i.e., $di_1^* = Xi_1 b_1 + ui_1 > 0$;

= 0, otherwise.

In the second specification, the delinquency variable is payments in arrears for two months or more on debt or bills, i.e.,

di_2 = 1, if in 2004, the household was behind two months or more in its debt or bill

payments, i.e. if $di_2^* = Xi_2 b_2 + ui_2 > 0$;

= 0, otherwise.

A maximum-likelihood probit estimation with Xi_1 and Xi_2 as the vectors of regressors in *SFS* gives us estimates of the sets of parameters (b_1 and b_2) for the two delinquency equations.

Several specifications of the probit model were considered for each of the two delinquency variables. We kept a minimum set of demographic variables (age, gender and current marital status); all other demographic and monetary variables were then selected into the model based on their statistical significance. Using our estimation results, the standard normal cumulative distribution function and a common set of regressors, we then obtain a distribution of the probability of household delinquency for the various years (1999-2006) of the *CFM* sample. Below, we describe the main findings of our estimation.

3.2 Definitions of Variables

Here we define the variables used in our estimations that have not been previously defined.

Age: Age of the household head.

Gender: Gender of the household head (equals 1 if male; 0 otherwise).

Marstat: Current marital status of the household head (equals 1 if married; 0 otherwise).

Hldsize: Total number of family members in the household.

Univcd: The household head has certificate or degree (equals 1 if yes; 0 otherwise).

Networth: Total assets minus total debt.

Log_nworth: Logarithm of household's networth.

Log_liqtoasst: Logarithm of household's liquid assets minus logarithm of total assets.

Log_liqtoinc: Logarithm of household's liquid assets minus logarithm of total income.

3.3 Estimation Results

The estimation results for the mortgage delinquency and for the debt or bill delinquency are presented in Table 3. Results indicate that high values of household's net worth and the logarithm of the ratio of liquid assets to total assets are associated with a lower likelihood of mortgage delinquency. On the other hand, DSR is positively correlated with the incidence of mortgage delinquency. None of the demographic variables are statistically significant. The inclusion of DSR in the model makes the statistical contribution of household income to the incidence of mortgage delinquency insignificant.

Table 3: Estimation results[a]

	Mortgage Delinquency	**Debt or Bill Delinquency**
	Coefficient	Coefficient
age	0.0077528	-.1795404***
gender	0.2672547	.0271604
marstat	0.0337049	-.2417224*
hldsize	N.A.	.1006345***
univcd	N.A.	-.3115093***
networth	-6.31e-07*	N.A.
log_nworth	N.A.	-.0428079***

Table 3: Estimation results[a]

	Mortgage Delinquency	Debt or Bill Delinquency
	Coefficient	Coefficient
log_liqtoasst	-.01154219***	N.A.
log_liqtoinc	N.A.	-.0739173***
dsr	0.0087156**	.0047366**
constant	-3.10913***	-.688934***

a. *significant at 10% level; ** significant at 5% level; *** significant at 1% level

These results are consistent with intuition. A higher DSR means that households must devote a larger fraction of their income to debt payments. Households are more likely to fall behind on their mortgage debt payments if their DSR is high, hence the positive correlation. Liquid assets can easily be converted into cash by households to meet their mortgage debt obligations. Therefore, the more liquid assets households have relative to their total assets, the less likely they are to be delinquent, hence the negative correlation. Moreover, we should mention that various types of scaling of the liquid assets (and their logarithms) were tried in the model specification and the logarithm of the ratio of liquid assets to total assets was chosen based on its statistical importance. The logarithm attests to the presence of some non-linearity in the response of the ratio of liquid to total assets - a small fraction of liquid assets relative to total assets is associated with a larger reduction in the probability of mortgage debt delinquency. High net worth households are less likely to fall behind in their mortgage debt payments, also confirming our intuition.

Age of the household head is statistically significant with a negative coefficient in the debt or bill delinquency equation, which indicates that older households are less likely to fall behind on debt or bill payments than younger households. The significance of the age variable is consistent with the life cycle hypothesis of consumer behavior and might also capture other household features, such as, financial planning skills. Other demographic variables that are negatively correlated with debt or bill delinquency are current marital status and the fact that the household head has a university certificate or degree. Married and highly educated household heads are expected to be more responsible for their financial obligations. Larger household size, however, comes with a higher probability of being delinquent. The fact of being divorced or widowed or separated is not statistically significant, neither is the employment status of the household head.

High values of the logarithm of household's net worth and the logarithm of the ratio of liquid assets to total income are associated with a lower likelihood of debt or bill delinquency. Again, several types of scaling of the liquid assets were considered and the chosen regressor was based on its statistical importance. The choice of logarithms yet again highlights the statistical significance of non-linearities. Moreover, the statistical relevance of the logarithm of the ratio of liquid assets to total income for the likelihood of debt or bill delinquency, in some ways, captures how households' propensity to set aside liquid savings from their income serves them well in paying their debt or bills on time. As expected, DSR is also found to be positively correlated with the incidence of debt or bill delinquency. The inclusion of DSR, however, makes the statistical contribution of household income and outstanding credit card debt (deemed important in the literature) to be insignificant.

3.4 Indentification of a DSR Threshold

The banking industry's credit granting decision is influenced by the level of DSR that the household is currently faced with. The industry standard for identifying financially vulnerable households is often based on a DSR number of 40. Djoudad and Traclet (2007) use this industry threshold to sort financially vulnerable households in the *CFM* sample. In this section, we want to revisit the issue of identification of the DSR threshold based on our measure of vulnerability - the probability of mortgage debt delinquency. The choice of the probability of mortgage debt delinquency as the preferred measure of vulnerability is based on the fact that it is a cleaner measure of credit risk than the probability of debt or bill delinquency, which captures household's vulnerability in meeting its financial obligations beyond just debt. However, since we restrict ourselves to mortgage debt delinquency only, we should expect our DSR threshold number to lie below the one used in the financial services industry.

Based on the historical patterns of aggregate DSR and default rates for Canadians, the Bank has so far tried to identify the levels of aggregate DSR that are associated with periods of financial stress. Our goal here is to exploit the cross-sectional variations of DSR and delinquency rates of households and determine a DSR threshold for sorting out financially vulnerable households in the *CFM* sample. Since we lack any historical perspective on the nature of the association between DSR and delinquency rates for households, we will have to identify the DSR threshold with the help of the marginal responsiveness of delinquency rates to changes in DSR. Hence, we first bucket households in DSR groups that increase by 5, until the value of DSR reaches 65. The last DSR group captures households with DSR greater than 65 and less than or equal to 100. This last group is deliberately kept broader in order to capture reasonably large number of households within it; this is because roughly 99 per cent of all *CFM* households have DSR less than or equal to 65. For each DSR group, we then calculate the weighted mean of the partial derivative of probability of mortgage debt delinquency with respect to DSR. Finally, we identify a DSR threshold as the value of DSR beyond which there is a prominent increase in the weighted mean of the partial derivative of probability of mortgage debt delinquency with respect to DSR. We identify a DSR threshold for years 1999-2006 of the *CFM* survey, calculate an average value of the thresholds identified for each year and then compare that average value with the industry standard of 40. Our analysis suggests that a critical DSR threshold beyond which there is a prominent increase in household's propensity to be mortgage delinquent is a number between 40 and 45. Although a little higher than expected, our analysis conforms with the financial services industry standard of identifying vulnerable households on the basis of a DSR value of 40.

3.5 Stress Testing Exercise

Here, we assess how the DSR simulations using the *CFM* survey data affect the estimated probabilities of delinquency for Canadian households. The simulated paths of DSR and associated variables for Scenarios 1 and 2 are plugged into our estimated delinquency equations. We are then able to generate distributions of delinquency rates for the simulation horizon (2007-2009). The figure shows the evolution of the weighted averages of DSR and probabilities of mortgage debt delinquency for the ten-year period between years 1999 and 2009, under Scenario 1.

3.6 Caveats

This work suffers from a number of limitations. First, although we prefer to have a measure of total household debt delinquency, the formulation of the *SFS* questionnaire renders us unable to disentangle debt payments in arrears from bill payments in arrears.

Secondly, since the *CFM* dataset lacks some potential explanatory variables of delinquency (e.g., past bankruptcy and immigration status), we have to limit the set of regressors to those variables that are common to the two datasets. This may induce some bias in the estimates of the delinquency equations.

Thirdly, since the *SFS* is not available on a regular basis and the question regarding debt delinquency has differed across surveys, we cannot test for the stability of the estimated coefficients of the delinquency equations over time.

Finally, our identification of the DSR threshold relied upon the empirical correlation between DSR and the likelihood of mortgage debt delinquency. This is in line with the prevalent practice of the banking industry of using the DSR as an instrument to sort out financially vulnerable households. However, in order to use DSR as an instrument of credit policy, one needs to empirically validate a causal relationship between DSR and the likelihood of mortgage debt delinquency. Even if there is an empirically validated positive correlation between DSR and the likelihood of mortgage debt delinquency, there is no guarantee that selecting in households based on a DSR threshold (and hence a specific level of credit risk tolerance) will empirically lead to the realization of the intended level of credit risk. Therefore, in order to adequately manage the credit risk associated with the mortgage loan portfolio, one needs to account for the possible endogeneity of the credit policy instrument. This implies that despite the general concurrence of our DSR threshold with the one used in the financial services industry, the analysis, from the point of view of credit risk management is, however, incomplete.

4 Conclusion

The objective of this work is to improve our assessment of the evolution of household indebtedness and financial vulnerabilities to changing economic conditions. In order to achieve this goal, we first conduct a thorough comparison of the *SFS* and the *CFM* surveys. We find that the two surveys are broadly comparable, despite some methodological differences in the way they are conducted. We then use the *CFM* survey data to perform simulations of our measure of household indebtedness - the DSR. Our analysis based on the estimations of household delinquency rates conforms with the DSR threshold that is used by the financial services industry for selecting households who are financially at risk. Finally, we assess the impact of changing economic conditions on the financial vulnerabilities of Canadian households. We find that reductions in households’ incomes will have a more significant impact on the DSR than a proportional increase in interest rates. Using the estimated delinquency equations, linking the DSR and household debt delinquency rates, we find that this increase in DSR would significantly increase the financial vulnerabilities of Canadian households.

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