A Tool for Assessing Financial Vulnerabilities in the Household Sector

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- *An environment of low interest rates, coupled with the rapid pace of innovation in the financial sector, has contributed to a significant increase in the indebtedness of Canadian households.*
- *Data showing the indebtedness of individual households are useful for assessing how the proportion of households with high debt burdens is changing.*
- *This article presents an innovative framework that uses household-level microdata to simulate changes in the distribution of the debt-service ratio under various stress scenarios. This tool will enable researchers to refine their analyses of current risks to the financial health of Canadian households.*

In recent years, an environment of low interest rates, combined with a rapid pace of innovation in the financial sector, has contributed to a significant increase in the indebtedness of Canadian households. In the short run, this increase has boosted consumer spending and economic growth; it has also led to increased debt-payment obligations for Canadian households. These obligations are measured by the debt-service ratio (DSR), which represents the portion of their income that households devote to servicing their debt obligations. A rising DSR could cause a steady deterioration of household financial health.

The Bank of Canada regularly assesses the potential financial risks related to household indebtedness in its *Financial System Review*.[1] Some of this analysis is based on aggregate data for the household sector. These data have limitations, however, since they do not contain information on changes in the distribution of indebtedness across different households and, in particular, on how the proportion of households with potentially high debt burdens evolves. Thus, research published in the *Financial System Review* has increasingly used household microdata to assess current risks in the household sector and to conduct simulations of changes in the distribution of the DSR under various stress scenarios.

This article presents a detailed account of the Bank's method of analyzing the impact of economic shocks on the household sector through the use of microdata. We begin with a discussion of the microdata and a critical DSR threshold of financial vulnerability.

1. See, for example, Bank of Canada (2007) and Djoudad and Traclet (2007).

We then describe a new framework to simulate the impact of various economic shocks on the household balance sheet and perform several simulation exercises to illustrate the range of applications that can be produced using this tool. We conclude with comments on future directions for refining the Bank's household sector risk analyses.

A Comparison of the Microdata Sets

The Bank's DSR simulations use the Ipsos Reid Canadian Financial Monitor (CFM) household microdata because they are available on a regular basis. Statistics Canada's Survey of Financial Security (SFS) also provides household microdata, so it is useful to examine whether the two sources are broadly similar. We describe key features of these data sets and compare their descriptive statistics.

Description of the data sets

Like the SFS, the CFM contains Canadian household balance-sheet information. The data sets differ, however, in important ways. First, survey frequency and sample size differ. The CFM has conducted a monthly survey of approximately 1,000 households (for an annual total of 12,000) since 1999. The SFS surveys are less frequent, with the last two waves taking place in 1999 and 2005. As well, the SFS sample size varies between waves: about 16,000 households were surveyed in 1999 compared with 5,000 in 2005. The regular and timely updates of the CFM data are important factors that allow us to analyze changes over time in household financial conditions.

Second, the CFM provides superior coverage of debt payments, with details on credit cards, bank loans, and mortgages in every survey year. The SFS provides information on mortgage payments for 1999 and 2005 and only began to include data on non-mortgage payments in 2005. This is also an important difference, because the analyses of changes in the DSR over time require detailed information for both mortgage and non-mortgage debt over extended periods.

Third, the methods of collecting the data are different. Although both surveys aim to capture data on Canada's major demographic and geographical subgroups, the CFM conducts mail surveys, while SFS data are gathered via telephone and personal interviews. One important concern of a household financial survey is to capture the distribution of income and wealth across households. Since income and wealth are highly concentrated within a few "rich" households, both the CFM and the SFS oversample high-income households in order to collect reliable information for this group. The methodology used for the CFM makes it less likely to capture detailed information on very wealthy households.[2]

Finally, the presentation of variables differs. In the CFM, quantitative information on debts, assets, income, and payments is coded in ranges, while the SFS provides dollar values exactly as reported by respondents.[3]

Definition of variables

To facilitate the comparison, the main variables used in the analysis were constructed to be as consistent as possible over the two data sets. Our key variables are defined as follows:

(i) total household debt: the sum of balances outstanding on all forms of debt, including credit cards, mortgages, personal loans, and personal lines of credit (PLC)

(ii) total assets: liquid assets plus registered savings plans, registered pension plans, real estate, and vehicles

(iii) total household income: the sum of all income of household members.

The debt-service ratio (DSR) is as follows:

$$DSR = \frac{payments}{income} \text{x} 100,$$

where payments (both principal and interest) include those on credit cards, auto leases, personal loans, personal lines of credit, and mortgages, while income is that of the household.

Results of the comparison

We compared the contents of the CFM and SFS data sets for 2005 under several categories: debt, assets, and income (Table 1).[4] The results are reported in average dollar values for households belonging to each of five quintiles. In terms of debt, the numbers

2. In the CFM, half of the sample is reserved for households with an annual income above $60,000 and the other half for those with income less than $60,000. In the SFS, 10–15 per cent of the sample is for households with total income above $200,000 or with investment income exceeding $50,000.

3. The CFM numbers used in this article represent the midpoints of the ranges. For the highest range, which is unbounded at the upper end, the lowest value of the range is assigned. For example, the highest range for income is $150,000 and over, and a value of $150,000 is assumed for each household in this upper range. This feature means that CFM averages for the highest income group in Table 1 will be biased downwards relative to SFS averages.

4. Information from 2005 is used because it is the most recent year for which both surveys are available.

Table 1

The Data Sets Compared
2005 averages

		Income quintiles				
		1st	2nd	3rd	4th	5th
Debt	CFM	$12,779	$28,293	$51,267	$78,497	$106,283
	SFS	$12,860	$26,941	$49,961	$76,347	$118,803
Income	CFM	$19,852	$37,138	$57,481	$85,000	$132,036
	SFS	$11,500	$28,202	$45,296	$71,417	$140,851
Assets	CFM	$88,314	$189,292	$277,762	$375,646	$615,503
	SFS	$107,319	$200,191	$375,801	$503,376	$937,791

Note: CFM=Canadian Financial Monitor; SFS=Survey of Financial Security

are comparable. Under income, although the SFS numbers are lower than those of the CFM for the first four quintiles (the differences range from $8,000 to $14,000), they are also broadly comparable. The differences are likely caused by using the midpoint of the range of income reported by CFM respondents. Under assets, however, we observe a large discrepancy in the highest quintile, with an average asset value of $615,503 reported for the CFM and $937,791 for the SFS. Again, this is because the highest range in the CFM is open ended, and our calculations use the lowest value in this range.[5]

It is evident that the two data sets are broadly comparable in reporting debt and income, which are necessary for DSR calculations. We primarily use the CFM data set for our risk analysis, because it provides detailed information on debt payments, as well as more regular and timely updates. Since the SFS data provides information on mortgage delinquencies, we use it to identify a DSR threshold (see Box).

Characteristics of Financially Vulnerable Households

The financial services industry considers that households that devote more than 40 per cent of their income to service their debt are financially vulnerable. Over the 1999–2007 period, among households with positive debt, the fraction with a DSR higher than 40 per cent fluctuated between 2.8 per cent and 4.1 per cent and stood at 3.2 per cent in 2007.[6] Although this is a relatively small number of households, the share of debt they hold is much larger, representing about 6.5 per cent of total household debt in 2007. We group these households by several characteristics, including: income, education, and work status, using data reported in the CFM for 2007. Table 2 shows the results for the income classifications. We observe a negative relationship between income class and the measure of vulnerability: As income goes up, households become less vulnerable, with the poorest 20 per cent of households approximately 3.5 times more likely to be vulnerable than the richest 20 per cent. Under education, among households whose heads have a college diploma, those with a high school diploma, and those without a high school diploma, we find the greatest vulnerability among households with lower education. Work status also matters. Comparing households headed by full-time workers with self-employed and non-working households, self-employed households were about 1.96 times more likely to be vulnerable than full-time workers and 1.89 times more likely than non-working households.

Table 2

Households with Debt-Service Ratio Higher than 40 Per Cent: 2007

	Income quintiles				
	1st	2nd	3rd	4th	5th
Households (%)	5.61	3.95	3.76	1.74	1.60

DSR Simulations: Methodology and Assumptions

For our simulations, we create scenarios that demonstrate how the financial situation of households (i.e., their DSR) reacts to various economic shocks. Since movements in the DSR correspond to movements in both the debt-to-income ratio and interest rates, we assess the effect of different economic scenarios on each of the three components of the DSR (debt, income, and interest rates) separately and then combine these elements to estimate how the DSR is affected overall.

Changes in the ratio of debt to income

To simulate the effect of shocks on the distribution of debt payments, we need to determine the ways in which debt responds to movements in various economic variables. Since the available microdata are

5. See footnote 3.

6. We exclude households with a measured DSR equal to or above 50 per cent, given the possibility that some of these very high debt burdens may reflect reporting errors. The role of reporting errors is being examined further, but it is important to note that, over time, the proportion of households above the 40 per cent vulnerability threshold is virtually unaffected by the exclusion of these households.

Identifying Financially Vulnerable Households

Establishing a DSR threshold

A growing literature is attempting to quantify the effects of household bankruptcy and delinquency on the lending decisions of financial institutions.[1] In these studies, household income and debt payments are significant factors influencing credit-granting decisions. These two important variables are summarized in one statistic: the debt-service ratio (DSR). Currently, the industry standard for identifying financially vulnerable households is often based on a DSR number of 40 per cent.[2] Research reported in the Bank's *Financial System Review* has also used this threshold value of 40 per cent to group vulnerable households.

As a guideline for evaluating household vulnerability, we examine the relationship between the mortgage-delinquency rates of households and their DSR and confirm whether the critical DSR threshold we calculate from this examination is broadly consistent with the industry benchmark of 40 per cent. To obtain mortgage delinquency rates for our calculations, it is necessary to combine the information provided in two separate data sets: the Ipsos Reid Canadian Financial Monitor (CFM) and Statistics Canada's Survey of Financial Security (SFS). The CFM data set provides information that allows us to calculate the DSR and uses household characteristics similar to the ones we use but does not report mortgage delinquencies. We therefore use SFS data on mortgage delinquencies to estimate an equation that relates mortgage-debt delinquency to the DSR and other household characteristics[3] (see the Technical Appendix for details on the estimation methodology and results). Using this equation and a common set of regressors, we are able to evaluate how mortgage-debt delinquency varies with the DSR[4] for the years 1999 to 2006 of the CFM sample.

Based on this information, we identify a critical DSR threshold of 35 per cent, above which there is a significant increase in households' propensity to be delinquent on their mortgages (see the Technical Appendix for details). Given that the industry standard is based on a broader definition of financial obligations than just mortgage debt, our DSR threshold appears to be broadly consistent with the financial services industry benchmark of 40 per cent.

1. See, for example, Chatterjee et al. (2007); Livshits, MacGee, and Tertilt (2007); and Meh and Terajima (2008).

2. Note that the industry standard is often determined on the basis of financial obligations beyond just debt.

3. See Domowitz and Sartain (1999); Stavins (2000); Fay, Hurst, and White (2002); Gross and Souleles (2002); Pyper (2002); and Dey and Traclet (2008) for a list of household characteristics used in the literature.

4. Mortgage-debt delinquency for the 2007 CFM survey was not generated because of some irreconcilable data issues.

cross-sectional survey data that do not necessarily track the same households, we cannot calculate the growth in credit and income levels between two periods for the same households.

We can, however, construct growth rates for a cluster of households having similar characteristics, such as employment status, level of education, and place of residence.[7] To construct the data set and estimate the determinants of credit growth, we use annual observations over 64 categories. Our criteria are as follows:

(i) age: groups from 18–24 years, 25–34 years, 35–49 years, and 50 years and over

(ii) employment status: households that receive income from an economic activity, and those that derive income from other sources, e.g., students, retirees, and the unemployed

(iii) education: those that have completed up to 13 years of schooling and those whose education includes grade 13 up to a university degree

(iv) status as a homeowner or a tenant.

Finally, given that the economy of Alberta has developed differently from the economies of the other provinces in recent years in terms of growth in incomes, wages, investment, property values,

7. This approach (i.e., creating pseudo panel data) is relatively new. According to Biao (2007), the first to use it were Dargay and Vythoulkas (1999). It was subsequently adopted by Dargay (2002); Bourguignon, Goh, and Kim (2004); Navarro (2006); and Biao (2007), among others. This approach raises a number of questions and challenges, e.g., the choice of characteristics to delineate the groups of consumers.

consumer spending, etc., we differentiate between households residing in Alberta and those living elsewhere.

As noted above, most financial institutions consider a DSR of 40 per cent to be the threshold above which a household could begin to struggle to meet its repayment commitments. It also becomes more difficult for these households to obtain loans, because financial institutions scrutinize their credit requests more closely and, as a result, such households may become constrained. Our methodology takes this institutional feature into account and groups households according to this criterion as well. Thus, we created a total of 128 household groups for each year.

For every household group, we compute average debt for each category of borrowing (credit cards, secured and unsecured personal lines of credit, car loans, other loans, and mortgages), income, the DSR and house values.[8] In addition, for each household, we include the interest rate (proxied by the value of the overnight interest rate on the day the survey questionnaire was completed).

Using the household groups described above, we estimate equations that determine the amount of credit available, based on the following variables: income, house prices, net housing wealth, and the overnight interest rate. We also include in our equations a parameter that captures the difference in credit growth for households with a DSR above 40 per cent. Since, as noted above, the banking industry's credit-granting decisions are influenced by the household's current level of DSR, we expect, all else being equal, that credit growth rates will typically be weaker for households with a DSR above 40 per cent.

The results of the estimations indicate a negative and significant relationship between credit growth and changes in interest rates.[9] The relationship is positive and significant for income and housing equity. Although some preliminary results indicate that substitutions have occurred among consumer-credit instruments (between personal lines of credit and other type of loans) because of changes in housing prices, for this article, the shares of consumer-credit components are kept constant over the simulation horizons.[10] Future work will consider a less restrictive approach, however. The results also confirm our hypothesis that growth of credit for households with a DSR above 40 per cent will, on average, be lower than growth of credit for those with a DSR below 40 per cent.

For the scenarios in our simulations, we construct the distribution of credit growth across households using a macroeconomic outlook that includes assumptions about the average aggregate growth rates for income, house prices, and interest rates. We then evaluate how debt responds to changes in interest rates, income, house prices, and housing wealth by applying the estimated relationships to each household.

Because we assume that households are heterogeneous in regard to income, we use the simulated distributions of income (described in the next section) with a mean that is consistent with aggregate growth.

Changes in household income

To simulate the second element of the DSR, household income, households are categorized according to four income classes. Since households are heterogeneous, we allow for the fact that the average income growth (and the variance) may vary across income groups. Income growth also varies across households within each income group. The advantage of this approach is that it can accommodate alternative risk scenarios. Following a negative shock to the labour market, for example, it is possible that the average income growth of households belonging to the lowest-income groups (as shown in Table 2) will be affected more than that of households belonging to the other groups.[11] Alternatively, we could assume that average growth rates across all income groups are the same. In the stress scenarios presented in this article, we exploit some heterogeneity by assuming the same mean level of income growth for each of the four income groups but allow for variances to differ across these classes.[12]

8. Housing wealth is the difference between the current market value of the house and the amount of mortgage credit house outstanding. Since the end of the 1990s, innovations in the financial sector have provided households with more ready access to their housing wealth, through either mortgage refinancing or personal lines of credit. For this reason, we view housing wealth as a potential determinant of the demand for mortgages and personal lines of credit.

9. For our estimations, we use weighted least squares with a corrected covariance matrix.

10. For further details, see Djoudad (2008).

11. Table 2 indicates that vulnerable households are not evenly represented in different income groups.

12. Empirical evidence provided from our panel data suggest that the variance of income growth for the households in the lower-income group is higher than for those in the higher-income group.

Given these assumptions, we combine the distributions of credit and income growth to construct the distribution of debt over income across all households. The debt-to-income distribution is then combined with interest rate information (discussed next) to simulate the distribution of the DSR across households.

Effect of changing interest rates on debt payments

The third element that will affect our simulations is interest rates. We make the following assumptions regarding the effects of changing interest rates on debt payments. First, shocks to interest rates will affect only the amount of interest paid, not the principal. Thus, from the CFM data set, we must estimate how much of the payment is applied to the interest and how much to the principal. Payments will depend on the path taken by interest rates and on the growth of indebtedness.

Second, we consider that payments made on credit cards equal 2 per cent of the current outstanding balance, the minimum required by the credit card companies. The household must therefore repay an amount corresponding to 24 per cent of the annual balance each year, regardless of the interest rate. Since all other categories of consumer lending (personal loans, personal lines of credit, and car loans) are held at variable rates, the assumed profile for interest rates has an immediate effect on these debt payments. This assumption over (under) estimates debt payments for variable-rate mortgages as interest rates increase (decrease).[13]

We also make assumptions about mortgage renewals. Since the CFM survey data do not indicate the date on which mortgages mature, for fixed-rate mortgages, we need to make assumptions on how many households must renew their mortgage each year and will thus be affected by the new interest rates. The CFM data include eight different mortgage terms (1-year, 2-year, 3-year, etc.). We assume that households whose mortgages have terms of one year or less renew their loans every year. For terms exceeding one year, we assume that the proportion of households renewing will be equal to one divided by the term of the mortgage. Thus, for a 5-year mortgage, 20 per cent (1/5 = 20 per cent) of households will renew their mortgages each year. For 10-year terms, 10 per cent (1/10 = 10 per cent) of households will renew each year.

We further assume that the distribution of mortgages by type (fixed vs. variable) will remain stable at its most recent level. Although the proportion of households with a variable-rate mortgage should change gradually, as term and risk premiums vary over the cycle, we use a simplifying assumption for the simulation exercises in this article and maintain these shares constant. Finally, the distribution of mortgage-holders by term among fixed-term mortgages remains constant in our exercises.

Simulation Exercises

The final step in our analysis is to use this framework to simulate how changes in indebtedness and interest rates will affect debt-payment obligations. To illustrate, we present two different scenarios, with each representing a single shock rather than a complete risk analysis. The first evaluates how higher indebtedness levels could affect the distribution of the DSR, and the second assesses the impact of higher risk premiums on this distribution.

In the first scenario (the indebtedness scenario) we assume that the level of interest rates remains unchanged over the simulation horizon. We suppose that growth rates for total credit (8.7 per cent), and income (5 per cent) will be similar to those observed over the 2000–2007 period. We also assume that house prices rise at an annual rate of 5 per cent. To isolate the effect of a rising proportion of debt to income, we assume that monetary policy will not respond, but a more complete risk analysis should incorporate changes in the policy rate.

The second scenario (the risk-premium scenario) assesses the effect of an increase in risk premiums on the distribution of the DSR. We consider a crisis scenario in which the spread between mortgage rates and government bond yields rises immediately to historical highs of 322 basis points and persists at this higher level, which is about 200 basis points higher than the starting point of the simulations. Again, to show the marginal effect of risk-premium shocks, we assume that this shock is not offset by monetary policy actions.[14]

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13. We assume that the principal payments, as a share of debt, will remain constant while interest payments will vary with interest rate movements. In practice, for variable-rate mortgages, total payments are constant, while the share of principal and interest payments will change.

14. Other research published in the *Financial System Review* has considered scenarios where the overnight rate increases towards historical norms, and the term premiums rise from their current level to their historical yield. In such scenarios, we can allow risk premiums to adjust relative to the overnight rate as well.

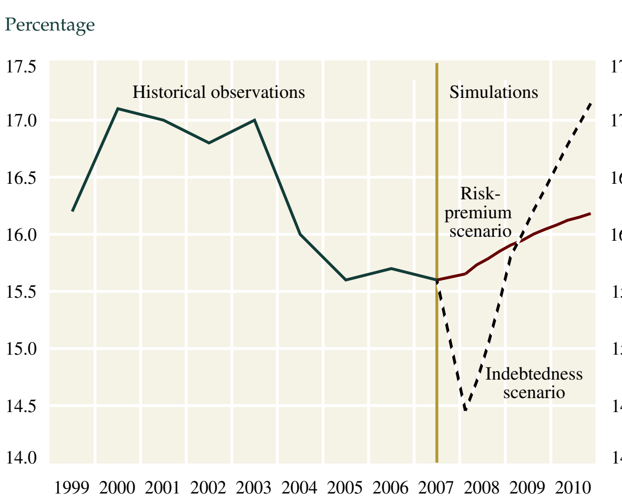
In our scenarios, we assume that increases in house prices will affect all house values similarly. Given that net housing wealth is the difference between house values and mortgages, the distribution of mortgage credit growth will affect the distribution of net housing wealth at every period.

Results

Table 3 and Chart 1 show the evolution of the average DSR and its distribution for different periods. In the first scenario, the increase in debt over income raises the DSR from 15.6 per cent at the starting point to 17.1 per cent 12 quarters later. The proportion of households with a DSR above 40 per cent rises from 3.1 to 6.1 per cent over the same horizon. The proportion of debt carried by these households varies from 6.5 per cent at the beginning of the simulations to 13.6 per cent 12 quarters later. [15]Assuming a constant ratio of debt to income, the assumed increase in the risk premium will, over 12 quarters, increase the average DSR from 15.6 per cent to 16.2 per cent 12 quarters later. The number of vulnerable households and the proportion of debt they carry rise to 4.2 and 9.6 per cent, respectively, from their initial points. Both exercises assume that monetary policy is passive.

Chart 1

Average Debt-Service Ratio



Source: Ipsos Reid, Bank of Canada calculations

15. At the beginning of the simulations, the interest rates are lower than in 2007. This will make the interest payments over the first periods of the simulations lower than they were in 2007, as households will also renew their previous fixed-term mortgages at lower rates, before the indebtedness increases significantly. This causes a relative drop in the DSR over the first quarters.

Table 3

Simulation Results (Per cent)

Quarter	Initial	Ratio of debt to income (trend) Q4	Q8	Q12	Risk-premium shock Q4	Q8	Q12
Average	15.6	15.4	16.4	17.1	15.8	16.0	16.2
Proportion of households with DSR > 40%	3.1	3.6	4.9	6.1	4.1	4.1	4.2
Proportion of debt held by households with DSR > 40%	6.5	7.5	10.9	13.6	9.2	9.5	9.6

Conclusion

In this article, we build on the framework used in the Bank of Canada's *Financial System Review* to assess the evolution of household indebtedness and financial vulnerabilities in response to changing economic conditions. To achieve this, we first compare the microdata sets generated by the Canadian Financial Monitor (CFM) and Statistics Canada's Survey of Financial Security (SFS). We find that the surveys are broadly comparable, despite methodological differences, which enables us to use their combined information content for the identification of the threshold value of the debt-service ratio (DSR). We then present a framework for simulating the DSR and illustrate how it can be used by analyzing the effects of two different scenarios on the distribution of the DSR and their impact on vulnerable households.

We are working to strengthen the framework with the goal of using it to incorporate a more consistent macroeconomic outlook in our analyses of current risks to the Canadian household sector. In addition, we plan to improve this methodology by allowing the shares of consumer-credit components to vary in relation to house-price movements, since rising housing equity has likely contributed to the significant shift towards secured personal lines of credit. We also plan to relate the proportion of fixed- and variable-rate mortgages to household expectations of the future path of interest rates.

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Technical Appendix: The Relationship between the DSR and the Probability of Mortgage-Debt Delinquency

We use Statistics Canada's Survey of Financial Security (SFS) data set to estimate the probability of mortgage-debt delinquency for Canadian households using explanatory variables identified in the literature and the debt-service ratio (DSR). This information is used to identify the critical DSR threshold used in the article. Here we describe our estimation method.

Estimation methodology

The propensity of household *i* to be delinquent can be described by

$$d_i^* = X_{ib} + u_i ,$$

where d_i^* is the propensity to be delinquent; X_i is a set of regressors; *b* is a set of parameters; and u_i is an error term.

The delinquency variable represents mortgage payments in arrears for two months or more, i.e., $d_i = 1$, if, in 2004, the household was two months or more behind on its mortgage loan payments, i.e., if $d_i^* = X_{ib} + u_i > 0$, and $d_i = 0$, otherwise.[1]

Note that the delinquency variable is not total debt in arrears, since the SFS questionnaire does not report that variable. A maximum-likelihood probit estimation with X_i as the vector of regressors in the SFS gives us an estimate of the set of parameters (*b*).

We considered several specifications of the probit model. We kept a minimum set of demographic variables (age, gender, and current marital status); all other demographic and financial variables were included in the model based on their statistical significance.

1. The 2005 SFS survey reports information on mortgage-debt delinquency for 2004.

Estimation results

Following the literature, we chose the variables for our model based on their ability to explain households' ability to repay their debts. Our results indicate that high values of household net worth and the logarithm of the ratio of liquid assets to total assets are associated with a lower likelihood of mortgage delinquency. Since households can easily convert liquid assets into cash to meet their mortgage-debt obligations, the more liquid assets they have relative to their total assets, the less likely they are to be delinquent and, hence, the negative correlation. Various types of scaling of the liquid assets (and their logarithms) were attempted in the model specification, and the logarithm of the ratio of liquid assets to total assets was chosen based on its statistical significance. The logarithm indicates the presence of a high degree of non-linearity in the response of the ratio of liquid assets 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. Moreover, households with high net worth are likely to have favourable loan terms and will be less likely to fall behind in their mortgage-debt payments, also confirming our intuition.

The DSR, on the other hand, is positively correlated with the incidence of mortgage delinquency. 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. The demographic variables are not statistically significant.

Identifying a DSR Threshold

We use the model of mortgage-debt delinquency estimated with the SFS data set, the standard normal cumulative distribution function, and a common set of regressors to obtain a distribution of the

Technical Appendix: The Relationship between the DSR and the Probability of Mortgage-Debt Delinquency (cont'd)

probability of mortgage-debt delinquency for the years 1999 to 2006 of the CFM sample. We first bracket households in DSR groups that increase by increments of 5 per cent, then calculate the average probability of delinquency for households in each grouping. Finally, we identify a DSR threshold as the value of DSR beyond which there is a significant increase in the probability of delinquency.

To illustrate, we plot the probability of mortgage-debt delinquency in 2002 for each of the DSR groups (Chart A1). A critical DSR threshold for 2002 seems to be 35 per cent, since we find a large increase in the probability of mortgage-debt delinquency above this level.

Chart A1

The Debt-Service Ratio and the Probability of Mortgage-Debt Delinquency, 2002