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The Framework for Risk Identification and Assessment

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Abstract

Risk assessment models are an important component of the Bank's analytical tool kit for assessing the resilience of the financial system. We describe the Framework for Risk Identification and Assessment (FRIDA), a suite of models developed at the Bank of Canada to quantify the impact of financial stability risks to the broader economy and a range of financial system participants (households, businesses and banks). These risks are tail-risk events that are rare and severe but plausible. FRIDA combines models that quantify the impact of risks on both aggregate macrofinancial variables and different types of financial system participants, thus allowing us to understand the channels through which severe shocks could be transmitted and amplified within the financial system. By including sectoral models, FRIDA can consider the rich institutional features and heterogeneity that characterize different parts of the financial system and capture the various channels through which they can be affected by shocks. Like any model, FRIDA faces model uncertainty. Consequently, results from FRIDA are used in combination with expert judgment to form an overall assessment of financial stability risks.

Bank topics: Economic models; Financial stability; Housing; Financial institutions
JEL codes: C, C3, C5, C6, C7, E00, E27, E37, E47, D1, G0, G21

Résumé

Les modèles d'évaluation des risques occupent une place importante parmi les outils d'analyse dont la Banque du Canada se sert pour jauger la résilience du système financier. Dans cette étude, nous décrivons le Cadre d'identification et d'évaluation des risques, une série de modèles conçus à la Banque pour quantifier l'incidence des risques liés à la stabilité financière sur l'économie dans son ensemble et sur divers participants au système financier en particulier (ménages, entreprises et banques). Les risques considérés sont des risques extrêmes correspondant à des événements graves et rares, mais plausibles. Le Cadre regroupe des modèles qui quantifient l'incidence des risques à la fois sur les agrégats macrofinanciers et sur différents types de participants au système financier. Il nous permet donc de comprendre les canaux par lesquels des chocs majeurs pourraient s'amplifier et se propager au sein du système. En intégrant des modèles sectoriels, le Cadre peut tenir compte des particularités institutionnelles appréciables et de l'hétérogénéité qui caractérisent les différentes composantes du système financier ainsi que cerner les divers canaux par lesquels celles-ci peuvent être touchées par des chocs. Comme tous les modèles, ceux du Cadre comportent des incertitudes qui leur sont inhérentes. C'est pourquoi on combine les résultats obtenus au jugement de spécialistes pour évaluer globalement les risques liés à la stabilité financière.

Sujets : Modèles économiques; Stabilité financière; Logement; Institutions financières
Codes JEL : C, C3, C5, C6, C7, E00, E27, E37, E47, D1, G0, G21

1. Introduction—overview of the Framework for Risk Identification and Assessment

Risk assessment models are an important component of the Bank's analytical tool kit for assessing the resilience of the financial system.[1] A resilient financial system is one that can withstand and recover from severe but plausible adverse shocks. More specifically, these models allow us to understand the channels through which such shocks could be transmitted and amplified within the financial system. They also allow us to quantify the impact of various potential financial stability risks for a range of financial system participants and the broader economy. Financial stability risks are tail-risk events. In other words, they are rare but, should they occur, could impair the functioning of the financial system to the point where the economy could be severely affected.

The Framework for Risk Identification and Assessment (FRIDA) includes a model to quantify the impact of risks in terms of aggregate macrofinancial variables and sectoral models to quantify the impact on financial system participants. We do not attempt to measure the probability of these events, only their impacts should they occur. Using these separate models, rather than a single general equilibrium model, allows us to account for the rich institutional features of, and heterogeneity within, each sector and to capture the various channels through which each sector can be affected by shocks.[2] In contrast, a general equilibrium model would require a simplified representation of the financial system, hence limiting our ability to understand the channels through which shocks would be transmitted and amplified within the system.[3]

At this stage, FRIDA covers households, businesses and domestic systematically important banks (D-SIBs). We aim to expand our coverage of other financial institutions over time. While our coverage of system participants is not complete, given the importance of D-SIBs in the Canadian financial system, FRIDA provides us with a system-wide perspective. Figure 1 provides a schematic overview of FRIDA.

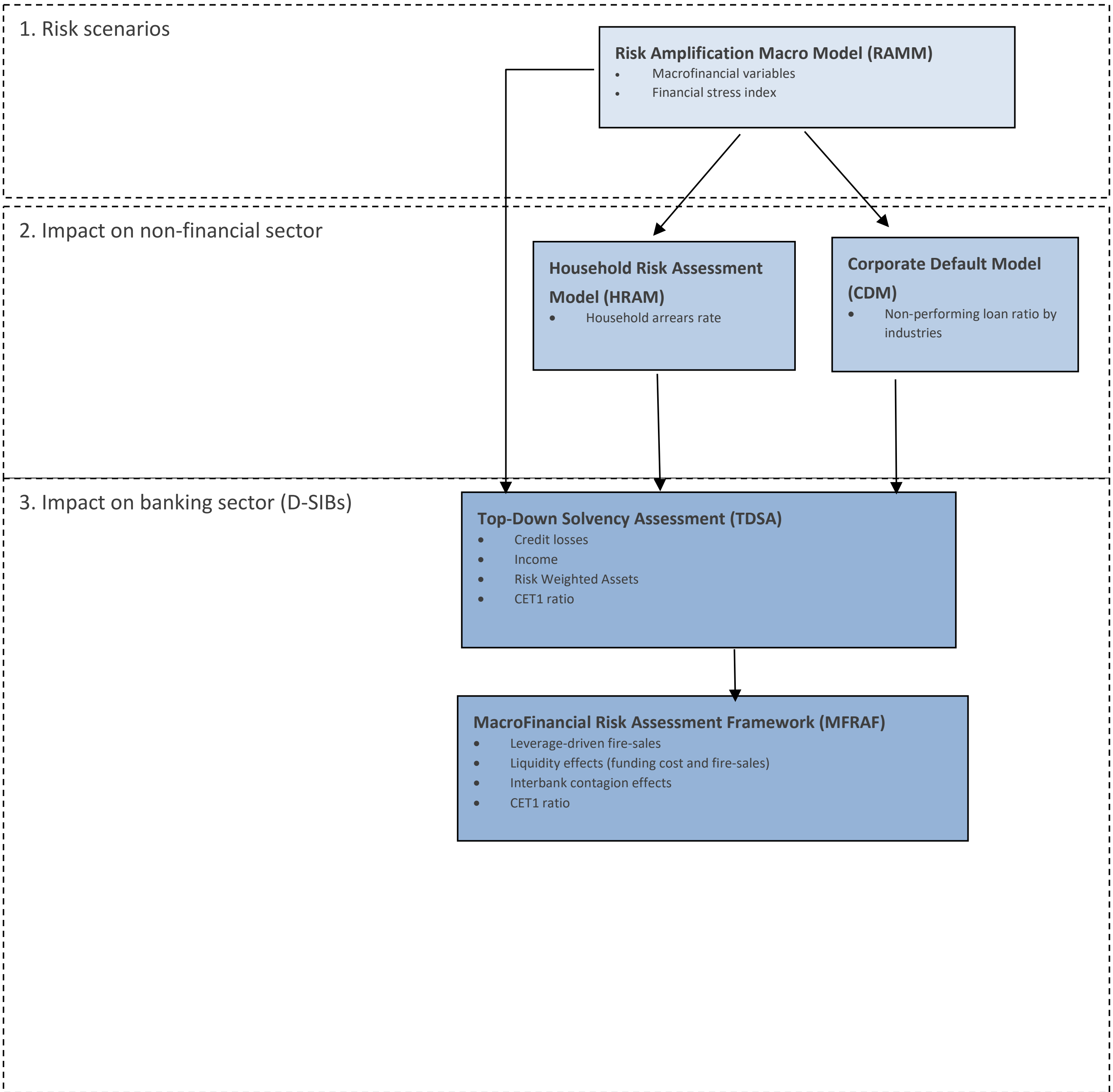
Using FRIDA provides greater rigour to the analysis of risks within a coherent, systematic and tractable framework. Like any model, however, FRIDA models face uncertainty associated with their parametrization and specification. Uncertainty about parameters relates to the strength of economic relationships, while uncertainty about model specification is more fundamental and relates to the structure of the economy (Kozicki and Vardy 2017). Consequently, results from models are used in combination with expert judgment to form overall assessments. While this is true for any model-based analysis conducted at

[1] For more information, see Christensen et al. (2015).
[2] For instance, banks are heterogenous in terms of asset and liability composition, face multiple sources of risk (e.g., credit, liquidity, market), and face several regulatory constraints.
[3] Other central banks also use suites of models to assess the robustness of the financial system. See ECB (2017) and Syversten et al. (2015).

the Bank, this is particularly important when assessing the impact of tail-risk events because they are, by definition, much less frequent and thus more difficult to capture and quantify in models estimated with historical data. The use of judgment is particularly important since Canada has not experienced significant financial risk events in recent decades.[4] This judgment can be informed by the experience of other countries that have experienced significant stress events. Finally, judgment can be required to capture structural changes in the economy (e.g., due to changes in the regulatory environment) that can influence how the materialization of risk scenarios would affect the financial system.

[4] While Canada was affected by the global financial crisis, the impact on the Canadian financial system was generally more limited than it was in other countries. For instance, Canadian banks fared relatively well during the crisis for several reasons (Arjani and Paulin 2013) and did not require government bailouts.

Figure 1. FRIDA overview



This technical report is structured as follows. Section 2 describes the Risk Amplification Macro Model (RAMM) used to generate tail-risk scenarios. Section 3 describes the two models used to quantify the impact of risk scenarios on the non-financial sector (i.e., households and businesses). Section 4 describes the two models used to quantify the impact of risk scenarios on the banking sector.

2. Generation of tail-risk scenarios with the Risk Amplification Macro Model[5]

Using a model to generate risk scenarios provides a rigorous framework that captures the interactions between macrofinancial variables in an internally consistent manner. Recessions that are accompanied by financial crises or elevated financial stress tend to be more pronounced and last longer (Reinhart and Rogoff 2009 and 2014). Elasticities and correlations between macrofinancial variables are different depending on the level of financial stress: shocks that occur during high financial stress periods have a larger impact on macrofinancial variables than those that occur during low stress periods. Therefore, to analyze financial stability risk scenarios, we need a model that captures the amplification effects resulting from financial stress that may not be visible in average historical relationships. It is important to note that the risk scenarios we generate should not be seen as a forecast of the most likely way that a risk could materialize.

2.1. Model overview and key considerations

We use the Risk Amplification Macro Model (RAMM), a Bayesian threshold vector autoregressive model (B-TVAR) that introduces non-linearities in a VAR framework by allowing macroeconomic dynamics to differ based on the level of financial stress.[6] In RAMM, the economy can be in one of two regimes, low or high financial stress, and a regime switch occurs endogenously when the level of financial stress crosses an estimated threshold. A threshold VAR approach to model the non-linearities associated with financial stress has two main benefits:

1. It provides results consistent with the observation that macroeconomic aggregates (e.g., output, unemployment) tend to react more to adverse shocks in the presence of high financial stress or a financial crisis.

[5] RAMM was developed by Gabriel Bruneau and Kerem Tuzcuoglu. RAMM has benefited greatly from work by Thibaut Duprey on the Financial Stress Index (Duprey, Klaus and Peltonen 2017) and on the effects of financial vulnerabilities and financial stress on macroeconomic conditions (Duprey 2018; Duprey forthcoming).

[6] We rely on Bayesian techniques to estimate the model because large VAR models cannot be estimated using frequentist approaches. By imposing priors and incorporating shrinkage on these priors, Bayesian inference results in better predictive powers for large VAR models. For more on Bayesian techniques in BTVAR models, see Bruneau and Chapman (forthcoming).

2. The regime change in RAMM is explicitly related to the threshold variable of interest (financial stress), thus associating the differences in macroeconomic dynamics with the effects of financial stress. In contrast, regime changes are due to unidentified drivers with other VAR-based methodologies with non-linearities, such as the Markov-switching VAR. The differences in macroeconomic dynamics between regimes therefore cannot be related to the level of financial stress.

The measure of financial stress used in RAMM is based on the financial stress index (FSI) methodology developed by Duprey, Klaus and Peltonen (2017). The FSI captures stress from the equity, bond and foreign exchange markets as well as from the banking sector and housing market. Moreover, the FSI considers the correlations across these market segments or sectors; as a result, stress occurring simultaneously on several markets has effects larger than the sum of the stress on individual markets.

Since Canada is a small open economy, it is likely to be affected by risks that originate outside its borders. It is therefore important for our model to be able to capture both domestic and foreign risk scenarios in order to quantify a range of severe but plausible risks that could affect the Canadian financial system. To that end, RAMM is composed of two sets (or blocks) of equations—a US block and a Canadian block—where US shocks can affect Canadian variables but not the other way around. These two blocks are modelled as separate B-TVARs with the US and Canadian FSIs as their respective threshold variables so that the aforementioned amplification effects associated with financial stress are accounted for in both blocks. The Canadian block includes current and lagged US variables to account for the effects of US variables on the Canadian economy.

2.2. Model description

Formally, RAMM is specified as follows:

$$Y_t^{US} = \begin{cases} \sum_{i=1}^{p} A_{1i}^{US} Y_{t-i}^{US} + D_1^{US} X_t + \varepsilon_{1t}^{US} & if\ FSI_{t-d}^{US} \leq \gamma^{US}\ \ where\ \ \varepsilon_{1t}^{US} \sim N\left(0, \Sigma_1^{US}\right) \\ \sum_{i=1}^{p} A_{2i}^{US} Y_{t-i}^{US} + D_2^{US} X_t + \varepsilon_{2t}^{US} & if\ FSI_{t-d}^{US} > \gamma^{US}\ \ where\ \ \varepsilon_{2t}^{US} \sim N\left(0, \Sigma_2^{US}\right) \end{cases}$$

$$Y_t^{CA} = \begin{cases} \sum_{i=1}^{p} A_{1i}^{CA} Y_{t-i}^{CA} + \sum_{j=0}^{q} B_{1j}^{CA} Y_{t-j}^{US} + D_1^{CA} X_t + \varepsilon_{1t}^{CA} & if\ FSI_{t-d}^{CA} \leq \gamma^{CA}\ \ where\ \ \varepsilon_{1t}^{CA} \sim N\left(0, \Sigma_1^{CA}\right) \\ \sum_{i=1}^{p} A_{2i}^{CA} Y_{t-i}^{CA} + \sum_{j=0}^{q} B_{2j}^{CA} Y_{t-j}^{US} + D_2^{CA} X_t + \varepsilon_{2t}^{CA} & if\ FSI_{t-d}^{CA} > \gamma^{CA}\ \ where\ \ \varepsilon_{2t}^{CA} \sim N\left(0, \Sigma_2^{CA}\right) \end{cases}$$

Where *US* denotes US variables, *CA* denotes Canadian variables, green indicates the low-stress regime and red the high-stress regime

The table below defines the variables and parameters in the model.

Variables & parameters	Definition
Y	Vector of stochastic endogenous macrofinancial variables
X	Vector of stochastic exogenous macrofinancial variables
ε	Vector of error terms
FSI	Financial stress index
γ	Financial stress index threshold
d	Time delay when the regime switch is triggered
p	Number of lags for the endogenous variables (can be different for each country)
q	Number of lags for the Y^{US} variables in the Canadian model
A	Autoregressive parameters of the endogenous variables
B,D	Parameters capturing elasticities between the endogenous and exogenous variables
Σ	Covariance matrix for the error terms

The model is estimated using monthly data starting in 1981. Table 1 lists a number of key endogenous variables considered for the United States and Canada.

Table 1. Illustration of endogenous variables in RAMM

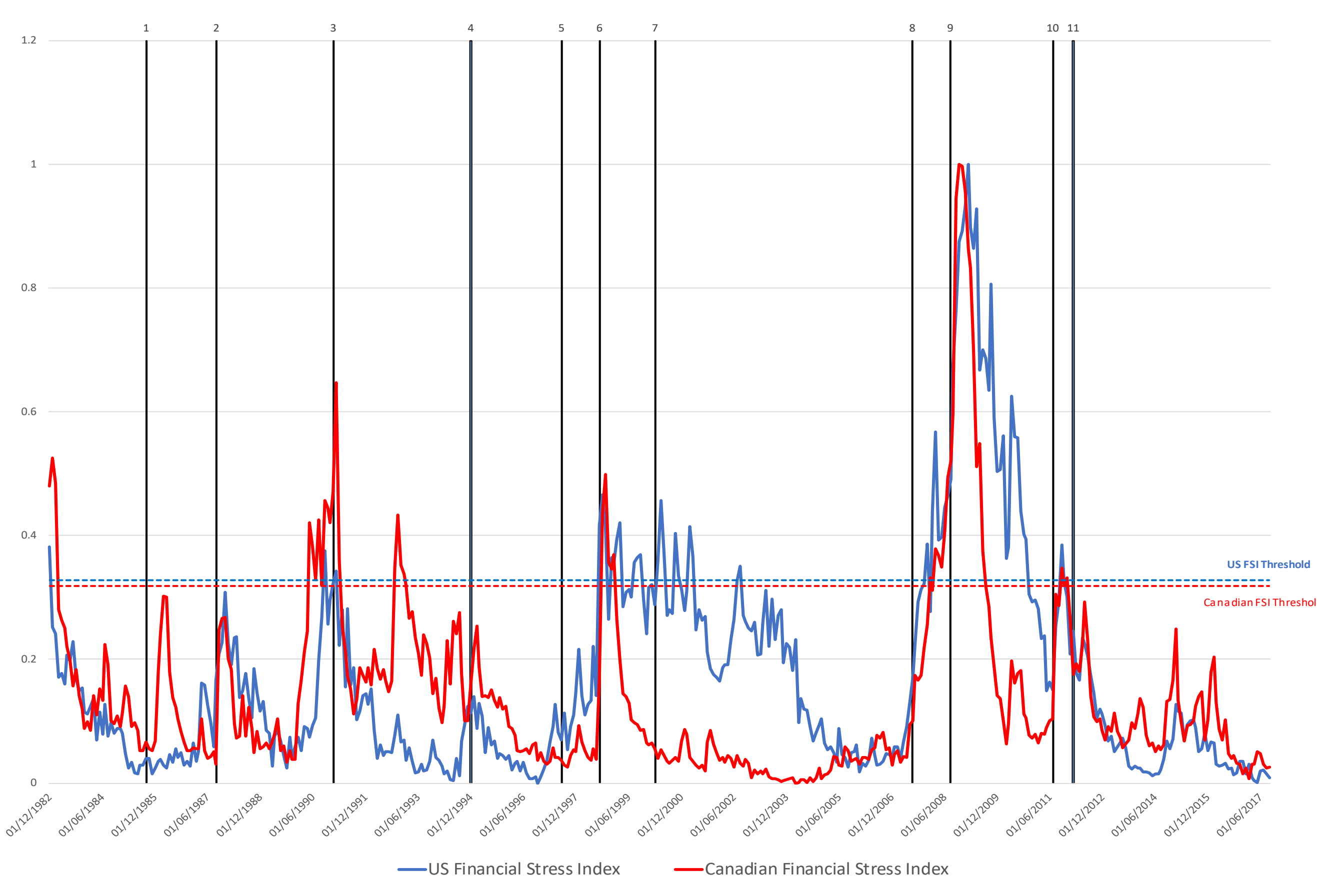
US endogenous variables (Y^{US})	Canadian endogenous variables (Y^{CA})
• Industrial production • Inflation • Risk-free rates • Corporate spread • US financial stress index	• Real gross domestic product • Inflation • Risk-free rates • Unemployment • Corporate spread • House prices • Canadian financial stress index

The model is estimated using Bayesian techniques, in particular Monte Carlo Markov Chain (MCMC) techniques with Minnesota (shrinkage) priors, which are commonly used in large VAR models. The estimated FSI threshold separates the coefficients in the two regimes in both the US and the Canadian block.[7] Figure 2 depicts the time series for the US and Canadian FSIs over the past 35 years. The high-stress regime occurs 13 per cent of the time in the United States compared with 11 per cent in Canada,

[7] The FSI is rescaled in both blocks to be bounded between 0 and 1.

which implies that over the 35-year sample period, the United States has been in the high-stress regime for two more years than Canada.

Figure 2. Canadian and US financial stress indices



Significant events:
1. Canadian small banks failure 2. Stock Market Crash 3. Canadian trusts failure, ERM Crisis 4. Mexican Peso Crisis 5. Asian Financial Crisis 6. Russian Debt Default; Lont-Term Capital Management Crisis 7. Dotcom Bubble Crash 8. Beginning of subprime crisis 9. Collapse of Lehman Brothers 10. European Sovereign Crisis (1st Greece Bailout) 11. European Sovereign Crisis (2nd Greece Bailout)

It is the interactions of initial conditions (both in terms of macrofinancial variables and FSIs) and the severity of the shocks that can lead the FSI to cross the threshold, causing a switch in regimes. Since the switch is endogenous to the evolution of variables in the model, the economy can go in and out of the high-stress regime over time (i.e., the economy is not forced to stay in the high-stress regime once it has crossed the threshold).

Figure 3 and Figure 4 illustrate that a similar increase in the Canadian FSI is associated with different dynamics of real gross domestic product (GDP) and unemployment, depending on the level of financial stress. Since shocks are not identified in the model, the increase in the Canadian FSI in these figures should not be interpreted as an FSI shock (i.e., the FSI increase could be due to a range of reasons, including in response to other shocks).

Figure 3. Impulse response function

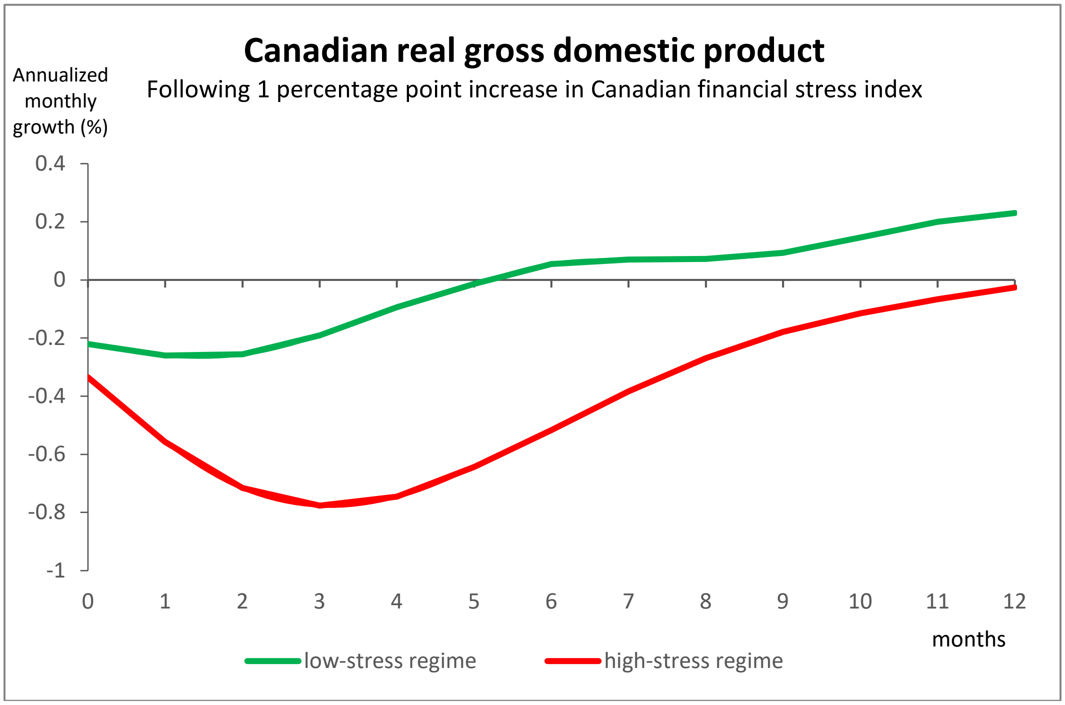
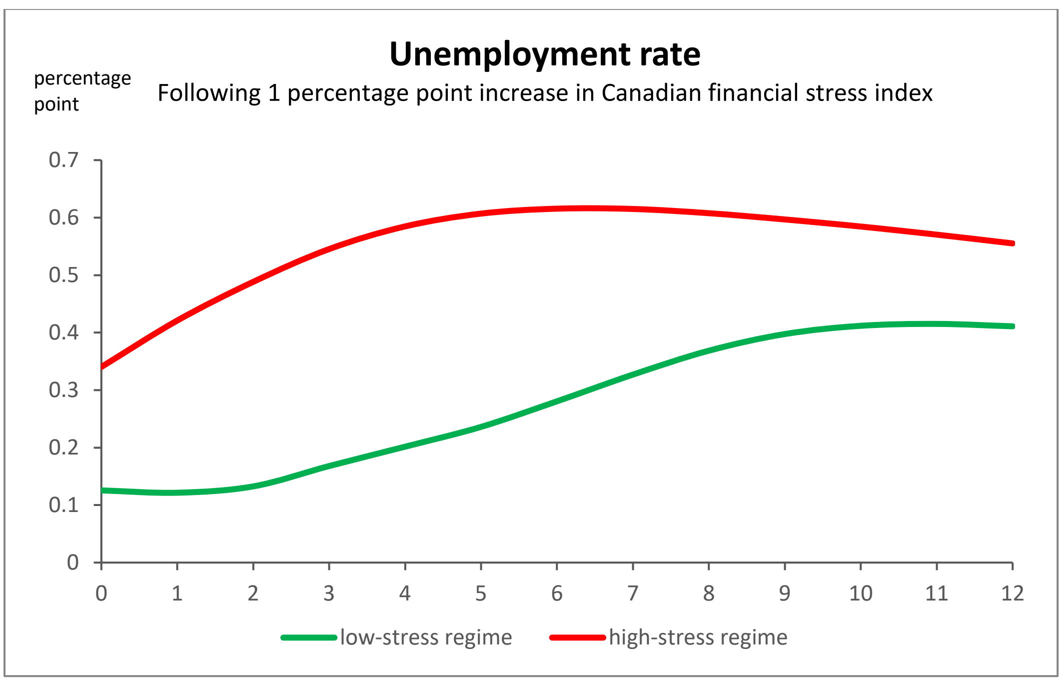


Figure 4. Impulse response function



The transmission of shocks from the United States to Canada in RAMM takes place through two mechanisms:

1. Shocks to US macrofinancial variables (GDP, exchange rate, interest rates, etc.) are transmitted to Canadian macrofinancial variables as a result of the economic links between the two countries and the integrated nature of their financial markets. This mechanism is captured in the model because US variables (Y^{US}) are included in the Canadian block.
2. The transmission of US shocks to Canada can be amplified because of financial stress. This mechanism is more pronounced when the US block is in the high-stress regime, which is reflected in higher coefficients (B_{2j}^{CA}) under high stress (B_{2j}^{CA}) than in low stres (B_{1j}^{CA}) on US variables (Y^{US}) in the Canadian block. High financial stress in the US block does not automatically imply that the Canadian block is also in the high-stress regime. It is, however, more likely that the Canadian block is also in the high-stress regime given the transmission of shocks from the United States to Canada.

Table 2 shows the four possible configurations for the financial stress regimes in the United States and Canada.

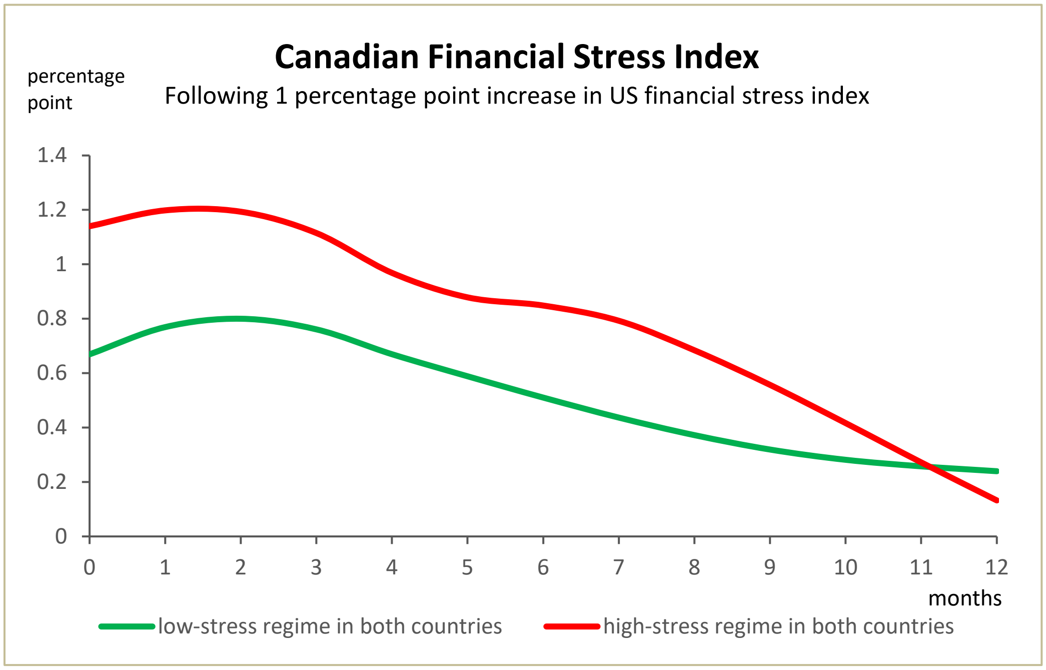
Table 2. Possible financial stress regime configurations in RAMM

Low US FSI / Low Canadian FSI (82%)	Low US FSI / High Canadian FSI (5%)
High US FSI / Low Canadian FSI (7%)	High US FSI / High Canadian FSI (6%)

Note: The numbers in parantheses refer to the frequency of each of these combinations over our sample period (1981–2017).

When both the United States and Canada are in low-stress regimes, the amplification effects of financial stress on macrofinancial variables within the US and Canadian blocks and from the US block to the Canadian block are very limited. In contrast, when the two countries are in high-stress regimes, there are significant amplification effects associated with financial stress both within each block and from the US block to the Canadian block. First, the amplification effects of financial stress translate into a more negative impact on macrofinancial variables within each country. Second, since the deterioration in macrofinancial variables in the United States is more severe under high financial stress, the impact on Canadian macrofinancial variables is also stronger. Figure 5 illustrates that the increase in the Canadian FSI following an increase in the US FSI is more pronounced when both the United States and Canada are in the high-stress regime than when they are both in the low-stress regime.

Figure 5. Impulse response function



2.3. Model limitations and use of judgment

Like any model, RAMM has limitations, some of which are intrinsic to the approach used and cannot be adjusted for, while others can be addressed using judgment.

The first limitation is related to the fact that Canada has a limited history of financial stress events, at least over the 35 years for which data are available and the model is estimated. This limitation has two implications:

1. There is more uncertainty around parameter estimates in the high-stress regime because there are fewer observations to estimate the model.
2. The model likely underestimates the impact of risk scenarios that are further in the tail. This limitation is common for any estimated model and can be addressed by applying judgment on some components. For instance, the level or persistence of financial stress can be increased above what is suggested by the historical data, or the reaction of key macroeconomic indicators to FSI shocks can be set higher than the model estimates suggest. Satellite models or auxiliary data, including data from other countries that have experienced more pronounced financial stress events, can be used to inform this judgment.

Since RAMM is a large model (i.e., it includes hundreds of parameters to be estimated with limited data), algorithms typically used to estimate parameters are not very stable (i.e., estimates are not reliable and convergence issues are likely). To obtain a stable estimation, we put strong Bayesian priors (shrinkage in particular), which is a form of judgment.

It is challenging to identify shocks in large empirical models like RAMM. It is necessary to have a relatively large set of variables embedded in RAMM for two reasons. First, we want to be able to consider various risk scenarios. Second, the models that follow RAMM in FRIDA require the profile of specific variables from the risk scenario in order to be simulated. Future work will be conducted to consider shock identification in a smaller specification of RAMM, which would be supplemented with satellite equations to be able to generate the profile of all the variables necessary to simulate the models that follow RAMM in FRIDA.

3. Models to assess the impact of risk scenarios on the Canadian non-financial sector

In this section we present the two models used to quantify the impact of risk scenarios on the Canadian non-financial sector: the Household Risk Assessment Model, for the household sector, and the Corporate Default Model (CDM), for the non-financial corporate sector. It is important to quantify the impact of risk scenarios on households and businesses to understand how these two sectors would be affected if financial stability risks were to materialize. Moreover, households and businesses act as a channel through which risk scenarios transmit to banks (through credit risk): if households and businesses were unable to face their bank loan obligations when risks materialize (i.e., if they default on their loans), banks would face credit losses on these exposures, which could in turn affect their own resilience. In the context of FRIDA, it is therefore necessary for our household and corporate sector models to quantify the impact of risk scenarios in terms of default rates for households and businesses because these will feed into our banking sector models to quantify credit losses.

3.1. Household Risk Assessment Model[8]

The Household Risk Assessment Model (HRAM) simulates the impact of risk scenarios on variables at the household level (e.g., income, debt) in a manner consistent with the aggregate evolution of these variables specified in the risk scenario. In the context of FRIDA, exogenous risk scenarios are generated using RAMM and household arrears rates consistent with the scenario are provided by HRAM.[9]

[8] HRAM has been developed by Tom Roberts and Brian Peterson.
[9] HRAM also generates other household vulnerability measures, such as the proportion of households with a high debt-to-income ratio or the proportion of households with a high debt-service ratio. HRAM is regularly used to assess vulnerabilities in the Canadian household sector. See for instance, Cateau, Roberts and Zhou (2015) and Schembri (2016).

Household microdata is important for assessing the impact of risk scenarios on household loans in arrears because debt, income and assets are not uniformly distributed across households (Cateau, Roberts and Zhou 2015). As a result, the ability of households to repay their debt when faced with negative shocks depends on characteristics such as their levels of debt and their asset holdings. For instance, households that face higher debt burdens, have fewer financial assets or lower home equity are more likely to default on their debt obligations when they are affected by negative income shocks. Failure to account for these distributional effects would therefore result in a biased assessment of the impact of risk scenarios on household default rates and subsequently on bank credit losses.

This section provides a high-level description of HRAM. For a detailed technical description of the model, see Peterson and Roberts (2016).

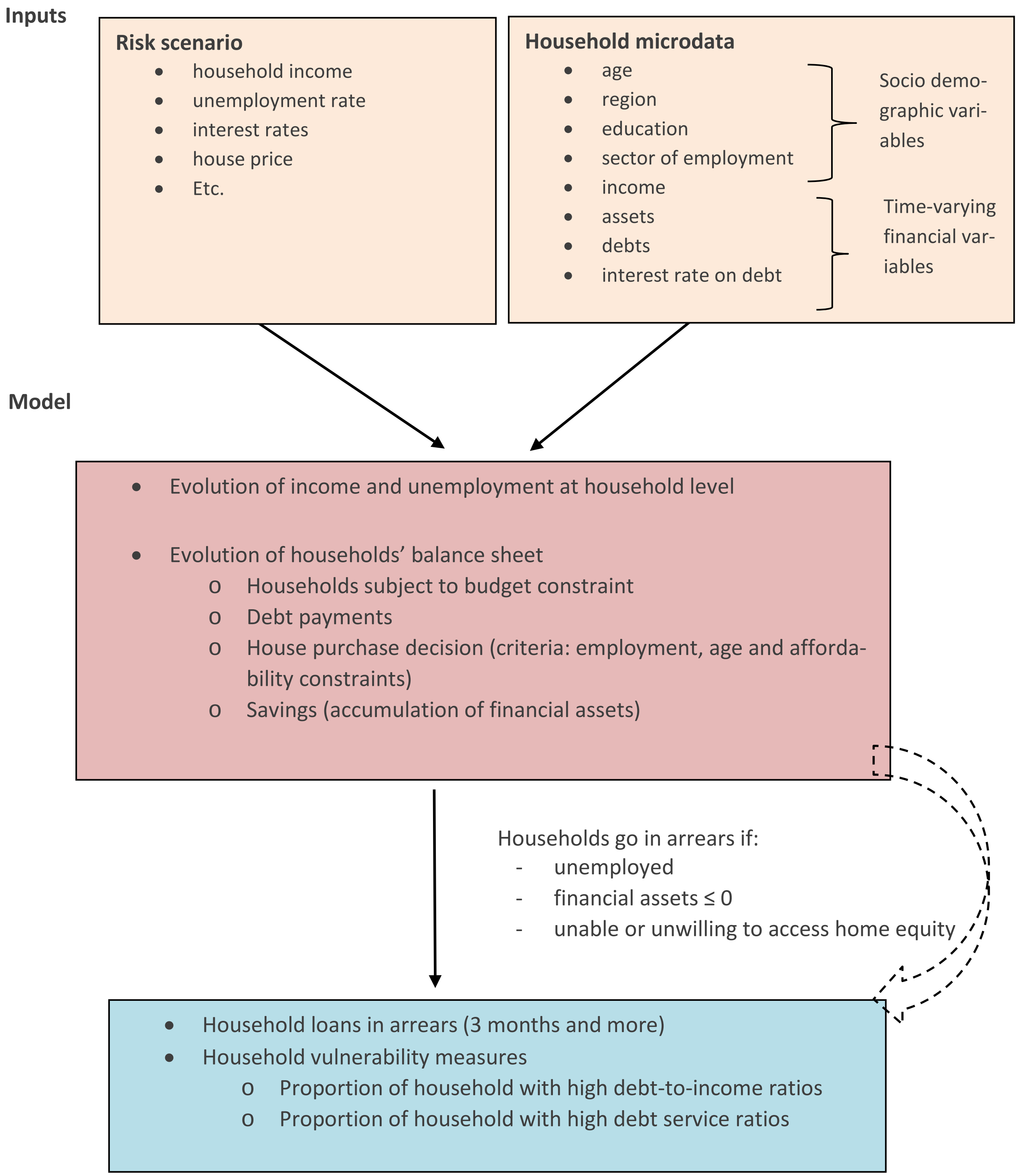
3.1.1 Model overview

HRAM has three main characteristics:

1. HRAM incorporates a significant amount of household heterogeneity, both in terms of socio-demographic characteristics (e.g., age, education) and time-varying financial characteristics (e.g., income, assets, debt). Accounting for these sources of heterogeneity is important for capturing varying degrees of vulnerability to negative shocks.
2. HRAM accounts for a variety of financial frictions faced by households, notably regarding mortgages. For instance, HRAM accounts for two basic constraints faced by first-time homebuyers: a wealth constraint (i.e., minimum down payment required when purchasing a house) and a debt-service constraint (i.e., maximum mortgage payment relative to income).
3. HRAM captures dynamics that are non-linear at the household level. A key example is the idiosyncratic unemployment shock process, which is randomly assigned across households (the household-specific risk of job loss depends on several factors, including age, region and sector of employment). Unemployment in turn is a key risk driver of the inherently non-linear default outcome because unemployed households cover their minimum level of consumption with supplementary income (e.g., employment insurance), if any, and the depletion of their financial savings. The allocation of first-time homebuyers is another example of non-linear dynamics: households that become first-time homebuyers experience an abrupt increase in indebtedness as they take a mortgage.

Figure 6 provides an illustrative representation of HRAM. The model takes as input the profile of stressed macrofinancial variables from RAMM and uses household microdata as initial conditions to project the evolution of income, employment and balance sheets at the household level. Ultimately, households go in arrears on their loan obligations if they lose their job and do not have sufficient assets to face their loan obligations.

Figure 6. Household Risk Assessment Model overview



3.1.2. Evolution of income and employment in the Household Risk Assessment Model

In HRAM, household disposable income is a function of the household's permanent income and whether the household is employed or unemployed. Households receive unemployment compensation when unemployed and pay taxes on labour income. A household faces three sources of uncertainty regarding its income: (i) whether it is employed or unemployed, (ii) the duration of unemployment when unemployed, and (iii) uncertainty in its permanent labour income.

The aggregate risk scenario dictates the overall unemployment rate, the expected duration of unemployment and the nominal growth rate of labour income. Individual households are affected differently by unemployment duration shocks and idiosyncratic shocks to their permanent labour income, but in aggregate these shocks are consistent with the macro scenario. These individual shocks are allocated on the basis of households' characteristics. For instance, the relative layoff risk is associated with households' socioeconomic characteristics, such as level of education and sector of employment.

3.1.3. Evolution of household balance sheet in the Household Risk Assessment Model

Conditional on the profiles of unemployment, permanent income and financial assets given by the risk scenario, households face a budget constraint. Under this constraint, consumption and the evolution of financial assets (i.e., savings) must be equal to after-tax income plus the evolution of debt and financial asset returns net of debt payments. Households make debt payments if they have sufficient resources to cover them, while maintaining a minimum level of consumption if unemployed. HRAM does not explicitly model household behaviour. Instead, HRAM uses rules that provide a reduced-form representation of economic decision making to determine debt and assets. Consumption is determined residually, subject to a minimum level.

Debt payments depend on the evolution of interest rates and household debt in the risk scenario. Interest rates on consumer debt include a household-specific risk premium that is determined from the household microdata. Mortgage rates and the timing of mortgage renewal, and thus the resetting of fixed mortgage rates, vary with the original term of the mortgage.

HRAM considers first-time homebuyers (FTHB) and existing homeowners separately.

- In HRAM, households that do not own a house are eligible to be FTHBs if they satisfy the following criteria: (i) they are employed and are less than 50 years old, (ii) they satisfy two mortgage-related constraints: a wealth constraint (i.e., minimum down payment) and a debt-service constraint (i.e., a maximum monthly mortgage payment relative to income) that are consistent with underwriting guidelines set by Canadian regulatory authorities. FTHBs are randomly drawn from the set of households eligible to become FTHBs in a manner consistent with mortgage debt growth of FTHBs in the risk scenario. Households that become FTHBs are assumed to buy the median-priced entry-level house for their region and to choose a five-year fixed-rate mortgage at the rate prevailing in the scenario at this period.

- For existing homeowners, the evolution of mortgage debt at the individual level is influenced by changes in income, interest rates and house prices in the risk scenario such that in aggregate it is consistent with the evolution of mortgage debt for existing homeowners in the risk scenario.

The decision rules for consumer debt are simple: (i) unemployed households are not allocated additional consumer debt (except for a drawdown on existing lines of credit), (ii) households that did not have consumer debt do not acquire any, and (iii) households that already had consumer debt and are employed can take on more consumer debt.[10] Overall, decisions at the individual household level are set to be consistent with the profile of consumer debt growth in the aggregate scenario.

Households are assumed to save in the form of financial assets, subject to a minimum level of consumption and debt payments. If households do not have sufficient resources to satisfy their debt payments and minimum consumption, they draw down on their financial assets (resulting in negative savings) until they have zero financial assets.

Households also face fluctuations in their housing assets consistent with the evolution of house prices in the risk scenario.

If households do not have sufficient resources to satisfy their debt obligations and minimum consumption and have depleted their financial assets but have equity in their home, they can tap into their home equity to face their obligations by either using a pre-existing home equity line of credit (HELOC) or selling their house. If they sell their house, they face transaction costs (realtor, legal and administrative fees), which we assume to stand at 5 per cent of the value of the house.

If households have (i) depleted their financial assets and (ii) have negative home equity after accounting for selling costs, have positive equity but choose not to sell,[11] or do not own a house, they go into arrears.

3.1.4. Model limitations and use of judgment

As explained before, HRAM does not explicitly model household behaviour. It relies instead on laws of motion that provide a reduced-form representation of economic decision making regarding debt and

[10] We assume that households that did not have consumer debt do not take on consumer debt because insight into household decisions remains limited.

[11] A user-modifiable parameter determines the proportion of homeowners who will sell when facing arrears, conditional on having positive home equity. The decision to sell is assigned randomly across these households.

assets. These laws of motion are informed by econometric estimation (e.g., debt growth for existing debt-holders), standard economic concepts and accounting identities such as household budget constraint (debt payments and financial savings from one period to the next), and the economic literature (e.g., analysis of layoff risk by Chan, Morisette and Frenette 2011). In some cases, our knowledge of decision-making behaviour at the household level still remains limited (e.g., quantifying more specifically how household characteristics drive debt accumulation, what drives a household's decision to default on its consumer loans, how and when a household decides to sell its house if it faces financial stress).

HRAM provides the flexibility to incorporate a high degree of detail at the household micro level that other modelling approaches (e.g., structural model with heterogenous households) cannot accommodate. However, this flexibility highlights the importance of understanding which mechanisms ultimately influence overall outcomes the most, so we can decide what to prioritize.

Peterson and Roberts (2016) provide detailed information on the model calibration and estimation. Judgment is used in calibrating some aspects the model and in the setting of several model parameters. For instance, assumptions about the path of arrears in a baseline scenario of normal economic conditions are needed. These assumptions are then used as a comparison benchmark for a risk scenario. Setting model parameters requires knowledge of the Canadian household sector and housing markets (e.g., minimum level of consumption for unemployed households relative to their consumption under full employment). Sensitivity analyses can be conducted to understand the sensitivity of the results to key model parameters because the latter can be modified by model users (Peterson and Roberts 2016).

3.2. The Corporate Default Model (CDM)[12]

3.2.1. Model overview and key considerations

The impact of risk scenarios on the business sector is assessed using the Corporate Default Model (CDM). The CDM quantifies the impact of risk scenarios on the credit performance of loans extended to businesses by D-SIBs, as measured by the non-performing loan ratio (NPLR).

The CDM is a panel error correction model where both components of the NPLR—the level of non-performing loans (NPL) and the level of total loans (TL)—are modelled separately for a set of non-financial

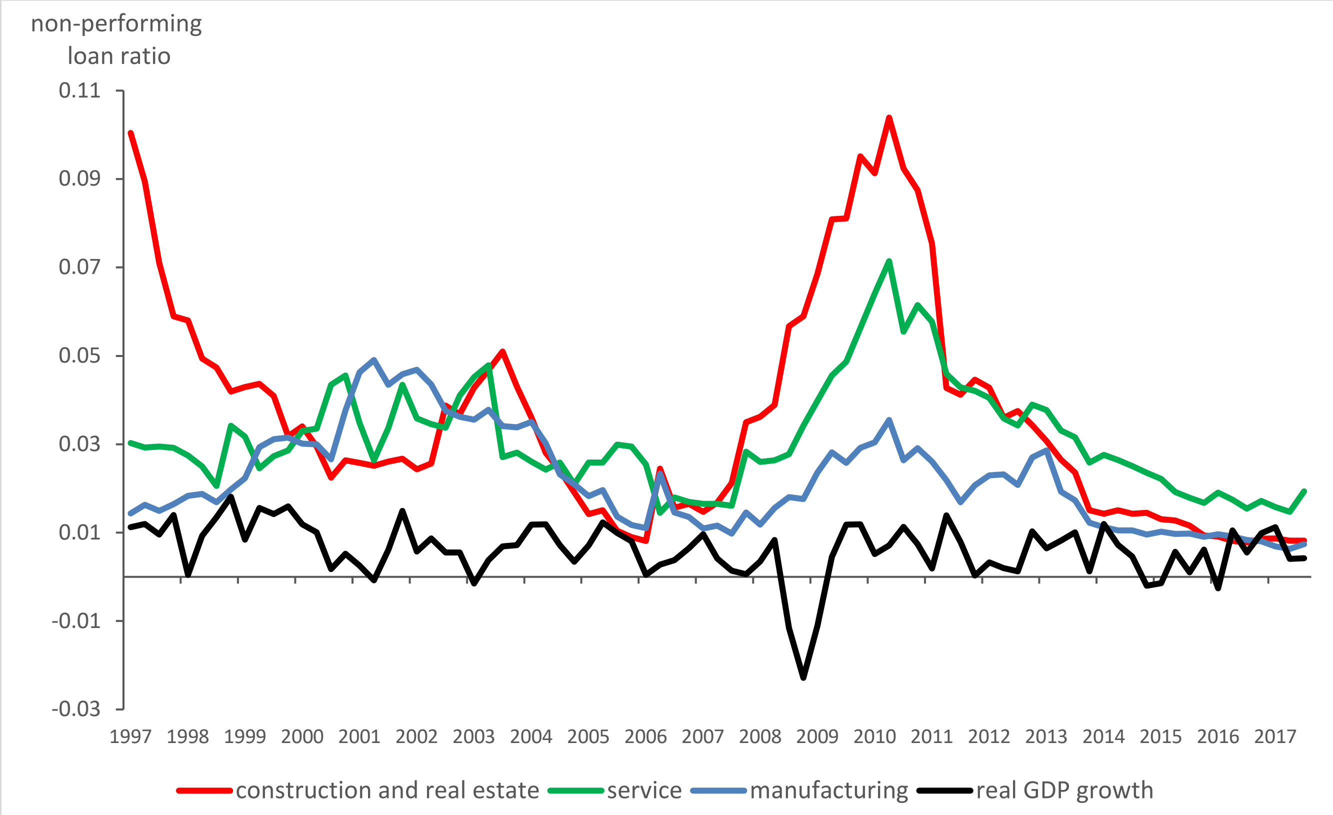
[12] The CDM was initially developed by Gabriel Bruneau and Ramdane Djoudad and has benefited from enhancements by Jasmine Hao and Thibaut Duprey and from suggestions by Sofia Priazhkina.

industries and are explained by macrofinancial variables.[13] The rationale for considering a methodology that combines panel and error correction techniques is the following:

1. There are significant differences in the dynamics and levels of NPLR across industries over time (Figure 7), suggesting that the drivers of default vary by activity sector. For instance, the evolution of real estate prices is likely to influence the performance of loans to the construction and real estate sector, while commodity prices are likely to affect the performance of loans to the energy sector. Using a panel approach where we estimate NPL and TL by industries allows us to capture these cross-sectional differences and to have better estimates of the relationships between macrofinancial variables and NPLRs for the various sectors that banks lend to.
2. An error correction model (ECM) captures both short- and long-term relationships between NPL and macro-financial drivers and between TL and macrofinancial drivers, respectively, thus accounting for the persistent impact of severe recessions. In contrast, a model in growth rate would capture transition effects only (i.e., the NLPR would deteriorate during a recession but improve as soon as the economic growth rate is positive). Capturing long-lasting effects is important because financial stability risks are typically tail-risk scenarios with a more pronounced and more persistent impact on the level of GDP. The persistence in NPLRs in the recovery phase was observed following the 2008–09 recession for instance (Figure 7). Failing to account for the persistence in NPLRs would lead to a downward bias in our quantification of credit losses for banks in the next step of FRIDA.

[13] The industries considered in the CDM are based on the Standard Industrial Classification (SIC). Banks report their loan exposures and performance of loans to these industries in the A2 regulatory return form.

Figure 7. **NPLRs vary across industries and can exhibit persistence following recessions**



Modelling the two components of the NPLR separately is necessary to consider their long- and short-term relationships with macrofinancial drivers. Moreover, using the NPLR as the dependent variable would impose that NPLs and TLs have the same macro drivers and that they are affected by these drivers with the same timing, which are strong assumptions. For instance, NPLs start increasing relatively rapidly when the economic situation deteriorates. In contrast, TLs adjust more slowly since they reflect banks' decisions to adjust credit provision to the economy, and these take time to affect the stock of loans.

3.2.2. Model description

The estimation follows a two-step process, where we estimate the long-term relationship first and then the short-term relationship.

The long-term relationship (error-correction specification) is specified as follows:

$$y_{sit} = \beta_{1si} d_{si} + \beta_{2si} x_{sit} + \varepsilon_{sit}^{lt}$$

Where

- y_{sit}: variable of interest (s represents total loans or non-performing loans) for industry i at time t
- d_{si}: deterministic regressors (e.g., dummy variable and constant)

- x_{sit}: macrofinancial variables from the risk scenario

The short-term adjustment process (error-correction mechanism) is described as follows:

$$\Delta y_{sit} = u_{si} + \alpha_{si} ec_{sit} + \sum_{j=1}^{p} \gamma_{sij} \Delta y_{sit-j} + \sum_{k=0}^{q} \theta_{sik} \Delta x_{sit-k} + \varepsilon_{sit}^{st} ,$$

Where the error correction is computed by

$$ec_{sit} = y_{sit-1} - \beta_{1si} d_{si} - \beta_{2si} x_{sit-1}$$

NPL and TL data come from bank regulatory returns.

The macrofinancial drivers for TL include GDP, short- and long-term interest rates, non-residential investment, house prices, commodity prices and the exchange rate, while those for NPL include total loans, GDP, unemployment rate, exchange rate and stock prices.

The CDM is estimated over 1994Q2–2017Q4 using linear methods that capture the cross-sectional dependence.[14]

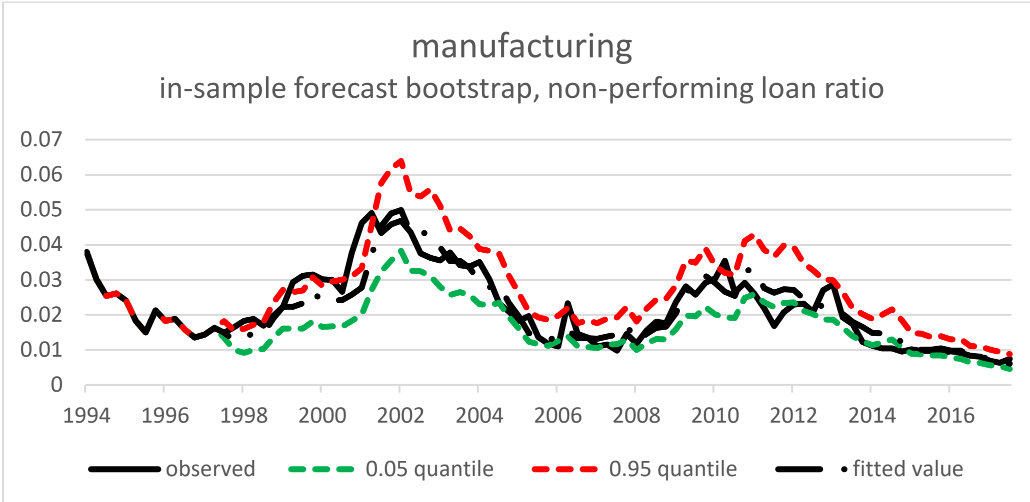
To assess the impact of risk scenarios on the NPLR, we simulate the CDM with macrofinancial variables from the scenario following a two-step process where the simulation is conducted for TL first and then for NPL because TL is a regressor for NPL. This generates only a point estimate for the NPL and the TL for each industry since the estimated model does not account for the uncertainty surrounding the simulated macrofinancial drivers or for the uncertainty of potential idiosyncratic sectoral drivers that are not considered in the CDM. Because our interest resides in tail-risk scenarios, uncertainty is particularly relevant; we therefore want to be able to consider the variation surrounding the point estimates. To achieve this objective, we resample residuals using bootstrapping techniques that maintain both the autocorrelation and the cross-sectional dependence observed in the data. Simulated NPLRs are obtained by dividing simulated NPL by simulated TL for the entire distributions.

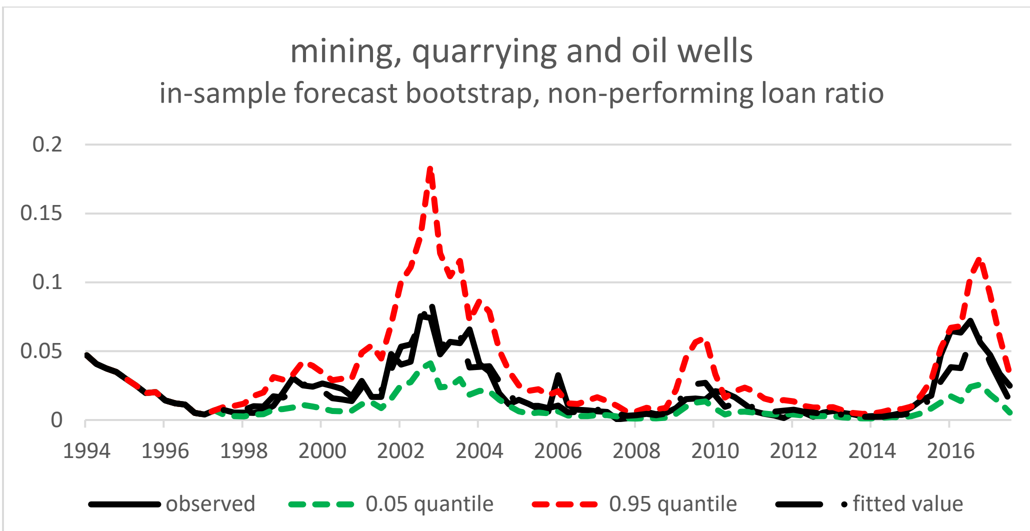
Figure 8 shows the in-sample dynamic forecasts with bootstrapping for three industries, illustrating the importance of accounting for uncertainty.[15] Without bootstrapping, we could not account for the more severe realizations of loan performance deterioration.

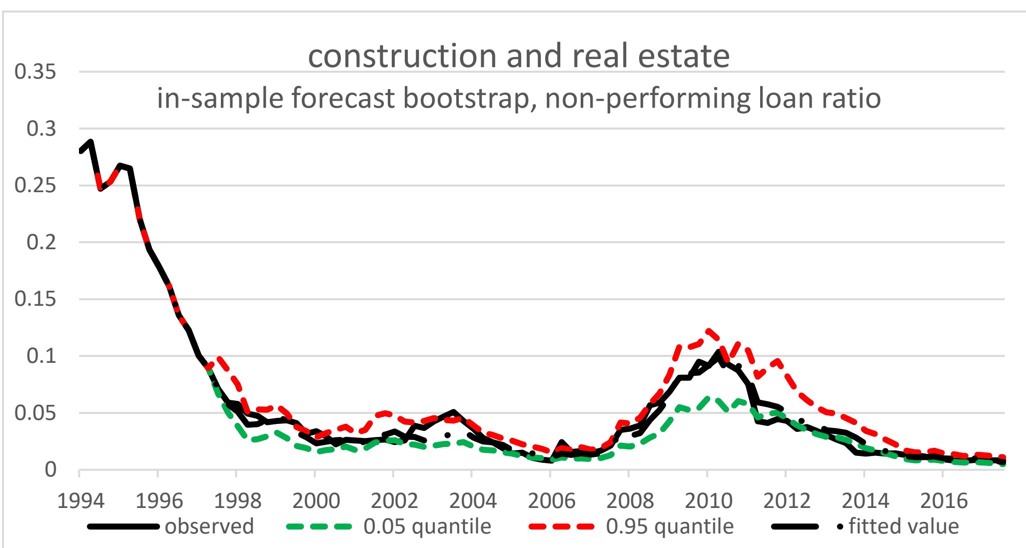
[14] Bruneau and Djoudad (forthcoming) use an extension of the dynamic ordinary least Squares approach using seemingly unrelated regressions (Mark, Ogaki and Sul 2005) to estimate heterogenous cointegrating vectors. This estimation method provides unbiased estimators with standard normal distributions but also corrects for the presence of short-term cross-section dependence. For the estimation of the short-run (error-correcting) relationship, they use seemingly unrelated regression estimation techniques to correct for the presence of short-term cross-section dependence.

[15] In-sample dynamic forecasting takes the observed exogenous variables as given but uses the values of lagged NPL and TL as estimated with the model, not their observed values.

Figure 8


manufacturing
in-sample forecast bootstrap, non-performing loan ratio
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016
observed
0.05 quantile
0.95 quantile
fitted value


mining, quarrying and oil wells
in-sample forecast bootstrap, non-performing loan ratio
0.2
0.15
0.1
0.05
0
1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016
observed
0.05 quantile
0.95 quantile
fitted value


construction and real estate
in-sample forecast bootstrap, non-performing loan ratio
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1994 1996 1998 2000 2002 2004 2006 2008 2010 2012 2014 2016
observed
0.05 quantile
0.95 quantile
fitted value

3.2.3. Model limitations and use of judgment

Like any model, the CDM has limitations.

As explained earlier, a panel approach allows us to capture the fact that the drivers of loan performance may vary across industries. However, the set of potential explanatory variables considered remains limited to the macrofinancial variables that have an impact on all sectors. The quality of the estimated relationships may thus vary across industries, with a poorer fit for those where drivers of default would go beyond the macrofinancial variables considered.

The CDM does not consider the financial health of the corporate subsectors (e.g., profitability, leverage, liquidity) while this may influence their default risk. Accounting for the role of financial health indicators, however, would require a forecast of these variables with the models used to quantify risk scenarios, thus raising another set of challenges.

We face data limitations: the NPL and TL series start in 1994, and the only recession in the data period is the 2008–09 recession. Consequently, for risk scenarios that would incorporate a more severe recession, the model may underestimate the impact on NPLRs. Therefore, we generally use the CDM with judgment to reflect the severity of the risk scenario (e.g., a very severe scenario would be associated with the tail of the distribution of bootstrapped NPLRs) or specific characteristics (e.g., a risk scenario including a severe house price correction would see the construction and real estate sector experience a pronounced deterioration in NPLRs). Starting with the complete distribution of simulated NPLRs, we capture the uncertainty around the projection. To be consistent with the risk scenario considered, we can select a subsample of the simulated NPLR distributions either by setting a fixed lower bound on the bootstrapped NPLR distribution or by selecting a specific percentile of the NPLR distribution (e.g., 95th percentile to capture the worst realizations). These judgment criteria can be informed by historical performance and can be applied to one or more industries (by increasing the number of industries to which we apply judgment, however, we restrict the sample of observations). In applying judgment in the CDM with these criteria, we keep the correlations across sectors consistent.

4. Models to assess impact of risk scenarios on the banking sector

To assess the impact of risk scenarios on the banking sector, we use two complementary tools. First, the Top-Down Solvency Assessment (TDSA) tool measures the impact of risk scenarios on bank solvency through credit losses and income by projecting banks' balance sheets, income statements and regulatory capital ratios. Second, the MacroFinancial Risk Assesment Framework (MFRAF) complements the TDSA by quantifying second-round effects, such as funding liquidity risk, fire-sale losses and interbank contagion risk, which may affect bank resilience beyond the impact on solvency captured in the TDSA. Both models are based on regulatory data reported by Canadian banks. Given our systemic focus, the TFSA and MFRAF consider D-SIBs only because D-SIBs account for more than 90 per cent of total banking sector assets.[16]

Since the Bank of Canada is interested in the banking sector as a whole, not individual banks, our focus is on the aggregate impact of risk scenarios on the banking sector. Nevertheless, because banks have different balance sheets reflecting variations in business models, they may be affected differently by the risk scenarios considered. Moreover, second-round effects are driven in part by the interactions of banks and the negative externalities associated with their reactions to shocks. Consequently, our models consider banks at an individual level to capture the effects associated with their idiosyncracies and the second-round effects due to their interactions, but we report results for banks in aggregate.

In the following two sections, we describe the key characteristics and mechanisms of the TDSA and MFRAF models. We also describe their limitations and how judgment is used in the context of these models.

4.1.Top-Down Solvency Assessment tool

4.1.1. Model overview

The purpose of the Top-Down Solvency Assesment (TDSA) tool is to measure the impact of risk scenarios on bank solvency through credit losses and income. The TDSA generates a projection of banks' balance sheets, income statements and regulatory capital ratios, with key inputs derived from RAMM, HRAM and CDM. While the other FRIDA models are economic models that capture behaviours, the TDSA is akin to an accounting tool in the sense that it provides a mapping of macrofinancial variables into banks' financial statements, although some subcomponents are estimated using economic models.

The TDSA considers future income in addition to existing capital buffers when assessing the capital impact of the stress scenario. In a solvency assessment model, net income before credit losses is an important source of loss-absorbing capacity for the banking system. The TDSA provides an estimate of the earning capacity of banks under stress using empirical relationships for some elements and conservative assumptions based on historical experience for others.

As described in Figure 9, the TDSA assumes that some elements of banks' balance sheets evolve in a manner consistent with the risk scenario. For example, loan balances are assumed to evolve according to aggregate credit growth in the risk scenario. Other balance sheet items, including cash, securities and

[16] Smaller banks would also be affected by risk scenarios, although the impact could vary given the differences in their business models.

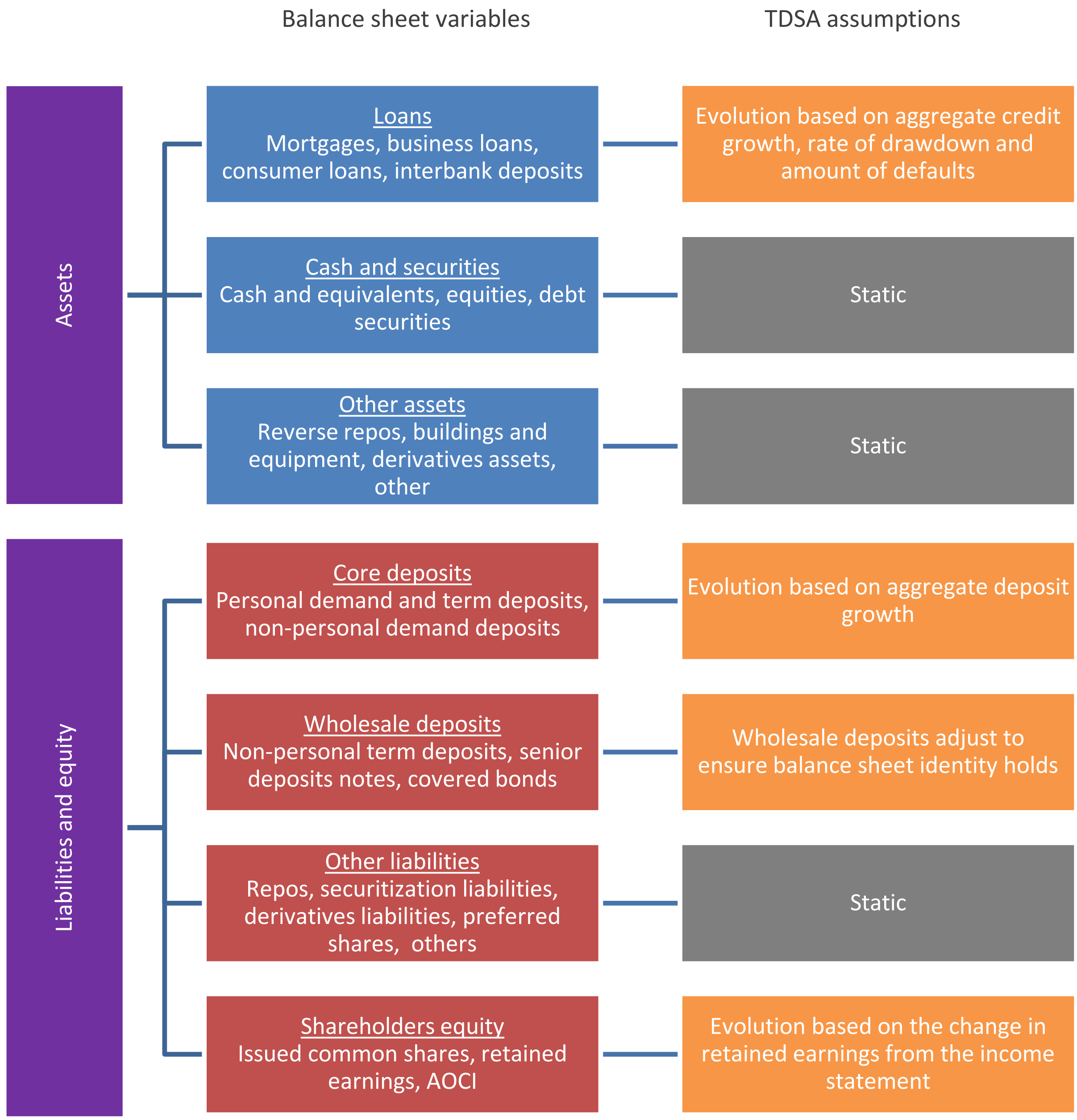
liabilities other than deposits, are assumed to be static throughout the scenario due to the difficulty of modelling the behaviour of these portfolios using macrofinancial variables.

The impact of liquidity stress is not considered. Simplifying assumptions are made around liquidity. For example, balances of cash and liquid securities are assumed to be fixed over the projection horizon. Moreover, banks are assumed not to experience funding runs. The interaction of the impact of first-round solvency on liquidity risk is considered in the MFRAF.

4.1.2. The evolution of balance sheet variables

Figure 9 and the section that follows summarize how balance sheet variables are projected in the TDSA.

Figure 9. Summary of TDSA balance sheet variables



- *Evolution of loans*

As the loan book generates the majority of banks' income and credit losses, the evolution of balances and the composition of the loan book are important elements of the solvency assessment of banks.

The TDSA uses a stylized loan book segmented into business and household loan portfolios, with further sub-portfolio segmentation that corresponds to the sectors modelled in HRAM and the CDM. Moreover, each of these sub-portfolios is divided geographically into Canadian, US and rest-of-the-world (RoW) exposures. The evolution of loan balances for a given sub-portfolio p at time t is described by the following formula:

$$Drawn_{p,t} = \left(1 + g_{p,t} - DR_{p,t}\right) \times Drawn_{p,t-1}$$

Where
$Drawn_{p,t}$: drawn loan balances
$g_{p,t}$: rate of loan growth
$DR_{p,t}$: default rate

Loan portfolios are assumed to grow or decline at rate $g_{p,t}$, which is equal to the rate of aggregate credit growth generated by RAMM for the corresponding sector (i.e., Canadian household credit, Canadian business credit, US credit). Credit growth for RoW exposures is calibrated to be consistent with the risk scenario narrative, based on expert judgment.

We use the simplifying assumption that defaulted exposures are written off in the period of default and are deducted from loan balances. This is a departure from the standard practice of banks wherein non-performing loans can be retained for a longer period. This is a conservative assumption because it precludes the possibility that a loan is restored to performing status following a default.

- *Evolution of deposits*

Banks' liabilities are made of *core deposits*, which consist of personal deposits and demand deposits of governments and businesses, and *wholesale deposits*, which consist of term deposits of businesses and governments and tradable debt instruments, such as senior deposit notes and covered bonds.

Core deposits are sourced from clients with which the bank has a pre-existing relationship and are typically the lowest cost funding source for banks. We assume that the growth rate of core deposits is equal to the growth rate of aggregate credit. This is roughly consistent with the Canadian historical experience for which deposit and credit growth have typically followed a similar pattern. For conservatism, we assume that there is no "flight to safety" wherein individuals shift from risk assets to bank deposits, as observed in 2008. Finally, we assume that there is no run on core deposits beyond the impact of a decline aggregate credit growth.

Wholesale deposits include a broad array of funding instruments and are typically more expensive than core deposits. They are generally used to fund trading book assets and as a marginal source of funding. In the TDSA, we assume that banks retain access to wholesale funding markets throughout the risk scenario.[17] We adjust the level of wholesale deposits mechanistically to balance the evolution of assets relative to core deposits, i.e., upward to meet incremental funding needs that are not met by core deposits and downward if assets decline faster than core deposits.

- *Common shareholders' equity*

In the normal course of business, banks can increase equity capital by issuing new shares in capital markets or generating capital internally through retained earnings. In the TDSA, we make the simplifying assumption that banks cannot issue new capital because the cost of new equity can be prohibitively high in a stressed environment. Hence, changes in common equity are driven by changes in retained earnings only.

4.1.3. Income statement

In this section we explain the assumptions relative to the projection of the income statement for the purpose of calculating retained earnings (Figure 10).

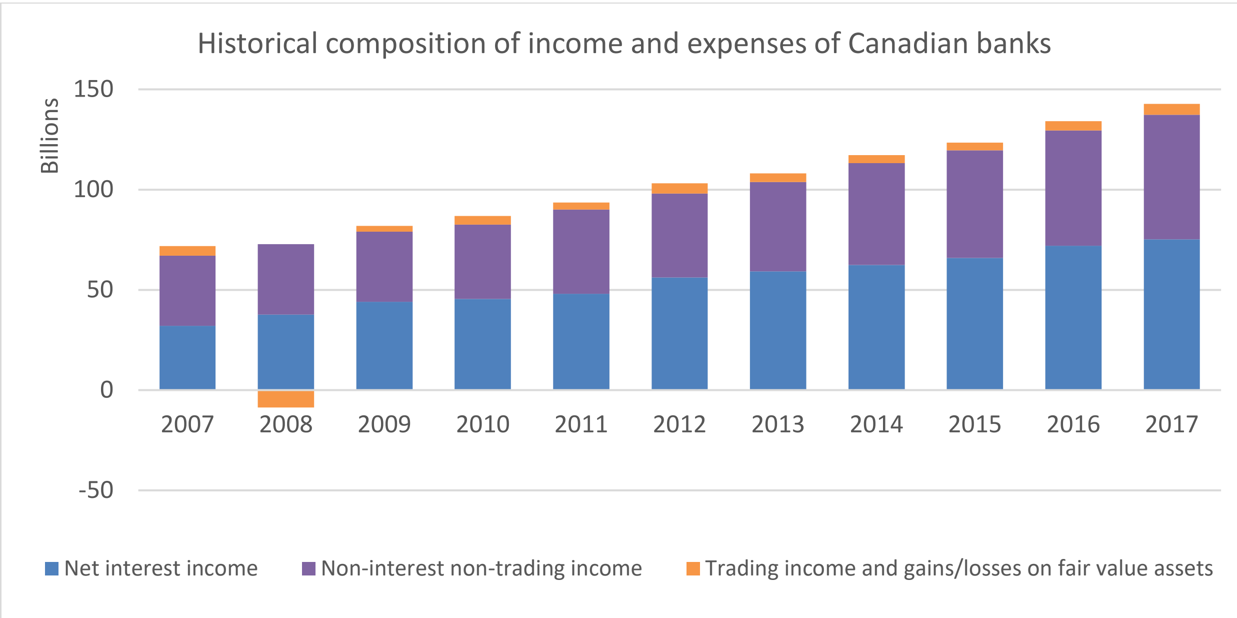
[17] This implies that wholesale funding remains available to banks even if their solvency deteriorated significantly. The interactions between solvency and funding liquidity risk are considered in MFRAF.

Figure 10. Summary of TDSA income statement variables

Income statement variable	TDSA assumptions
Change in shareholders equity	
=	
Net interest income	Interest income and expense are calculated for six classes each of assets and liabilities by multiplying balances by an estimate of the average interest rates earned and paid.
-	
Charge for impairment	Calculated for each portfolio by taking the product of EAD * PD * LGD. Collective provisions are used to smooth impairment charges over time to simulate forward-looking behaviour.
+	
Trading income	Static
+	
Non-interest non-trading income	Market sensitive income evolves according to the returns on a hypothetical bond/equity fund representing assets under management. Non-market-sensitive income evolves as a fixed proportion of loan balances.
-	
Non-interest expense	Expense split into fixed expenses, which remain unchanged, and variable expenses, which scale based on a constant ratio with pre-provision revenues.
-	
Provision for taxes	Average tax rate for the consolidated bank is fixed over the scenario.
-	
Common shareholder dividends	Most recent dividend is continued subject to regulatory restrictions on dividend distributions.
-	
Other distributions (dividends on preferred shares and payments to non-controlling interests)	Static

The stylized income statement used in the TDSA divides bank revenues into net interest income, non-interest non-trading income, and trading income and gains/losses on fair value assets.[18] As shown in Figure 11, net interest income and non-interest non-trading income account for more than 95 per cent of revenues. Consequently, we project these two sources of income using models. In contrast, we assume that trading income remains at a fixed level based on the observations from the previous two years.[19]

Figure 11



- *Net interest income*

Net interest income is the difference between the interest earned by banks on loans, securities and other interest-earning assets and the interest paid on deposits and other interest-bearing liabilities. The most important drivers of changes in net interest income are changes in the amount and composition of assets and liabilties and the relative movements in the interest rates associated with each.

To project interest income and interest expense in the TDSA, we divide the respective balances of interest earning assets and interest bearing liabilities into six portfolios. We then multiply the balances

[18] Trading income in the TDSA includes realized and unrealized gains and losses on instruments held for trading purposes and realized gains and losses from the sale of securities held for other than trading purposes. Trading income does not include the interest income earned on instruments held for trading, which is included in interest income or fees and commissions earned for trading on behalf of clients, which are included in non-interest non-trading income.

[19] It is easy to consider sensitivity analyses related to market risk wherein trading income is assumed to be in line with periods characterized by poor trading conditions.

of each portfolio by an average interest rate that is estimated by an empirical model.[20] The average interest rate is calculated for each portfolio as the interest income earned or interest expense paid on that portfolio divided by average balances.

The projection of average interest rates for the 12 portfolios uses an error-correction model that captures both long- and short-term drivers of interest rates earned on assets and paid on liabilites. The paths of interest rates are estimated using the combined data of the major banks, and the projection is then applied to each bank individually. The model is defined by the equation below, with the values of the independent variables taken from the risk scenario quantified with RAMM. This specification assumes that long-run movements in average rates are driven by both short- and long-term risk-free rates, while their cyclical behaviour is driven by fluctuations in credit risk and other macroeconomic variables. Given Canadian banks' significant US exposures, we use both Canadian and US macroeconomic variables.

$$\Delta R_t = constant + \alpha^* \left(R_{t-1} + \beta_1 ST_{t-1}^{CA} + \beta_2 LT_{t-1}^{CA} + \beta_1 ST_{t-1}^{US} + \beta_2 LT_{t-1}^{US} \right) + \gamma_1^* \Delta R_{t-1} + \sum_{i=1}^{m} \delta_i X_{i,t-1}^{CA} + \sum_{i=1}^{m} \varphi_i X_{i,t-1}^{US} + \varepsilon_t$$

Where
R: average interest rate earned or paid on a given portfolio of assets or liabilities (measured as ratio of interest income or expense over average balances)
ST: short-term risk-free rate
LT: long-term risk-free rate
X: vector of macrofinancial variables, including corporate credit spreads, GDP growth and equity price indicies
α: long-tem adjustment coefficient
ε: error term

- *Charge for impairment*

The charge for impairment is the expense associated with loan losses. In the TDSA, we differentiate between loan loss provisions for impaired assets (Stage 3 under IFRS 9) and loan loss provisions for performing assets (Stages 1 and 2 under IFRS 9). Provisions for impaired assets are incurred in the period in which the default occurs. Moreover, we make the conservative assumption that there are no

[20] Asset portfolios include business loans, mortgages, consumer loans, interbank deposits, securities and reverse repos. Liability portfolios include personal demand deposits, personal term deposits, non-personal demand deposits, non-personal term deposits (wholesale funding), subordinated debt, and other interest-bearing liabilities. These portfolios were chosen based on available data on interest income and expenses, and a mapping is applied to be consistent with the portfolios used for credit loss calculations.

recoveries on defaulted loans. Provisions for impaired assets are calculated for each portfolio p at period t according to the following formula:

$$prov\_imp_{p,t} = (Drawn_{p,t-l} + ddr_{p,t} \times Undrawn_{p,t-1}) \times DR_{p,t} \times LRDE_{p,t}$$

Where
$prov\_imp_{p,t}$: provision for impaired assets
$Drawn_{p,t}$: drawn loan balances
$Undrawn_{p,t}$: notional amount of undrawn credit facilities
$ddr_{p,t}$: drawdown rate associated with undrawn balances
$DR_{p,t}$: default rate
$LRDE_{p,t}$: loss rate on defaulted exposures

In the formula used to calculate credit losses, the exposure at default (EAD) is equal to outstanding drawn balances plus the notional undrawn amount multiplied by the drawdown rate. This approach is similar to the approach used to calculate expected losses under the Basel III regulatory framework. The formula implies that, just before default, a borrower draws down on existing credit facilities, increasing the banks' exposure to losses. The drawdown rate for each portfolio is calibrated based on the average drawdown rates estimated by banks to determine capital requirements, taking into account the proportion of undrawn exposures that are unconditionally cancellable.

Default rates for each sub-portfolio are based on the output of HRAM and CDM. However, the measure of credit performance for both models is a stock measure (i.e., a measure of total outstanding loans in arrears or non-performing loans at a point in time). To calculate credit losses, we must transform these outputs into default rates that are a flow measure (i.e., a measure of the number of defaults that occurs over a specific period of time). As described by the following formula, we assume that defaulted loans remain in arrears or as non-performing loans for an average of four quarters before being written off:

$$DR_t = NPLR_t - \left(\frac{4-1}{4}\right) NPLR_{t-1}$$

LRDEs are derived from the average downturn losses given default (LGD) estimated by banks for each portfolio as reported as part of their regulatory capital requirement filings. Depending on the risk scenario, banks' estimates of LGDs may be adjusted using expert judgment to account for higher expected losses on certain types of exposures. For example, in a risk scenario with a large decline in house prices, the LRDE for residential mortgages may be adjusted upward in proportion to the house price decline. The LRDEs calibrated in this way are applied uniformly across banks.

Banks may also incur additional provisions for performing exposures in a deteriorating macrofinancial environment in anticipation of future losses. In the TDSA, these provisions are incurred in the first quarters of the stress scenario and are released during the recovery to simulate the forward-looking provisioning behaviour of banks under the expected credit loss framework of IFRS 9.[21] While this mechanism reallocates credit losses to the early periods of the risk scenario, it does not affect the total amount of credit losses.

- *Non-interest non-trading income*

For D-SIBs, non-interest non-trading income includes a diversity of income streams, including the fee income generated from its core banking activities as well as income from a variety of other financial services, including wealth management, insurance and investment banking. Figure 13 provides a breakdown of non-interest non-trading income from 2013 to 2017.

In the TDSA, the evolution of non-interest non-trading incomes is given by the following formula:

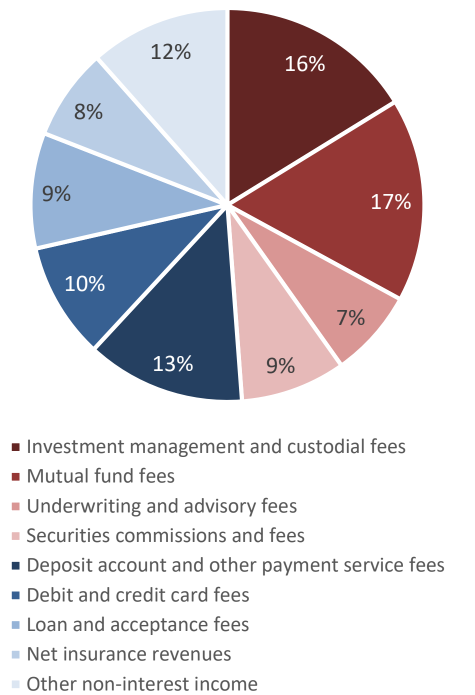
$$NINT_t = (1 + r_t) \times MS\_NINT_{t-1} + \rho \times \sum_{p=1}^{n} Drawn_{p,t}$$

Where:
$NINT_t$: non-interest non-trading income
r_t: return on a hypotherical portfolio of investment assets
MS_NINT_{t-1}: market-sensitive non-interest non-trading income
ρ: fixed ratio of non-market sensitive income to total loan balances
$\sum Drawn_{p,t}$: total loan balances

[21] IFRS 9 refers to the International Financial Reporting Standard for classifying and measuring financial assets, which was updated in the 2018 fiscal year. The previous standard (IAS 39) measured provisions for credit losses in accordance with an incurred loss model in which credit losses are only recognized once a loss event has been incurred. Going forward, entities will be using a forward-looking expected credit loss (ECL) model that will result in earlier recognition of credit losses.

We divide non-interest non-trading income into market-sensitive income (categories in brown in Figure 12) and non-market sensitive income (categories in blue) based on our assumptions for how these broad categories of income would behave under stress.

Figure 12. Breakdown of non-interest non-trading income



Market-sensitive income is assumed to grow in proportion to the returns on a hypothetical portfolio of investment assets including equities and bonds. Given that wealth management consitutes two-thirds of this category, this method seeks to proxy the change in assets under management that would occur in an environment of falling asset prices. Other sources of market-sensitive income derived from trading volumes and equity underwriting activity are also assumed to decline in proportion to this index. To be consistent with the stress scenario, the rate of return is calculated using financial market variables quantified with RAMM.

Non-market sensitive income consists of deposit and loan fees, debit and credit card fees, insurance revenues, and other non-interest non-trading income. These revenues are assumed to be reliable in any environment and grow in proportion to the overall loan book.

- *Non-interest expense*

Non-interest expense in the TDSA evolves according to the following formula:

$$TOT\_EXP_t = \tau \times Revenues_t + \max(\mu \times Revenues_t \, , FIXED\_EXP)$$

Where
TOT_EXP_t: total non-interest expense
τ: fixed ratio of variable non-interest expense to pre-provision revenues
μ: fixed ratio of variable non-interest expense to pre-provision revenues
$Revenues_t$: pre-provision revenues (i.e., net interest income plus non-interest income)
$FIXED\_EXP$: fixed non-interest expense

It is assumed that banks are able to reduce certain types of expenditure in response to declining revenues. Employee compensation, for example, may fall automatically as bonuses are reduced. In the TDSA, variable expenditures include employee compensation, advertising and donations, employee training and development and consulting fees. These expenditures are scaled down in a fixed proportion to revenues. The ratio of variable expenses to revenues, τ, is calculated using an average of the most recent two years of data.

It may not be possible to scale down other expenses in a stress scenario. For example, banks may be unable or unwilling to cancel a long-term real estate lease in response to a short-term decline in revenues. In the TDSA, these fixed expenditures include premises and equipment, office and general expenses, deposit insurance premiums, and audit and legal fees. These expenditures are assumed to scale up in a similar manner to variable expenditures when revenues are increasing, but are assumed to be fixed as revenues decline. The ratio of fixed expenses to revenues, μ, is calculated using an average of the most recent two years of data.

- *Provision for taxes*

D-SIBs operate in multiple tax jurisdictions and therefore face multiple tax rates. For simplicity, the TDSA calculates an average tax rate based on the total taxes paid at the consolidated entity level over the previous two years. This tax rate is then applied to banks' pre-tax net income in each period.

When pre-tax net income is negative, a deferred tax asset that reduces the size of the net loss in that period is generated. If the bank has positive net income in subsequent quarters, taxable income is reduced by the amount of accumulated deferred tax assets.

- *Common shareholders dividends*

Historically, Canadian D-SIBs have distributed between 40 and 50 per cent of their after-tax net income to shareholders in the form of dividends. Moreover, banks have also deployed excess capital into acquisitions of other banks and financial service firms or share repurchase programs, which return additional capital to shareholders. In the TDSA, we assume that banks maintain a fixed payout ratio (the ratio of dividends to after-tax net income) until their net income starts to decline. At that point, banks continue to pay their most recent dividend until the distribution of earnings is restricted due to a breach of the capital conservation buffer (CCB). Upon breaching the CCB, banks pay the lower of their pre-stress dividend and the maximum dividend permitted by the CCB framework.[22] The reduction in dividends that results from a breach of the CCB typically leads to an improvement in banks' internal capital generation. Finally, the model does not provide means for banks to deploy excess capital other than through dividends (i.e., acquisitions or share repurchases). As a result, scenarios that are not sufficiently severe

[22] The capital conservation buffer can also be breached if other measures of capital (tier 1 and total capital) breach their respective ratios. However, because we assume balances of additional tier 1 and tier 2 capital remain unchanged, these thresholds will not be breached before the Common Equity Tier 1 threshold.

to reduce banks' capital could lead to increases in regulatory capital ratios beyond banks' internal targets.

- *Other comprehensive income*

Other comprehensive income (which includes gains and losses on securities classified as fair value through other comprehensive income (FVOCI) and gains and losses from the currency translation of foreign operations) is assumed to be zero throughout the scenario. While other comprehensive income can be volatile from period to period, it has accounted for about only 3 per cent of total comprehensive income (net income plus other comprehensive income) since 2007.

4.1.4. Calculating Common Equity Tier 1 ratios

The primary output of the TDSA is the aggregate Common Equity Tier 1 (CET1) ratio of the combined D-SIBs, representing the overall solvency of the banking sector. Figure 13 summarizes the construction of this ratio.

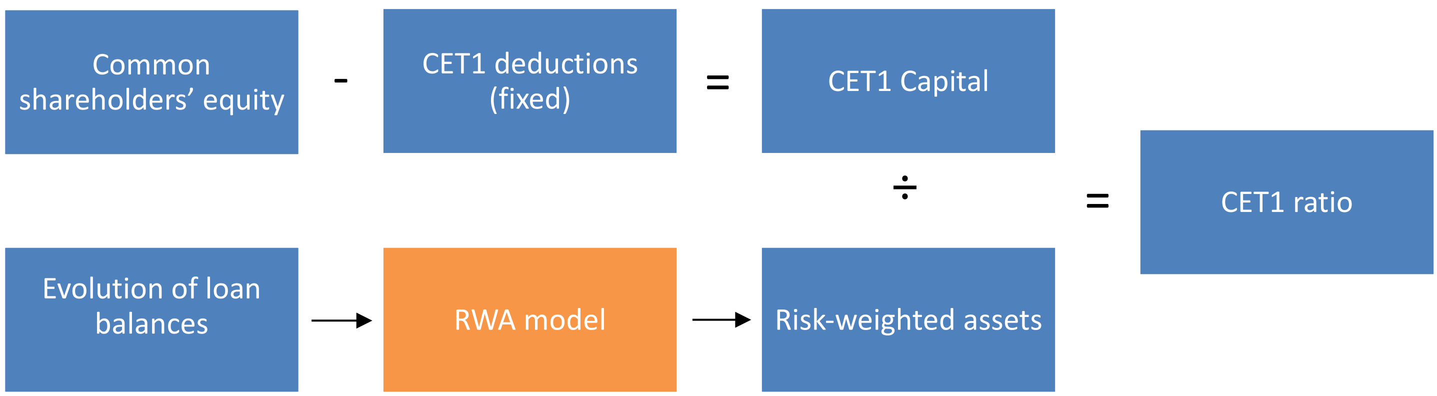
The numerator, CET1 capital, is calculated by subtracting regulatory deductions from common shareholders equity. These deductions include goodwill and intangible assets, deferred tax assets, and significant investments in the equity of financial instutions. With the exception of deferred tax assets, these items are assumed to be invariant to the stress scenario and remain at their initial level.

The denominator of the CET1 capital ratio is risk-weighted assets (RWAs). The TDSA models RWAs such that the path is consistent with the evolution of banks' exposures as well as changes in asset quality. The primary approach used by Canadian D-SIBs to calculate credit risk-weighted assets is the Internal Ratings-Based (IRB) approach. Under this approach, banks segment their credit exposures into portfolios (e.g., bank, corporate, soveriegn, mortgages and other retail) and then borrower grade categories. For each borrower grade, the bank must estimate its exposure at default (EAD) as well as two risk parameters that are used to determine risk weights: through-the-cycle probability of default (TTC PD) and downturn loss given default (downturn LGD). The TTC PD is calculated as a long-run average of one-year default rates for borrowers in the grade. The downturn LGD is estimated such that it reflects losses under economic downturn conditions in order to account for cyclical variability in loss severities.

In order to reflect changes in asset quality in the projection of banks' RWAs, we calculate a 10-year moving average of default rates using historical data and the projection of scenario default rates. The TTC PDs within each portfolio are assumed to evolve in proportion to this moving average. In scenarios with rising default rates, this mechanism will typically result in higher risk-weights and therefore higher RWAs.[23]

Other sources of RWAs include operational risk and market risk. Operational RWAs are assumed to scale in proportion to a three-year weighted average of banks' net revenues, consistent with the standardized approach used by banks. Market RWAs, however, are assumed to be fixed at their initial level throughout the stress scenario. Incorporating changes in risk-weighted assets resulting from changes in market risk will be considered in future versions of the model.

Figure 13



4.1.5. Model limitations and use of judgment

This approach to assess banking system solvency has some limitations.

Some risk factors are not considered in the TDSA, including market risk, operational risk and credit risk arising from exposures other than loans. Ways to estimate potential losses arising from these risks will be considered in the future.

The TDSA does not consider the potential impact that foreign currency translation of Canadian banks' foreign operations would have on banks' capital and their RWAs. This impact could be positive or negative depending on the direction and magnitude of foreign exchange movements as well as the relative performance of Canadian currency and foreign currency assets. Future versions of the TDSA will consider the impact of foreign currency translation on the solvency position of the banking system.

Finally, the TDSA does not account for all idiosyncracies of individual banks. When possible, the TDSA uses bank-specific information to project income and credit losses for individual banks. This is because a more accurate assessment of individual banks will provide a more accurate assessment of the system as a whole. For example, bank-specific information is reflected in the composition of assets and liabilities,

[23] Risk weights for exposures using the standardized approach are assumed not to change.

the composition of income and expenses, and the risk parameters used to calculated RWAs. For other components, however, the combined data of D-SIBs are used to project variables that are applied uniformly to all banks. For example, the portfolio-level probabilities of default and the path of interest rates earned and paid on liabilites are estimated for the combined banks. For this reason, the model may not provide an accurate assessment for individual banks. Nonetheless, the impact of these differences is expected to be muted once results are aggregated.

4.2. The MacroFinancial Risk Assessment Framework[24]

4.2.1. Model overview and key considerations

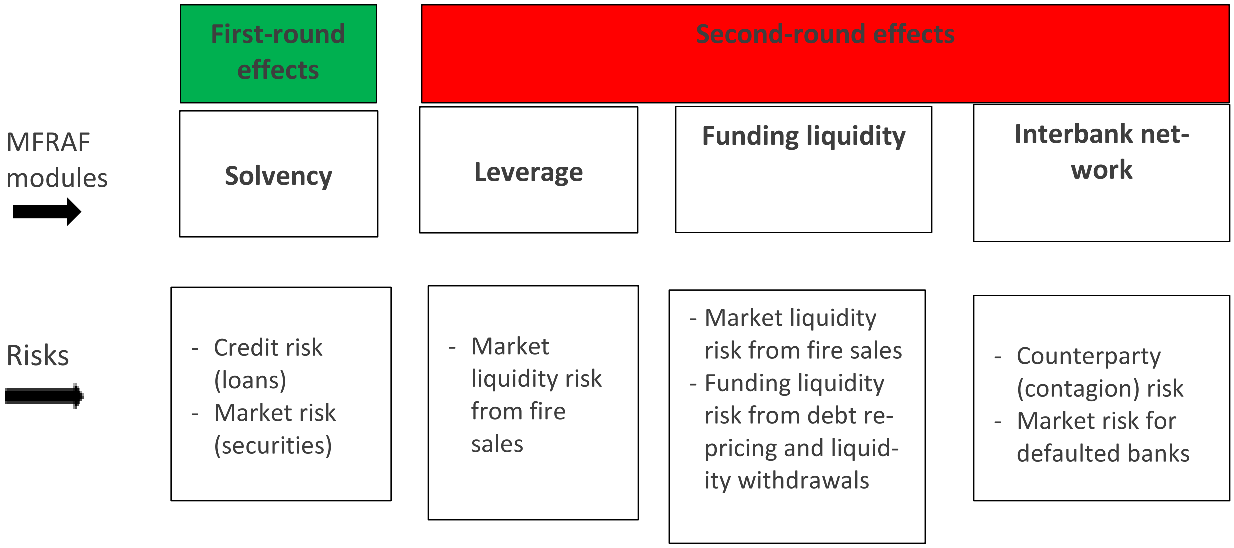
In addition to the impact of risk scenarios on bank solvency through credit losses and income quantified in the TDSA described in section 4.1., the resilience of banks can also be affected by liquidity risk, fire-sale losses and interbank losses. These are characterized as second-round effects because they result from the propagation or the amplification of the initial shocks. Therefore, it is necessary to complement our quantitative assessment of bank resilience with a model that captures these effects. We do so in FRIDA by using the MacroFinancial Risk Assessment Framework (MFRAF) to complement results from the TDSA. In this section, we provide a high-level description of the key mechanisms in MFRAF, and we explain how MFRAF is combined with other models in FRIDA, including the TDSA. For a technical description of MFRAF, see Fique (2017).

As explained before, our interest lies in assessing resilience for the banking sector as a whole, not individual banks. Nevertheless, since the second-round effects considered in MFRAF arise in part from the interlinkages that exist between banks, it is necessary to capture banks on an individual basis to account for the propagation and amplification channels. Moreover, in considering banks on an individual basis, we account for the role of their idiosyncrasies (exposures, funding structure etc.) in quantifying the channels through which banks are affected by a risk scenario. Like in the TDSA, individual bank results generated with MFRAF are subsequently aggregated to provide an assessment of the overall resilience of the banking system.

MFRAF has a modular structure that captures the various sources of risk being modelled (Figure 14). It should be noted that MFRAF does not generate all the drivers of banks' capital positions (e.g., MFRAF does not generate income and RWAs). It is therefore used in combination with the other models described above.

[24] MFRAF has been developed and enhanced by various Bank of Canada staff over time. The current version of MFRAF accounts for significant enhancements to the model by Sofia Priazhkina.

Figure 14. ***MFRAF modular structure and types of risks***



The TDSA relies on the static balance sheet assumption under which banks' balance sheets evolve in a manner consistent with the risk scenario and banks do not take management actions that would change the risk characteristics of their balance sheets. In contrast, MFRAF relies on different assumptions regarding banks' balance sheet evolution depending on modules.[25] The solvency module is based on the same assumption as in the TDSA, while the interbank network module assumes that interbank exposures remain the same as initial exposures (pre-risk materialization) throughout the scenario. In contrast, in the leverage and funding liquidity modules, banks engage in management actions to deal with the impact of the risk scenarios. On the one hand, banks engage in asset liquidations in both the leverage and the funding liquidity modules to restore compliance with the regulatory leverage ratio requirement and to cover maturing liabilities respectively, thus modifying the characteristics of their assets. On the other hand, banks can issue unsecured short-term wholesale securities to replace maturing liabilities in the funding liquidity module, thus modifying the characteristics of their liabilities.

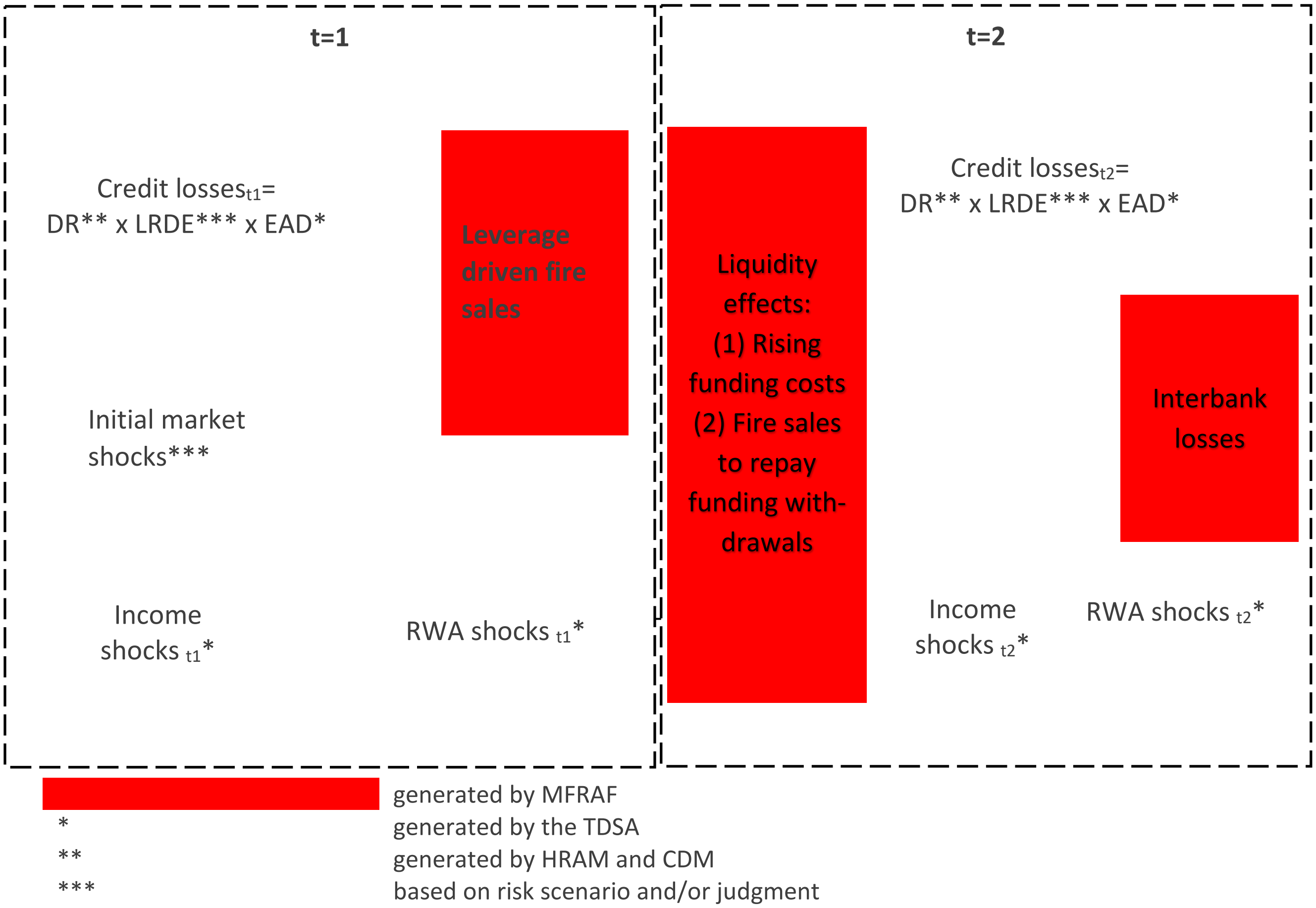
The effects quantified in MFRAF are all translated in terms of impact on banks' CET1 ratio to be able to decompose and explain the drivers of bank resilience relative to a single measure. This allows us to compare the quantitative impact of the various sources of risk that affect banks in a consistent manner.

MFRAF is a two-period model.[26] Figure 15 illustrates the timelines of events in MFRAF, the effects quantified in MFRAF and how MFRAF is combined with other models in the context of FRIDA to quantify the impact of risk scenarios on banks' capital positions.

[25] Like the TDSA, MFRAF considers the automatic restrictions on dividends distribution imposed by the capital conservation buffer.

[26] Second-round effects are more likely to occur when first-round effects are large. Consequently, MFRAF is typically run over the periods of the horizon that are characterized by the most severe first-round effects on banks.

Figure 15. **Timelines and effects quantified in MFRAF and integration with other FRIDA models**



4.2.2. Model description

- *Solvency module*

The solvency module in MFRAF considers two types of first-round losses: market losses and credit losses. Since the TDSA does not consider market losses, MFRAF introduces an additional source of potential first-round effects to these considered in the TDSA. In contrast, since the TDSA quantifies credit losses, credit losses in MFRAF are taken from the TDSA, albeit with considerations of distributional effects not captured in the TDSA as described below. Market and credit losses are then combined with income and RWA from the TDSA to quantify the total impact of first-round losses on the CET1 ratio.

Market losses are calculated simply by applying the market shocks from the risk scenario generated with RAMM to banks' initial securities holdings.[27] Since banks can have different securities portfolios, market losses can vary among banks under a common risk scenario.

Like in the TDSA, credit losses (or provisions for impaired assets) in MFRAF are equal to the default rate (DR) of loans multiplied by the corresponding loss rate on defaulted exposures (LRDE) and exposures at default (EAD) for each of the sectors to which banks lend. However, MFRAF considers the entire distribution of credit losses to account not only for the most likely but also the less likely realizations of the credit shocks under the risk scenario considered, thus complementing the analysis of credit losses in the TDSA. The stochastic component of credit losses in MFRAF comes from the distribution of default rates, which are generated with the CDM described in section 3.2.[28] In contrast, LRDEs and EADs are deterministic and are taken from the TDSA. To ensure consistency with the TDSA, we align the mean of the distribution of credit losses in MFRAF with the credit losses calculated in the TDSA.

Considering the distribution of credit losses is important for the assessment of second-round effects because it allows us to account for the effects associated with the range of possible realizations of credit shocks. Accounting for uncertainty in risk assessment is important given that we focus on tail-risk scenarios which are, by definition, characterized by elevated uncertainty.

- *Leverage module*

Because banks' capital is affected by credit, market and income shocks under a risk scenario, banks also experience a deterioration in their leverage positions, to the point where one or several banks could breach the regulatory leverage ratio requirement. In MFRAF, we assume that banks deleverage by selling securities to restore compliance with the requirement. These sales will typically push down the value of these securities, which can worsen leverage for all banks that hold similar assets because of mark-to-market (MTM)accounting rules, possibly forcing additional sales. Common securities holdings thus create an amplification and propagation mechanism in MFRAF consistent with the fire-sales effects observed during the 2008–09 financial crisis.

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[27] We make the simplifying assumption that all securities are mark-to-market (MTM). In practice, however, MTM accounting rules apply only to trading book securities and securities available for sale in the banking book, not to those that are held to maturity (HTM). This is because data on securities holdings we use do not distinguish between these categories]. Moreover, we ignore the effects of hedges or other strategies that would reduce the impact of market shocks on securities exposures because we do not have data on these. As a result, we may overestimate market losses.

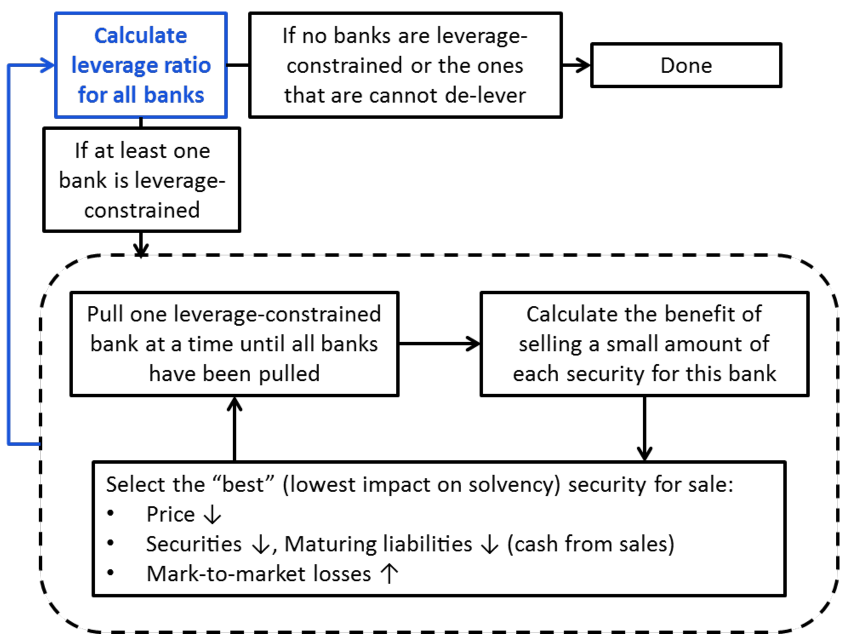
[28] To account for the distribution of household default rates as well, we use a modified version of the CDM that includes loans to households (mortgages and consumer loans) to capture the cross-sectional dependence, as with business loan exposures. We align the mean default rates with household exposures in this modified CDM on the arrears rates generated with HRAM.

In MFRAF, if a bank breaches the 3 per cent regulatory leverage ratio, we assume that if it can, it will reduce its leverage by selling securities.[29] MFRAF uses a mechanistic approach to model banks' deleveraging actions. First, banks sell securities only once they breach the requirement, i.e., they do not form expectations regarding future leverage ratios and do not consider pre-emptive actions to avoid regulatory breaches. Second, the liquidation of securities is driven exclusively by considerations related to minimizing the solvency impact of MTM losses and restoring compliance with the requirement for the leverage ratio (i.e., banks do not consider other implications of these sales, such as their impact on future income or their liquidity positions). Finally, banks do not form expectations about the actions of other banks and their potential price impact.

The impact of securities sales on market prices depends on the risk scenario considered and the market characteristics of the securities sold. The more banks sell, the more the market price declines, with the effect being greater for securities that are less liquid.[30]

The operation of the leverage module is described in Figure 16.

Figure 16. Schematic description of the leverage module and associated fire sales



- *Funding liquidity module*

The approach used in MFRAF's funding liquidity module was chosen to capture the key characteristics of bank liquidity risk highlighted during the 2008–09 financial crisis and to consider the microeconomic

[29] While deleveraging actions could include selling a broader range of assets in practice, we restrict the model to the sale of securities for two reasons. First, selling securities can be done relatively expediently, which makes it an attractive option to banks. Second, from a practical viewpoint, it is easier for us to determine an asset selection process and to calibrate prices for securities than for other types of assets (e.g., loans).

[30] The calibration of the price curves for each type of security is scenario specific and is based on market expertise and supporting models.

foundations of the behaviour of banks' creditors. In a stress situation, the mutually reinforcing deterioration in banks' funding liquidity and the liquidity of their assets holdings can lead to liquidity spirals (Brunnermeier and Pedersen 2009). To capture this interplay of funding and asset liquidity, we consider banks' liability structures and the composition of their assets.

Banks face funding stresses if creditors withdraw (i.e., do not roll over) funding that is coming to maturity over the second period in MFRAF. Creditors will make their decisions based on their view of the banks' future solvency (thus linking solvency and liquidity risk), the extent to which the bank relies on unstable funding sources and the quality of its assets (Morris and Shin 2016).[31] Moreover, the rollover decision of banks' creditors is influenced by their beliefs about the proportion of other creditors who withdraw funding (Rochet and Vives 2004).

There are three possible situations. First, if the bank is always solvent regardless of the fraction of creditors that withdraw, then no individual creditors have an incentive to withdraw. Second, if the bank becomes insolvent for all realizations of income and credit shocks, individual creditors have no incentive to roll over funding. Third, if there are positive probabilities of a bank staying solvent and being insolvent, the bank faces partial withdrawals.

When creditors withdraw funding, the bank repays the withdrawals using available cash and may have to liquidate assets to face its obligations if the proportion of creditors that withdraw is large. As in the leverage module, the asset sales lead to additional losses for banks. Therefore, the bank's capital position deteriorates and the bank could become insolvent. The probability of a bank becoming insolvent depends on its initial solvency position, the share of liquid assets it holds, the magnitude of credit and market shocks, and its profitability. It also depends on the degree of conservatism of the bank's creditors,[32] the cost of funding offered by banks to creditors and alternative investment offers available to these creditors. Some banks will retain access to funding markets but at higher prices, which will have a negative impact on their capital positions through reduced profits, while some other banks may be unable to access funding markets altogether.[33]

[31] Bank regulatory reforms (capital and liquidity) should reduce the likelihood of creditors withdrawing funding because they strengthen bank solvency by increasing the amount and quality of capital. They also improve banks' resilience to funding stresses by requiring banks to hold more liquid assets to face potential funding disruptions and to align the maturity of their assets and liabilities.

[32] In the model, the decision of creditors is delegated to risk managers whose remuneration depends on making the correct choice between lending to a bank and the bank remains solvent, which results in inflows for risk managers, versus withdrawing while the bank remains solvent which generates outflows. The more conservative risk managers are about this trade-off, the less likely the bank can obtain unsecured funding.

[33] A bank's ability to access funding markets is endogenously generated in MFRAF, which is an attractive feature because it means that the model can inform our assessment of the conditions under which banks can or cannot access external funding in stressed conditions.

In summary, MFRAF captures the effects of funding liquidity risk in terms of both fire-sale losses and rising cost of funding, which allows us to better explain how banks would be affected by funding liquidity risk.

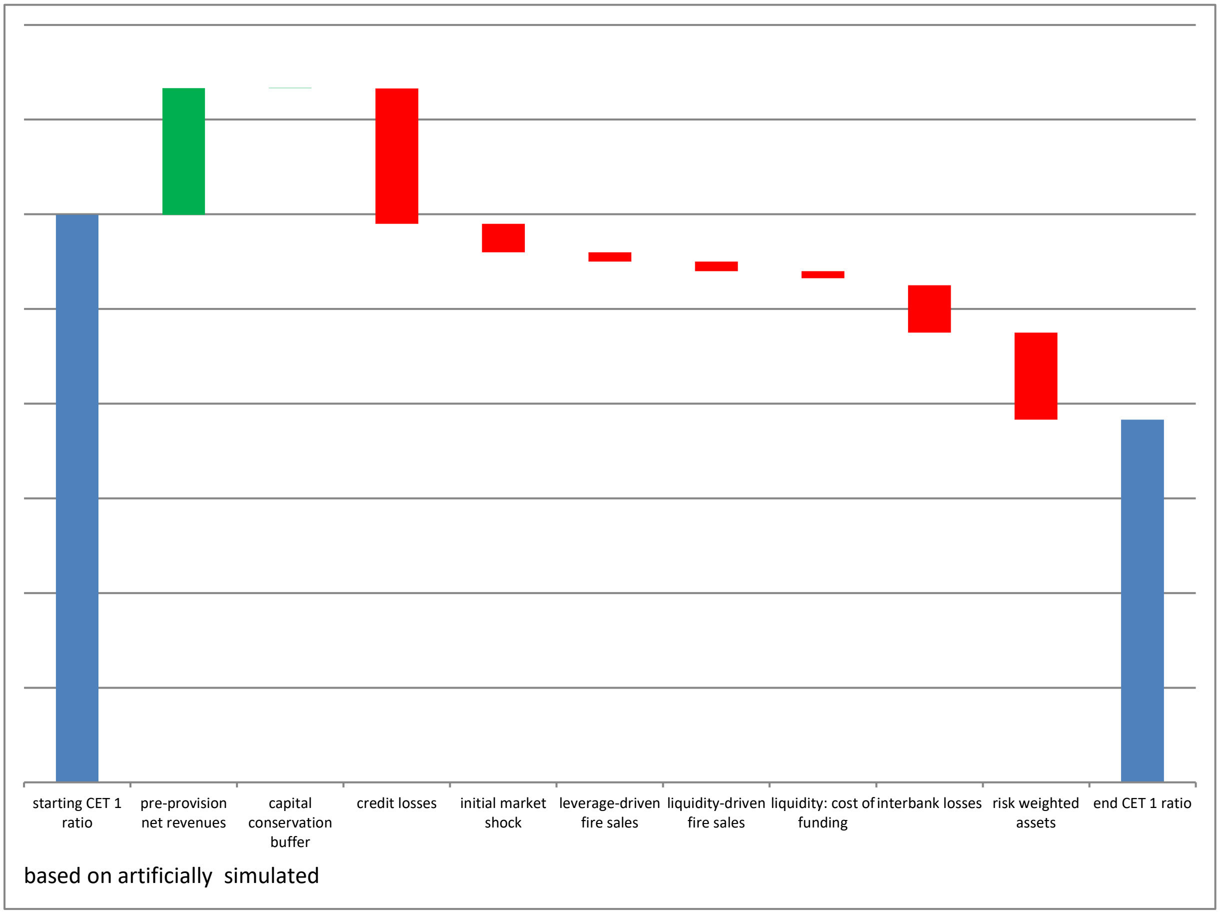
- *Interbank network module*

The final module in MFRAF captures the potential for banks to face counterparty credit losses due to their interbank exposures. After their capital position has deteriorated due to credit, market, fire-sales and liquidity losses and declining income, some banks may be unable to fulfill their interbank obligations (in part or in their entirety). Therefore, banks that have exposures to these banks would face additional losses, leading to a weakening in their capital positions (contagion-driven). This may, in turn, make them unable to fulfill their own interbank obligations, thus leading to a cascade of losses.
We consider that banks default on their interbank exposures when they become insolvent.
These network effects are calculated using the clearing payment vector developed by Eisenberg and Noe (2001). In this approach, interbank exposures are subordinate to all other debts, and banks repay their interbank counterparties a sum that is proportional to the amounts due. We modify the Eisenberg and Noe model to consider additional shocks on the assets of defaulting banks to reflect that their balance sheets may be further discounted due to liquidation costs, thus further affecting their ability to repay other banks. D-SIBs interbank exposures are very small (less than 3 per cent of total assets); consequently, interbank losses would be very limited.

4.2.3. Model outputs—illustration

All figures presented here are illustrative and are based on artificially simulated data.
As explained earlier, we translate the impact of all the losses captured in MFRAF on the CET1 ratio. This allows us to decompose the drivers of the evolution of banks' capital position in a risk scenario in terms of the various risks that affect banks (Figure 17).

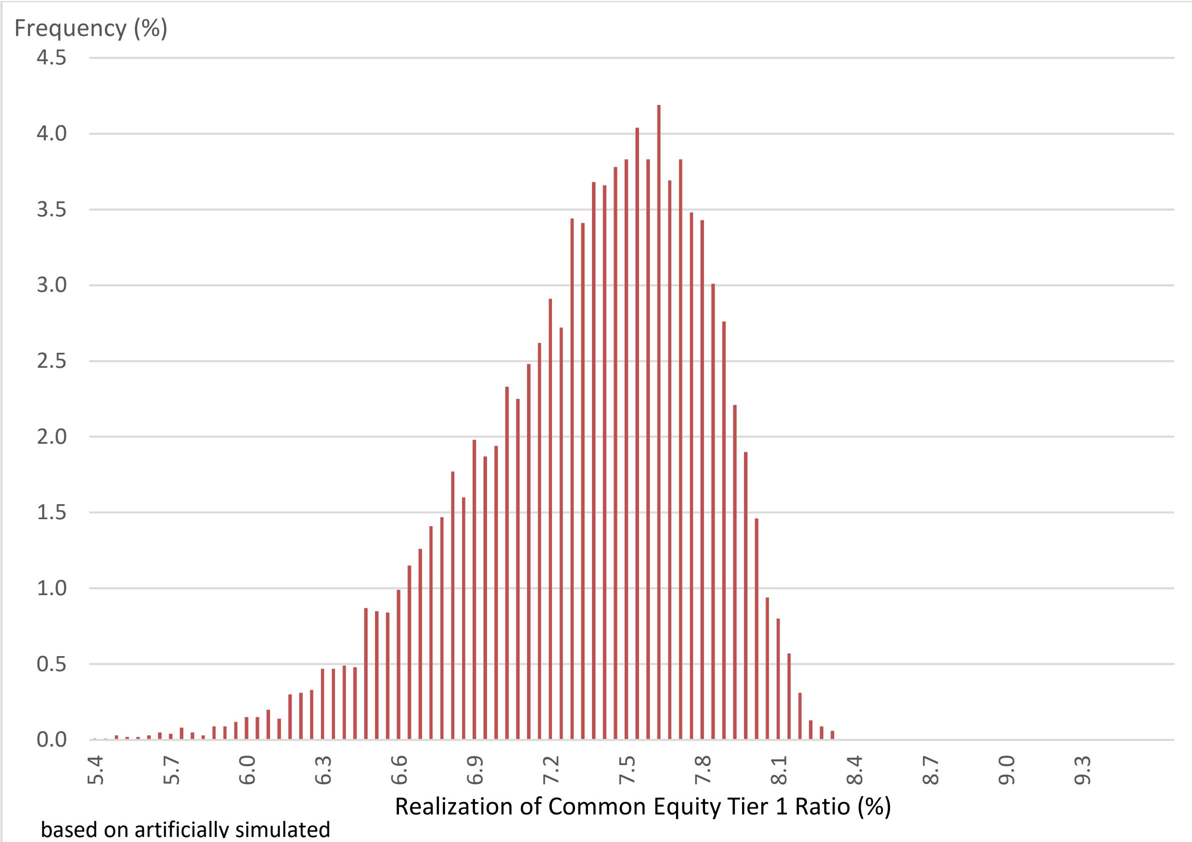
Figure 17. **Decomposition of CET1 ratio drivers**



Note: the green bars represent the positive contributors to capital positions, and the red bars the negative contributors.

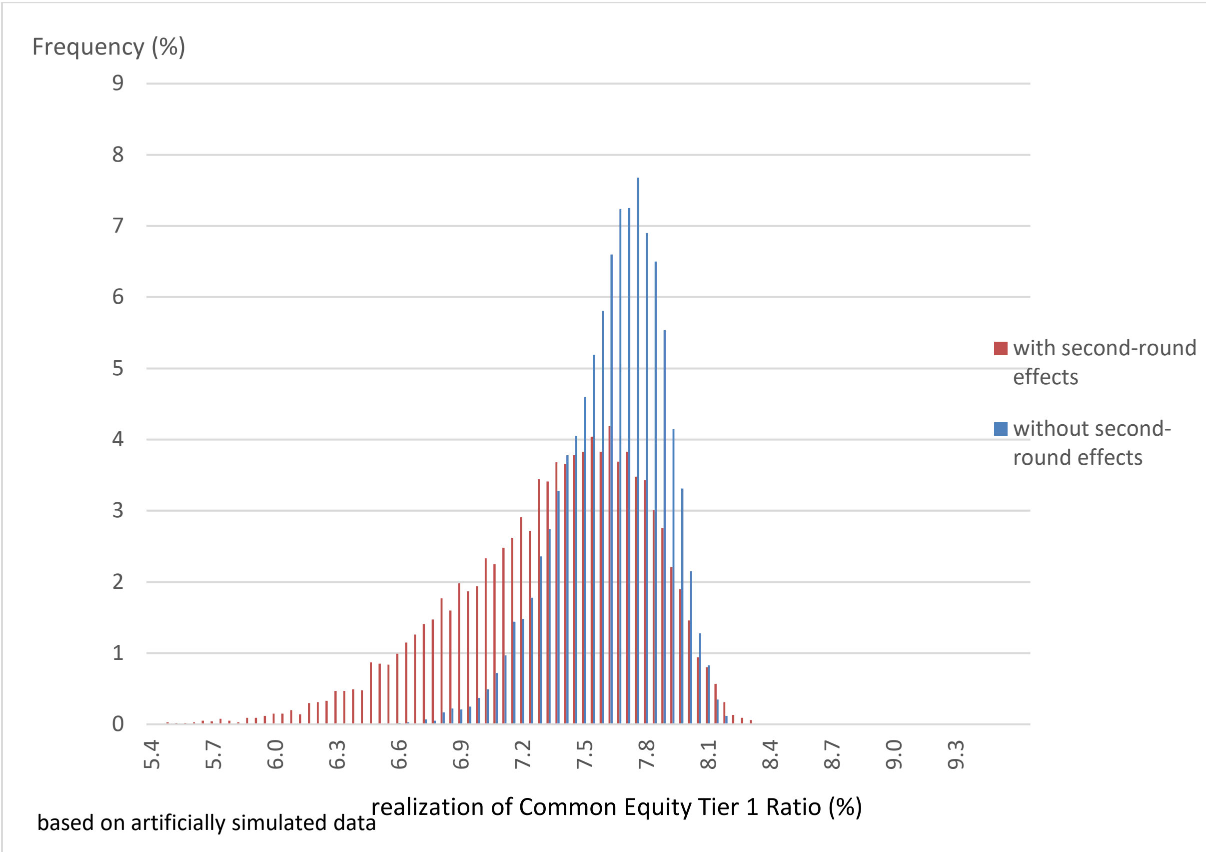
As explained earlier, MFRAF considers the entire distribution of credit losses associated with a risk scenario. Consequently, MFRAF generates the entire distribution of CET1 ratio for a given risk scenario, thus allowing to consider the range of impact that this scenario could have on banks (Figure 18). The more severe realizations (i.e., those associated with a lower CET1 ratio) are less likely to occur. Given the uncertainty associated with the type of tail-risk scenarios considered in financial system risk analysis, it is informative to be able to consider the potential range of impacts that these scenarios would have on bank resilience.

Figure 18. **Distribution of final Common Equity Tier 1 (CET1) ratio**



As explained before, ignoring second-round effects could lead to a biased assessment of banks' resilience. First- and second-round effects are related: the uncertainty associated with credit losses plays an important role for second-round effects. While the more severe realizations (i.e., higher credit losses) are less likely to happen, they are more likely to be accompanied with second-round effects, amplifying the overall impact on bank resilience. As illustrated in Figure 19, the distribution of the CET1 ratio with second-round effects displays a fatter tail than the one without second-round effects. When second-round effects are not considered, the worst potential impact of risk scenarios on capital positions is less severe than when these effects are considered. Moreover, the frequency of the better outcomes is overstated relative to the case where second-round effects are accounted for.

Figure 19. **Distribution of CET1 ratio with and without second-round effects**



4.2.4. Model limitations and use of judgment

MFRAF, like other FRIDA components, is subject to limitations and is used in combination with judgment.

MFRAF does not generate all the components of the CET1 ratio. As described before, we take some of these components (e.g., income and RWAs) from the TDSA. This implies potential inconsistencies among the CET1 ratio drivers because the TDSA does not capture some of the effects that MFRAF considers. First, the income generated with the TDSA is based on the balance sheet composition in the TDSA and therefore does not account for the assets sold by banks in MFRAF, which would affect income generation. Second, the RWAs used in MFRAF are generated by the TDSA and take the form of single point values corresponding to the point-estimates of credit losses, while MFRAF considers the distribution of credit losses and thus it would be more meaningful to consider the corresponding distribution of RWAs.

As mentioned before, the distribution effects captured in MFRAF come exclusively from the distribution of PDs while the other components of capital would be affected by uncertainty as well. This can be offset in part by applying judgment-based uncertainty on some other variables (e.g., income).

There are also some limitations due to data availability. For instance, there is very limited information on LGDs, which implies that the calibration of LGDs is based in large part on judgment. Another example relates to data on securities: we may overestimate losses on securities in MFRAF because we apply MTM to all securities given that we do not have a breakdown of securities by categories (trading book versus available for sale or held to maturity in banking book) and we do not have information on hedges.

Finally, banks do not have an optimization objective in MFRAF and management actions are limited to fire sales. In practice, however, banks could consider a broader range of actions to deal with the impact of shocks and meet their objective (e.g., risk-adjusted return, return to shareholders). These actions could, in turn, have an impact on bank resilience either positively (e.g., if banks can issue equity their capital positions would be stronger) or negatively, in the case of management actions with negative externalities (e.g., large asset sales, cutting liquidity lines to various counterparts). These effects are not accounted for in our assessment of bank resilience in MFRAF. We are investigating the development of a new model that could take these effects into consideration.

5. Conclusion

Risk assessment models are an important component of the Bank's analytical tool kit to assess the resilience of the financial system. They provide rigour to the analysis of financial stability risks within a coherent, systematic and tractable framework.

FRIDA combines a model to quantify the impact of financial stability risks on the economy in a manner that considers the amplification effects associated with financial stress and sectoral models to quantify the impact of these risks on households, businesses and banks. This combination of a macro model and sectoral models allows us to understand the channels through which shocks could be transmitted and amplified within the financial system. Given model uncertainty, results obtained with FRIDA are used in combination with expert judgment to form overall assessments.

Modelling risk assessments of financial stability is a relatively new but dynamic field, with ongoing progress in the literature as well as in central banks and other authorities. Therefore, as we continue to enrich our models and tools to assess and quantify risks for the financial system, we will enhance FRIDA over time to expand our risk assessment.

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