Canadian Financial Stress and Macroeconomic Condition

THIBAUT DUPREY
Financial Stability Department, Bank of Canada, Ottawa, Ontario

I construct a new composite measure of systemic financial market stress for Canada. Compared with existing measures, it better captures the 1990 housing market correction and more accurately reflects the absence of diversification opportunities during systemic events. The index can be used for monitoring. For instance, during the coronavirus disease 2019 pandemic, it reached a peak second only to the 2008 global financial crisis. The index can also be used to introduce non-linear macro-financial dynamics in empirical macroeconomic models of the Canadian economy. Macroeconomic conditions are shown to deteriorate significantly when the Canadian financial stress index is above its 90th percentile.

Keywords: financial crisis, financial markets, financial stress index, threshold vector autoregressive model

Introduction

Extreme financial market stress around the coronavirus disease 2019 (COVID-19) pandemic and the associated real economic damages highlight the importance of gauging the extent of macro-financial spirals. I develop a new measure of financial market stress for Canada consistent with the narrative of stressful events and illustrate the role of financial stress as a non-linear propagation of shocks in the Canadian economy.

Periods of systemic financial stress are characterized by a sharp correction happening simultaneously on those key markets that provide the most important sources of funding to the Canadian economy. The Canadian financial stress index (CFSI) builds on the methodologies of Illing and Liu (2006), Hollo, Kremer, and Lo Duca (2012), and Duprey, Klaus, and Peltonen (2017). Using data from 1981 onward, I consider financial stress that spans seven market segments, namely the equity market, the Government of Canada bonds market, the foreign exchange market, the money market, the bank loans market, the corporate bonds market, and the housing market. The systemwide nature of financial stress is reinforced by combining correlation and importance weights. Correlation weights ensure that the index only picks up episodes when several markets are severely impaired at the same time. Importance weights ensure that the markets most important for the funding of the Canadian economy contribute more to the stress index. In other words, the index emphasizes the periods in which it is harder for investors and borrowers to substitute away assets that face market stress.

The innovation is twofold compared with the two existing measures of financial stress for Canada (Cardarelli, Elekdag, and Lall 2011; Illing and Liu 2006). First, they do not cover stress on the housing market, although it is a crucial source of shocks for the Canadian economy. Indeed, Canada experienced a major housing market correction in the 1990s. Because of its elevated imbalances, the housing market is an important source of concern for policymakers in Canada (International Monetary Fund 2017). Second, stress that is systemic is most likely to contribute
to macroeconomic downturns. Therefore, it is important to capture this systemic notion to accurately quantify the role of financial stress. Existing indexes are computed as the sum of stress on individual markets. However, this method ignores the correlation across market segments that occurs during systemic events. Using a portfolio analogy, the presence of correlated risks means that the risk of the portfolio is greater than the sum of the risk of the individual assets.

I capture this idea using a portfolio aggregation method: during systemic stress events, the CFSI is greater than the sum of stress on individual components. The CFSI can be useful for at least two purposes. First, it is a useful metric for benchmarking the intensity of financial stress against historical episodes. For instance, the stress associated with the COVID-19 pandemic reached a level comparable only to that of the 2008 global financial crisis. Second, financial market stress is often associated with non-linear macro-financial dynamics that can amplify negative shocks. Above its 90th percentile, the CFSI is typically associated with more fragile macroeconomic conditions in Canada. I illustrate how financial stress and worsening macroeconomic conditions amplify each other in the context of a Bayesian threshold vector autoregressive model (TVAR). The model explicitly relates episodes of high financial market stress, as signalled by the CFSI, to a deeper correction of gross domestic product (GDP).

In practice, the CFSI is part of the tool kit for the risk management framework of the Bank of Canada (Poloz 2020), allowing for an analysis of the state dependence of policy measures (Poloz 2016). The CFSI is an input to non-linear macro-financial models used to gauge risks, such as the risk amplification macroeconomic model (RAMM; Traclet and MacDonald 2018) and the growth at risk model (Duprey and Ueberfeldt 2020). Indeed, non-linear macro-economic models are becoming increasingly popular in an attempt to capture tail events by postulating the existence of different macroeconomic dynamics in periods of severe financial stress. In the context of a Bayesian TVAR, monetary policy has a more severe impact on output when financial conditions are tighter (see, for the United States, Balke 2000; for Canada, Li and St-Amant 2010). For the United Kingdom, Chatterjee et al. (2017) find support for a feedback loop between real and financial stress. Another strategy relies on a Markov-switching vector autoregressive model (VAR) in which the change in regime is driven by an unobserved Markov chain rather than an observable measure of financial stress, as in the Bayesian TVAR. For the United States, Hubrich and Tetlow (2015) show that regime changes into high financial stress coincide with known crisis episodes and are highly detrimental to real economic activity.

In the next section, I present the new CFSI. Next, I highlight the advantages of the CFSI over alternative measures and then the heightened macroeconomic costs associated with elevated financial market stress in Canada. The final section concludes.

**Measuring Financial Stress in Canada**

Financial stress is defined as simultaneous financial market turmoil among the most important asset classes and is reflected by (a) the uncertainty in market prices, (b) sharp corrections in market prices, (c) a widening of spreads, and (d) the degree of commonality across asset classes. Asset classes are split along several dimensions: equities or bonds, long-term assets or short-term commercial papers, and financial or real assets (e.g., housing), denominated in Canadian dollars or foreign currencies.

**Existing Tools and Limitations for Canada**

The construction of an index of financial market stress relies on three fundamental steps: collecting, aggregating, and back-testing measures of stress.

**Collecting Measures of Stress**

The most common set of data relies on equity prices, government bond yields, and exchange rates. A limited dataset such as the one used by Duprey et al. (2017) allows for the inclusion of more than 50 years of data while ensuring large cross-country comparability. However, some indexes that focus on specific countries embed much more data. For instance, the National Financial Conditions Index of the Federal Reserve Bank of Chicago (Brave and Butters 2011, 2012) includes more than 100 different time series of financial activity with varying frequencies, at the cost of a shorter time span. One major shortcoming common to most existing indexes is that they fail to directly capture developments in the housing markets. This is essential for Canada because one of the most stressful events occurred in the early 1990s, with a sharp correction to housing prices in Toronto and Vancouver. Likewise, this is a key concern in Canada moving forward because housing prices skyrocketed in Toronto and Vancouver in 2016–2017. One of the early contributions to this literature, Illing and Liu (2006), develops an index for Canada, but it excludes housing.

**Aggregating Measures of Stress**

Various aggregation methods can be used to combine individual stress into a stress composite (for a survey, see Kliesen, Owyang, and Vermann 2012). The main methods rely on (a) the loadings onto the first principal component (Brave and Butters 2011; Hakko and Keeton 2009; Kliesen and Smith 2010), (b) the relative weights of the different markets they represent (Illing and Liu 2006), (c) variance-equal weights for standardized components (Cardarelli et al. 2011; European Central Bank 2009), or (d) cross-correlations of the different sub-indexes (Hollo et al. 2012; Oet et al. 2011).

Principal-components analysis is the easiest method. It identifies the trend, common to all underlying data, to avoid “informationally redundant” data. However, interpreting the meaning of the common components
is not straightforward, even more so when allowing for time-varying factor loadings. Instead, simpler time-varying correlation weights allow for easy interpretation and decomposition of the contributing factors. In addition, systemic stress should not be limited to the summation of individual stress (Allen and Carletti 2013): this is the supra-additivity property of systemic tail risk. During stressful periods, the overall level of financial market stress would be larger than the sum of financial stress on its constituent markets as a result of risk that cannot be diversified away. Correlation weights are consistent with this approach and allow for an explicit decomposition between the systemic and non-systemic part of financial stress by isolating the contribution of correlated components. As a result, correlation weights are the method favoured in this article, although, similar to Illing and Liu (2006), I combine it with sectoral weights to account for the relative importance of different sectors over time.

**Back-Testing Measures of Stress**

Once a financial stress composite has been successfully built, its ability to contemporaneously signal known stress events should be back-tested. Simple measures of financial stress such as Duprey et al.’s (2017) Country-Level Index of Financial Stress (CLIPS) capture almost all of the known crises in Europe but also react to additional stress events that were deemed not stressful enough to unfold into a full-fledged crisis. To ensure the financial stress composite is a fair representation of the sequence of financial crises, the aggregation technique could be optimized to capture a limited list of expert-identified events. To that extent, Chatterjee et al. (2017) suggest using information weights to avoid redundant data and discount those that do not match the narrative of financial stress events. Unfortunately, these tools are of limited use in Canada, a country that, according to Laeven and Valencia (2013), never experienced a systemic banking crisis because its financial system was much more resilient to the 2008 global financial crisis (Huang and Ratnovski 2009). As a result, there is less guidance about what an index of financial stress should look like in Canada. Therefore, I build on a narrow set of indicators from Duprey et al. (2017) already back-tested on European data, and I compare the CFSI with a 2003 Bank of Canada survey of stressful events.

**Construction of the Canadian Financial Stress Index**

The current index of financial stress for Canada developed by Illing and Liu (2006) was optimized to fit stress events as of 2003 and does not include several important dimensions, such as housing or the supra-additivity property of systemic stress. Along seven market segments, the new monthly index combines 43 time series from 1981 onward (18 to measure market stress and 25 to measure market size), with some features from Duprey et al. (2017; market stress is supra-additive) and Illing and Liu (2006; each market is weighted by quantities). The construction of the CFSI is represented in Figure 1.3

**Seven Different Market Segments**

The proposed CFSI is composed of measures of financial stress that capture seven different markets. The parsimonious nature of the dataset—I use 18 time series to compute 19 stress indicators covering more than seven markets—ensures that I capture different aspects of similar stress periods without having too much redundant information (see Table A.1 in Appendix A for more details). In addition to the equity (EQU), government bonds (GOV), and foreign exchange (FOR) markets, captured in a way very similar to that of Duprey et al. (2017), I consider the money market (MON), the bank loans market (BAN), the corporate sector (COR), and the housing sector (HOU).

Stress $s_{t,m}$ on each market segment $m = \{EQU, GOV, FOR, MON, BAN, COR, HOU\}$ is captured by the average of two $(I = 2)$ or three $(I = 3)$ raw stress measures $r_{t,m,i}$ that are transformations of the data—realized volatilities, interest rate spreads, or variations compared with a local maximum or minimum. Indeed, financial stress can be characterized by larger volatilities, widening spreads over the risk-free rate, or price corrections for large assets. I mostly use simple transformations but include a more complex measure, such as the distance to default, which is a standard measure of systemic banking risk, averaged over all Canadian financial institutions (MacDonald, Van Oordt, and Scott 2016).

The different raw stress indicators $r_{t,m,i}$ do not have the same unit, so an additional normalization is required before aggregating them into the seven market stress components $s_{t,m}$. Each raw stress indicator is normalized to lie in $[0; 1]$ by using the empirical cumulative distribution (rank) over an expanding window (see, e.g., Duprey et al. 2017; Hollo et al. 2012).

New data are normalized against historical data in a recursive manner.

Stress on each market segment is computed as the average of the $I$ raw stress indicators $r_{t}$ for this market:

$$s_{t,m} = \frac{1}{I} \sum_{i=1}^{I} \text{rank}_{[0,1]}(r_{t,m,i}).$$

Stress on each market segment is displayed in Figure 2. Equity market stress is high during the stock market crash of October 1987, the burst of the dot-com bubble in the 2000s, and the 2008 global financial crisis. Stress on the government bonds market is the highest during the 1980s and early 1990s, when government debt was higher and Canada experienced two downgrades, in October 1992 by Standard & Poor’s and in February 1995 by Moody’s. Moody’s further downgraded Canada in April 2000, but it was quickly followed by better ratings from all three main rating agencies in the 2000s. Stress on the corporate bonds market was also high during the 1990s and in 2015 with the
Figure 1: Construction of the Canadian Financial Stress Index

Notes: Stress on each market segment corresponds to the average of two or three stress measures described in Table A.1 in Appendix A and normalized using the empirical cumulative distribution over a backward-expanding window, starting with a fixed window until 1991 (i.e., 10 years since the start of the index in 1981). A–BBB = difference in the yield of A-rated and BBB-rated corporate bonds.

Source: Author.

For market segments $m \neq m'$, the covariances $\sigma_{t,m,m'}$, volatilities $\sigma_{t,m}^2$, and correlations $\rho_{t,m,m'}$ are computed using an exponentially weighted moving average (EWMA) method:

$$\sigma_{t,m,m'} = \lambda \sigma_{t-1,m,m'} + (1 - \lambda)(\sigma_{t,m} - 0.5)$$

$$\sigma_{t,m}^2 = \lambda \sigma_{t-1,m}^2 + (1 - \lambda)(\sigma_{t,m} - 0.5)^2$$

$$\rho_{t,m,m'} = \frac{\sigma_{t,m,m'}}{\sigma_{t,m} \sigma_{t,m'}}.$$ 

The EWMA method is computed pairwise and is a simpler alternative to a multivariate GARCH that would require the estimation of a larger number of parameters. Optimizing over a cross-country dataset of 27 European financial stress indexes, Duprey et al. (2017) found that a smoothing parameter $\lambda = 0.85$ generates a monthly financial stress index that is closest to a multivariate GARCH. Therefore I also choose $\lambda = 0.85$, which strikes a balance between the stability of the estimate and the ability to include new observations. The time-varying cross-correlation matrix $C_t$ combines all pairwise correlation coefficients $\rho_{t,m,m'}$.

Supra-Additive Aggregation Method

Similar to Hollo et al. (2012) or Duprey et al. (2017), I aggregate the different market segments by relying on a portfolio theory approach that weights each sub-index $s_{t,m}$ by its cross-correlation $\rho_{t,m,m'}$ with the others, where $m' \neq m$. By aggregating correlated sub-indexes, I show that the resulting index reflects increased systematic risk as a result of a stronger co-movement across market segments. In contrast, less correlated market segments result in a lower composite index because the risk can be diversified away across market segments.

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doi:10.3138/cpp.2020-047

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The cross-correlations are presented in Figure 3. During stressful periods, around 1990, 1998, 2008, and 2015, cross-correlations tend to be positive. This means that there is little room for hedging across market segments. Most market segments tend to co-move, which is a key characteristic of systemic stress. In particular, the median pairwise correlation across market segments started to increase from extremely low levels in 2003 and peaked in 2008.

**Time-Varying Importance Weights**

Consistent with Illing and Liu (2006), I also weight each market segment \(m\) by its size in the overall Canadian economy \(\omega_m\). For instance, the growing volume of residential mortgage loans should be reflected by a higher importance of housing market stress in the overall financial stress composite. Each market segment is weighted by the volume of lending it is associated with as a proportion of total lending (Table A.2).

The equity market is weighted using equity finance by Canadian businesses. The government bonds market is weighted using the amount of outstanding government bonds with medium- to long-term maturities issued in Canadian dollars by the different levels of government. The foreign exchange market is weighted by the amount of funding for governments and corporations denominated in foreign currencies (loan, securities, or bonds). The money market is weighted by the amount of short-term commercial papers issued in Canadian dollars by corporations and treasury bills issued in Canadian dollars by the different levels of government. The banking sector is weighted by the amount of business or consumer loans issued in Canadian dollars by chartered banks, excluding residential mortgages. The corporate bonds market is weighted by the amount of medium- to long-term bonds and debentures issued by Canadian businesses in Canadian dollars. Finally, the housing market is weighted by the amount of residential mortgages held on balance sheets by financial institutions, including chartered banks, credit unions, mortgage credit companies, and financial trusts.

Figure 4 displays the evolution of the weights of each market segment over time \(w_t = [w_t, LEDU, w_t, GOV, w_t, FOR, w_t, BAN, w_t, HOU, w_t, COR, w_t, MON]\).

### Overall Financial Stress Index

The financial stress composite is as follows:

\[
CFSI_t = (w_t \odot s_t) \cdot C_t \cdot (w_t \odot s_t)'
\]

(5)

where \(w_t\) is the 1 × 7 vector of market segment weights with \(\sum w_{m,t} = 1\); \(s_t\) is the 1 × 7 vector of standardized stress bounded in \([0, 1]\) for each market segment \(m\); \(\odot\) denotes the element-wise multiplication such that \(w_t \odot s_t\) is also a 1 × 7 vector; \(C_t\) is the 7 × 7 time-varying matrix of cross-correlation among all pairs of market segments. As a result, the CFSI is also bounded on \([0, 1]\).

**The Canadian Financial Stress Index Contemporaneously Signals Known Stressful Events**

Next, I compare episodes of high financial stress with the narrative of episodes of financial stress in Canada.

### The Canadian Financial Stress Index Compared with a Narrative of Stressful Events

Figure 5 shows the contribution of each market segment to the CFSI. It emphasizes the role of cross-correlations in identifying episodes of heightened financial stress. Cross-correlations are represented by the white area below the black CFSI line. The index can be extended backward to start as early as 1964, but with more limited data (see Appendix B).

The peaks of the CFSI coincide very well with known events of financial stress. The main spikes of financial stress, namely 1982, 1990, and 2008, coincide with periods of recessions and corrections in industrial production and housing prices. The decomposition of financial stress shows that 1982 was driven by the housing, banking, equity, and money markets; 1990 was driven by the housing, money, and government bonds markets; and 2008 was driven by the banking, housing, money, and equity markets. In March 2020, during the COVID-19 pandemic, the CFSI had the strongest one-month increase, reaching a peak second only to the 2008 global financial crisis.

However, it is worth noting that financial market stress does not always bring macroeconomic underperformance, and macroeconomic underperformance does not always yield severe financial market stress. For instance, the
Figure 2: Normalized Stress on Each Market Segment: (a) Equity Market (EQU), (b) Government Bond Market (GOV), (c) Foreign Exchange Market (FOR), (d) Money Market (MON), (e) Banking Market (BAN), (f) Corporate Bonds Market (COR), and (g) Housing Market (HOU)

Notes: Stress on each market segment corresponds to the average of two or three stress measures described in Table 2 and normalized using the empirical cumulative distribution. Vertical bars for the government bonds market display downgrades and upgrades by rating agencies.

Source: Author’s calculations.
banking crisis of 1985–1986 with the bailout of the Canadian commercial banks and the liquidation of Northland Bank of Canada did not trigger a recession. This regional banking crisis did not spill over to the rest of the economy, in part thanks to the actions of the Bank of Canada and federal authorities. The default of Russia and associated collapse of LTCM in 1998 triggered an international financial market shock, with limited consequences for the Canadian real economy. The oil price shock of 2015 triggered a recession in Canada, with higher financial market stress driven by the corporate sector, but the disruption to the financial system was limited.

**Visual Inspection of the Canadian Financial Stress Index against Alternative Metrics**

Next, I compare the CFSI with alternative financial stress measures for Canada (Figure 6). Simple measures of financial stress usually capture stress in one specific segment of the market. The corporate bond spread in Figure 6a is sometimes used in the absence of financial stress composites. It signals well the 1982 and 2008 crises as well as the 2015 oil price shock. However, it does not signal well other events occurring more specifically in the banking sector (1985–1986) or in the housing market (1990). Alternatively, the volatility index in Figure 6b is a broader measure of financial market stress related to overall stock market volatility. As such, it places more emphasis on the stock market corrections, such as Black Monday in 1987, the Asian crisis of the late 1990s, and the burst of the dot-com bubble in the 2000s. The Senior Loan Officer Survey (Figure 6c) reports the change in domestic credit conditions for business loans from 1999 onward. It does not reflect the possibility of arbitrage between bank loans and market finance and does not include consumer loans or mortgage lending.

**Figure 3:** Pairwise Correlation among All Pairs of Market Segments: (a) Minimal, Maximal, and Median Correlation and (b) Pair-Wise Correlations at Each Point in Time

Notes: The left panel shows the minimum and maximum value at each point in time of all pairwise correlations (dashed lines) and the median pairwise correlation (solid blue line [solid black line in print]). The right panel shows the full set of 42 pairwise correlations.

Source: Author’s calculations.
Two indexes of financial stress are already available for Canada. The Illing and Liu (2006) index was constructed before the 2008 global financial crisis to coincide with pre-2008 stressful events specifically for Canada (Figure 6f). Cardarelli et al.’s (2011) index is available until 2010 for several countries, including Canada (Figure 6g). In addition, I report the CLIFS measure of Duprey and Klaus (2017), who expand the work of Duprey et al. (2017) to other non-European countries (Figure 6h). This last index is reported for the sake of comparison because the CFSI, although more complete, shares many similarities.8 None of these alternative indexes for Canada include housing...
Figure 5: The CSFI: Known Stressful Events in Canada

Notes: The black line is the CFSI. The colours (online version only) refer to the contribution of each market segment, as in Figure 1. The white area below the black line corresponds to the contribution of the cross-correlations across market segments. The list of events for the upper chart is as follows: (1) spike in interest rates; (2) Mexican debt crisis; (3) bailout of the Canadian commercial banks; (4) liquidation of Norland bank; (5) Black Monday; (6) start of the Vancouver housing crisis; (7) downgrade by Standard & Poor’s; (8) Mexican crisis and bailout package; (9) downgrade by Moody’s; (10) Russian default and Long-Term Capital Management bailout; (11) losses after the burst of the dot-com bubble; (12) 11 September 2001 terrorist attack in the United States; (13) start of the subprime crisis; (14) collapse of Lehman Brothers; (15) Greek bailout; (16) taper tantrum; (17) oil price (WCS) falls below $40; (18) oil price (WCS) falls below $20; and (19) coronavirus disease 2019 crisis.

The CFSI can be extended backward to 1964 but with less data; see Appendix B. The lower chart displays crisis episodes. Laeven and Valencia (2013) and Reinhart and Rogoff (2011) identify crises of different types (banking, equity, currency). House price corrections correspond to periods characterized by more than 10 percent year-over-year drop in real housing prices from peak to trough. Industrial production drops correspond to drops in the seasonally adjusted index of industrial production of at least six months, possibly intertwined with one month of positive growth. Recessions are defined by at least two quarters of negative real output growth. CSFI = Canadian financial stress index; WCS = Western Canadian Select.

Source: Author’s calculations.

Stress. The last one encompasses only a very limited set of inputs, and the first two do not satisfy the property of subadditivity of systemic financial stress. In addition, Illing and Liu’s (2006) index emphasizes the 1998 LTCM collapse as the most important financial stress event for Canada. This event was deemed to be somewhat stressful for the Canadian financial markets in a survey conducted by the Bank of Canada in 2003, but the magnitude of stress appears at odds with that of the 2008 global financial crisis. The CFSI correlates most with of Cardarelli et al.’s (2011) index.

Statistical Coherence of Financial Stress Composites

Finally, Table 1 compares the ability of the different financial stress indexes to contemporaneously signal episodes of financial stress. I consider the same list of financial stress episodes used by Illing and Liu (2006) when backtesting the validity of their index. They relied on a 2003 survey of 40 senior policy-makers and economists who were asked to identify the main financial stress events. In the absence of banking or financial crises reported for Canada, this survey—to which I add the stress episodes that have occurred since 2003—is the main source of external validation.

I assess the contemporaneous ability of the various indexes to signal the known stress events, not their ability to send early warnings. Financial stress indexes do not usually contain early warning properties to signal subsequent financial stress beyond what is already included in market prices. Financial stress indexes merely act as a thermometer of the intensity of financial stress at a given
Figure 6: Comparison with Alternative Financial Stress Indexes: (a) corporate bond spread; (b) VIX; (c) SLOS; (d) first principal component; (e) top five principal components; (f) Illing and Liu (2006); (g) Cardarelli, Elekdag, and Lall (2011); and (h) Duprey and Klaus (2017).

Notes: The CFSI is displayed in blue (black in print), left scale. The alternative index is displayed in dashed red (right scale, if the unit is different). The SLOS is a quarterly publication of the Bank of Canada that surveys senior loan officers on the change in credit conditions compared with the previous quarter. It reflects the number of weighted respondents reporting a tightening (positive number) or a loosening (negative number), but it does not reflect the magnitude of the tightening. The VIX is a proxy for overall risk aversion on the global markets. The principal-components analysis is conducted on the same normalized input as those used in the CFSI. I report either the first principal component or the average of the top five principal components. Combining the top five components yields better results in terms of the area under the receiver operating characteristic curve or Type 1 or Type 2 errors to get the peaks to contemporaneously signal known stress events, whereas combining the other top four components only yields a worse outcome. VIX = volatility index; SLOS = Senior Loan Officer Survey; CFSI = Canadian financial stress index.

Source: Author’s calculations, Bank of Canada; Cardarelli, Elekdag, and Lall (2011); Duprey and Klaus (2017); Illing and Liu (2006).
When restricted to the period from 1981 to 2003 used by Illing and Liu (2006; first set of rows in Table 1), the CFSI performs best in terms of contemporaneous identification of stress events, according to both the AUROC and the partial AUROC. For balanced preferences ($\mu = 0.5$) or preferences slightly biased toward an aversion to missing crises ($\mu = 0.6$) or an aversion to false signals ($\mu = 0.4$), the CFSI also performs best. When the most recent periods are added, including the 2008 global financial crisis and the 2015 oil price shock or the 1990 housing crisis (not identified in the 2003 survey), the CFSI performs better than other indexes (second set of rows). Similarly, when I exclude the 1998 and 2000 stress events that were ranked as only somewhat stressful in the survey, the CFSI performs best across all metrics (last set of rows). This is mostly because the CFSI identifies those events as being mostly driven by stress on the equity market, not by overall financial stress.

Figure 7 displays the receiver operating characteristic (ROC) curves of the different financial stress indexes. This is a visual representation of the ability of the stress indexes to contemporaneously signal the sequence of stress events referred to in the last set of rows of Table 1. The ROC of the CFSI shows that the CFSI always delivers a lower missed events rate than alternative stress indexes for any given false signal rate. The ROC curves of other indexes do not get as close to the top left corner of the chart, meaning that they tend to misclassify more expert-identified stress events, whatever the preference for Type 1 or Type 2 errors.

Last, I briefly compare the fit of the CFSI with the fit of various principal components. The ability of the principal components to contemporaneously identify the financial stress events in Canada is worse for any principal component taken individually compared with the CFSI (Table D.1 in Appendix D). From the sixth component onward, the AUROC is very close to 0.5, such that it is no better than a random guess. Combining principal components together can slightly improve the fit compared with the CFSI, but only when including the first and the fifth components, whereas the second, third, and fourth components deteriorate the fit. It suggests that the first and the fifth components may both reflect some aspect of the Canadian financial stress history, possibly one that emphasizes faster-moving variables that peak around 2008 and the COVID-19 crises and one that emphasizes the slower moving variables related to the housing market peak in the 1990s. However, the principal-components
**Table 1:** Ability of the Financial Stress Indexes to Contemporaneously Signal Known Stressful Events

| Financial Stress Index                        | Until 2003: Illing and Liu’s (2006) dates | $\mu = 0.5$ | $\mu = 0.6$ | $\mu = 0.4$ |
|-----------------------------------------------|-------------------------------------------|-------------|-------------|-------------|
| CFSI                                          | 0.85<sup>a</sup>                          | 0.79<sup>a</sup> | 0.31        | 0.10        | 0.59<sup>a</sup> | 0.23        | 0.18<sup>a</sup> | 0.47<sup>a</sup> | 0.42<sup>a</sup> | 0.01<sup>a</sup> | 0.57<sup>a</sup> |
| FSI of Illing and Liu (2006)                  | 0.83                                      | 0.74        | 0.31        | 0.18        | 0.51        | 0.06        | 0.48        | 0.43        | 0.55        | 0.01        | 0.44        |
| FSI of Cardarelli et al. (2011)               | 0.78                                      | 0.72        | 0.47        | 0.04        | 0.49        | 0.34        | 0.21        | 0.27        | 0.47        | 0.04        | 0.47        |
| CLIFS of Duprey et al. (2017)                 | 0.64                                      | 0.60        | 0.09        | 0.68        | 0.23        | 0.05        | 0.74        | 0.19        | 0.66        | 0.14        | 0.13        |
| Illing and Liu’s (2006) dates + 2008 global financial crisis + 2015 oil price shock + 1990 housing market correction | CFSI                                       | 0.82<sup>a</sup> | 0.76<sup>a</sup> | 0.26        | 0.24        | 0.51<sup>a</sup> | 0.24        | 0.26        | 0.38<sup>a</sup> | 0.44        | 0.08<sup>a</sup> | 0.44<sup>a</sup> |
|                                               | FSI of Illing and Liu (2006)              | 0.75        | 0.74        | 0.38        | 0.24        | 0.38        | 0.05        | 0.60        | 0.33        | 0.46        | 0.17        | 0.29        |
|                                               | FSI of Cardarelli et al. (2011)           | 0.75        | 0.73        | 0.41        | 0.12        | 0.47        | 0.36        | 0.19        | 0.27        | 0.41        | 0.12        | 0.41        |
|                                               | CLIFS of Duprey et al. (2017)             | 0.73        | 0.67        | 0.11        | 0.52        | 0.37        | 0.11        | 0.52        | 0.31        | 0.63        | 0.11        | 0.21        |
| Illing and Liu’s (2006) dates + 2008 global financial crisis + 2015 oil price shock + 1990 housing market correction – LTCM crisis – dot-com bubble burst | CFSI                                       | 0.86<sup>a</sup> | 0.82<sup>a</sup> | 0.17<sup>a</sup> | 0.27        | 0.57<sup>a</sup> | 0.17        | 0.27<sup>a</sup> | 0.48<sup>a</sup> | 0.38<sup>a</sup> | 0.09<sup>a</sup> | 0.47<sup>a</sup> |
|                                               | FSI of Illing and Liu (2006)              | 0.74        | 0.75        | 0.41        | 0.19        | 0.41        | 0.05        | 0.64        | 0.28        | 0.41        | 0.19        | 0.32        |
|                                               | FSI of Cardarelli et al. (2011)           | 0.74        | 0.73        | 0.48        | 0.10        | 0.42        | 0.15        | 0.54        | 0.23        | 0.48        | 0.10        | 0.37        |
|                                               | CLIFS of Duprey et al. (2017)             | 0.72        | 0.69        | 0.17        | 0.5         | 0.33        | 0.12        | 0.55        | 0.27        | 0.62        | 0.13        | 0.19        |

Notes: This table provides summary statistics that show how well different Canadian financial stress indexes contemporaneously signal the stressful events identified in the 2003 survey used in Illing and Liu (2006). It consists of the following events: August 1981 spike in interest rates, Latin American debt crises (early 1980s), Canadian commercial bank and Northland failures (1985), October 1987 stock market crash, early 1990s bank losses, Mexican crisis (1994–1995), Asian crisis (1997–1998), Russian debt default and LTCM bailout (1998), the burst of the dot-com bubble (2000), and terrorist attacks of 11 September 2001. Most respondents assessed the 1998 and 2000 events as only somewhat stressful. For other rows in the table, as robustness, additional events are either added or removed. AUROC is associated with an informative signal when it is above 0.5, whatever the preferences of the regulator. pAUROC is restricted to assess the informativeness of a signal under a subset of preferences of the regulator, in the range $\mu = [0.3; 0.7]$. $\mu$ is the cost associated with $T1$ (i.e., the share of missed crises). Conversely, $1 - \mu$ is the cost associated with $T2$ (i.e., the share of false signals). A higher $\mu$ is associated with an aversion to missing crises (thus a lower $T1$). When computing the different measures, the 12 months after a stressful event are removed unless another stressful event starts during this period. Otherwise, the assessment could be biased by the behaviour of the stress indexes during the recovery period. AUROC = area under the receiver operating characteristic curve; pAUROC = partial area under the receiver operating characteristic curve; T1 = Type 1 error; T2 = Type 2 error; U = usefulness indicator of Alessi and Detken (2011) that measures the signal’s ability to be informative under certain preferences $\mu$; CFSI = Canadian financial stress index; FSI = financial stress index; CLIFS = Country-Level Index of Financial Stress; LTCM = Long-Term Capital Management.

The best metric in favour of the CFSI.

Source: Author’s calculations.

Analysis does not allow for an easy interpretation of the components and uses constant factor loadings, such that I prefer to use the approach that relies directly on time-varying correlation weights.

**Financial Stress and Its Macroeconomic Impact**

In the previous sections, I described a new index of financial stress for Canada that improves on the existing measures. However, the reason economists care about financial stress is that it tends to be associated with a negative economic outcome. Figure 8 shows that high levels of financial stress above the 90th quantile of the CFSI are associated with negative real GDP growth. In this section, I provide a simple framework to illustrate the negative relationship between financial stress and economic growth.

**A Simple Threshold Vector Autoregressive Model**

A Bayesian TVAR model allows for macroeconomic dynamics to differ across regimes, identified by the level of an observed threshold variable. I use the CFSI as the threshold variable to make an explicit link between macroeconomic

doi:10.3138/cpp.2020-047 © Bank of Canada / Banque du Canada, October / octobre 2020
Figure 7: Receiver Operating Characteristic Curves for the Different FSIs

Notes: This figure displays the non-parametric ROC curves computed for all four Canadian financial stress indexes. It summarizes the ability of each FSI to contemporaneously signal the periods identified by experts as being stressful for the Canadian economy (a survey of economists conducted in 2003). When the curve gets closer to the top-left corner, it means that the peaks of the FSI coincide more with Canadian crises. Conversely, when the curve gets closer to the 45-degree line, it means that the peaks of the FSI do not coincide with the Canadian crises (the odds of the peaks of the FSI lining up with the crises is just a coin flip). The blue line represents the Canadian FSI presented in this article. The red dashed line represents Illing and Liu’s (2006) index. The black crosses refer to Duprey et al.’s (2017) Country-Level Index of Financial Stress. The green squares represent the ROC for Cardarelli et al.’s (2011) index. FSI = financial stress index; ROC = receiver operating characteristic.

Source: Author’s calculations.

The model is estimated on monthly data from December 1981 to December 2019. It includes the seasonally adjusted annualized growth rate of real GDP ($gGDP_t$), the seasonally adjusted annualized Consumer Price Index (CPI) inflation rate ($gCPI_t$), the three-month treasury bill rate ($R_t$), and the proposed measure of financial stress ($CFSI_t$). Defining the vector of endogenous variables $Y_t = [gGDP_t, gCPI_t, R_t, CFSI_t]$, the Bayesian TVAR with $P$ lags and a constant $\mu$ is

$$Y_t = \mu + \sum_{p=1}^{P} \left( \Gamma_p Y_{t-p} \right) + \Theta S_t \varepsilon_t.$$  

(6)

The Bayesian TVAR model distinguishes between periods with significantly different macroeconomic elasticities ($\beta_p$) that depend on the state of the economy $S_t \in \{L;H\}$. The state of the economy is defined as being in a low (or high) financial stress regime if the CFSI is below (or above) an estimated percentile $\tau$ of the CFSI, possibly lagged by $d$ periods. The Bayesian TVAR model can be thought of as a set of two VARs conditional on being above or below the cut-off level of financial stress $\tau$.

$$S_t \begin{cases} 
L, & \text{if } CFSI_{t-d} < \tau; \\
H, & \text{if } CFSI_{t-d} \geq \tau.
\end{cases}$$  

(7)

The Bayesian TVAR model is estimated with Bayesian techniques, following Bruneau and Chapman (2017). The CFSI is normalized using its minimal and maximal value so that it lies between 0 and 1, and the prior for the threshold variable can be modelled as a gamma distribution. The estimation of the threshold requires at least 10 percent of the observations in the high-stress regime to have a meaningful estimation of the macroeconomic dynamics in the high-stress regime. The regime-specific decomposition $\Theta^s$ of structural shocks $\varepsilon_t^s$ is the Cholesky matrix with the same order as in $Y_t$. I choose a model specification with three lags $P = 3$ and one delay $d = 1$, as suggested by the information criterion.

The log-likelihood of the Bayesian TVAR is highest for a cut-off level of financial stress $\tau$ in the 85 to 90 percent range. This means that episodes of high financial stress correspond mainly to the 2008 global financial crisis and the correction in housing prices in Toronto and Vancouver around 1990. Policy-makers should then be concerned when the CFSI is above its 90th percentile.
because the economy moves to a regime with amplified elasticities.

**Financial Stress Episodes Damage the Real Economy**

**Negative Real Shocks Increase Financial Stress**

*Figure 9* shows the impact of a real shock on GDP growth. It is more persistent in the high-stress regime and is associated with a larger increase in the CFSI. If a linear VAR is estimated instead, the two regimes of high and low financial stress are combined, and the impact of real shocks on the CFSI is diluted (black line).

**Positive Financial Stress Shocks Worsen Gross Domestic Product**

*Figure 10* shows the impact of a financial stress shock. It has a more persistent negative impact on real GDP growth in the high-stress regime. In the case of a linear VAR, the negative impact of financial stress shocks on real GDP growth may be underestimated (black line).

**Combination of the Regime Change and Financial Stress Shocks Act as an Amplification Mechanism**

*Figure 11* shows counterfactuals around two major episodes of financial stress: the housing market crash of the 1990s and the 2008 global financial crisis. I hold the policy rate at its historical value. I compute three counterfactuals and, together with the realized data, I obtain four cases: with or without financial stress shocks and with or without a transition from the low- to the high-stress regime. In all counterfactuals, real GDP would have been significantly higher. This suggests that financial stress has the greatest negative impact on GDP growth when there is a combination of financial stress shocks and a change to the high-stress regime. Financial stress shocks are an important source of concern for the macroeconomy mostly when they are amplified in the high-stress regime.15

**Conclusion**

I construct a CFSI that captures the intensity of financial market turmoil in Canada that spans seven market segments. The index emphasizes the periods in which it is harder for investors and borrowers to substitute away assets that face market stress.

The innovation is twofold compared with the existing measures of financial stress. First, I include stress on the housing market. This is a crucial source of shocks for Canada—for instance, around the housing market correction of 1990. Second, compared with the two existing measures of financial stress for Canada (Cardarelli et al. 2011; Illing and Liu 2006), I capture the co-movement across market segments, which tends to be stronger during systemic events. Those improvements lead to an index

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*Figure 8: Real GDP Growth per Quantile of CFSI*

Notes: The figure displays the average year-over-year GDP growth per quantile of the CFSI. It excludes the post-crisis periods (two quarters after each recession) because GDP growth and the CFSI may have different recovery speeds that would blur the relationship between increasing levels of financial stress and economic downturns. GDP = gross domestic product; CFSI = Canadian financial stress index; FSI = financial stress index.

Source: Author’s calculations.
that better aligns with known episodes of financial stress in Canada.

The CFSI can be helpful for at least two purposes. First, it helps benchmark the intensity of financial stress against historical episodes. Second, financial market stress is often associated with non-linear macro-financial dynamics that can amplify negative shocks. Above its 90th percentile, the CFSI is typically associated with more fragile macro-economic conditions in Canada. I illustrate how financial stress and worsening macroeconomic conditions amplify each other in the context of a Bayesian TVAR. The model explicitly relates episodes of elevated financial market stress, as reflected by the CFSI, with a deeper correction of GDP.

The results suggest that using financial stress indexes to signal rapidly deteriorating financial conditions can be useful to better capture the deterioration of macro-economic conditions when tail events materialize. Thus, the CFSI is included in either the RAMM (Traclet and MacDonald 2018) or the growth-at-risk model (Duprey and Ueberfeldt 2020), two models used in the risk management framework of the Bank of Canada (Poloz 2020) to weight risks to the outlook. Assessing macro-financial risks and their real economic implications is especially relevant in the context of the COVID-19 pandemic, during which financial stress reached levels comparable only to the 2008 global financial crisis.

Acknowledgements
I thank Gabriel Bruneau, Greg Tkacz, and Kerem Tuzcuoglu for their comments as well as seminar participants at

Figure 9: Impulse Response Function: Demand Shock: (a) Real GDP and (b) CFSI
Notes: The figure displays the response to an increase in the annualized real GDP growth by 1 percent. The black line corresponds to the median response in a linear VAR. The red dashed (or blue dotted) line corresponds to the median response in the threshold VAR when the economy is in the high-stress (or low-stress) regime. The bootstrapped confidence bands correspond to the one-standard-deviation confidence bands. GDP = gross domestic product; CFSI = Canadian financial stress index; VAR = vector autoregression.
Source: Author’s calculations.

Figure 10: Impulse Response Function: Canadian Financial Stress Shock: (a) Real GDP and (b) CFSI
Notes: The figure displays the response to an increase in the CFSI by 0.1. The black line corresponds to the median response in a linear VAR. The red dashed (or blue dotted) line corresponds to the median response in the threshold VAR when the economy is in the high-stress (or low-stress) regime. The bootstrapped confidence bands correspond to the one-standard-deviation confidence bands. GDP = gross domestic product; CFSI = Canadian financial stress index; VAR = vector autoregression.
Source: Author’s calculations.
Figure 11: Counterfactuals around the 1990 Housing Crisis: (a) Real GDP, (b) CFSI, and Counterfactuals around the 2008 Global Financial Crisis: (c) Real GDP, and (d) CFSI

Notes: Each row of the figure displays historical data (solid lines) and counterfactuals (other lines) around the stress events of 1990 and 2008 while still following the historical path for monetary policy. The three counterfactuals start after one year and are recovered from the estimated threshold VAR with a Cholesky decomposition of the shocks. The figure shows a counterfactual without the financial stress shocks (dashed red), a counterfactual with the same financial stress shocks but without regime change (dotted black), and a counterfactual without the financial stress shocks but with regime change as in the data (black asterisks). The horizontal black line in the right panels corresponds to the estimated threshold above which the economy falls into a regime of high financial stress with different macroeconomic elasticities. Real GDP is normalized to be 0 at the beginning of the period considered. GDP = gross domestic product; CFSI = Canadian financial stress index; VAR = vector autoregression.

Source: Author’s calculations.

the Bank of Canada and the 2018 Canadian Economic Association Congress in Montreal. I also thank Gabriel Bruneau for sharing his Matlab codes on the Bayesian TVAR model and Michal Lipsitz, who provided excellent research assistance. The views expressed in this article are my own and do not necessarily reflect the views of the Bank of Canada.

Notes
1 The April 2020 Monetary Policy Report (Bank of Canada 2020, Chart 9) features the CFSI.
2 For instance, in the Canadian case, one could consider daily payments data (e.g., cards; Galbraith and Tkacz 2013), data on bankruptcies (Allen and Basiri 2018), or data from consumer credit rating agencies (Kartashova and Zhou 2020).
3 The index can also be computed at a higher frequency (e.g., weekly), with additional assumptions: some variables need to be interpolated, and instead of using realized volatilities, one may instead use a generalized autoregressive conditional heteroskedasticity (GARCH) model to ensure more stability of the estimate at a higher frequency.
4 These transformations aim to capture the evolution of risks in key Canadian markets, but they also partly reflect the evolution of global risk premium to which Canada is largely exposed as a small, open economy (Bauer et al. 2018).
5 Because high values are associated with more stress, most of the raw indicators are right-skewed. The use of ordinal ranking therefore implies that the relative magnitude of the stress events during periods of high stress is lost. In the meantime, there are fewer data points with very large stress, and it may be harder to find an appropriate benchmark without looking at other data points in the same neighbourhood of the quantile distribution rather than looking at the actual distribution. However, the alternative—for instance, normalizing using variance-equal weights—is less robust to outliers with large values.
6 The index is robust to using a backward-expanding window,
a rolling window, or the whole sample to normalize the data.  

7 The covariance and volatilities are initialized at their long-run average. Figure C.1 in Appendix C displays an alternative CFSI when using a different λ parameter or when computing a multivariate GARCH.

8 I can back-cast the CFSI with fewer time series to start in 1964 instead of 1981, ultimately getting close to the few time series used in Duprey and Klaus (2017) since 1964.

9 For more details on the AUROC, see, for example, Fawcett (2006) for a technical overview and Schularick and Taylor (2012) for an application to crisis identification.

10 It is also standard to use the noise-to-signal ratio of Kaminsky, Lizondo, and Reinhart (1998). However, the ratio implicitly embeds a given trade-off between noise and signal. It can lead to counterintuitive results depending on the relative variation of the numerator or denominator. Therefore, I do not use this less robust method.

11 This simple approach is consistent with the quantile regression framework of Adrian, Boyarchenko, and Giannone (2019) for the United States or Duprey and Ueberfeldt (2020) for Canada.

12 In the beginning of the sample, no monthly GDP measure is available for Canada. I use the quarterly GDP measure spliced with the monthly seasonally adjusted index of industrial production. Similar results are obtained when using the monthly seasonally adjusted annualized growth rate of industrial production. Similar results are obtained when using a rolling window, or the whole sample to normalize the data.

13 Similar results would be obtained with a signs restriction.

14 The assumption of the absence of thresholds can be rejected: in the beginning of the sample, no monthly GDP measure is available for Canada. I use the quarterly GDP measure spliced with the monthly seasonally adjusted index of industrial production. Similar results are obtained when using a rolling window, or the whole sample to normalize the data.  

The covariance and volatilities are initialized at their long-run average. Figure C.1 in Appendix C displays an alternative CFSI when using a different λ parameter or when computing a multivariate GARCH.

15 This holds true for different lags or different delay parameters.

References

Adrian, T., N. Boyarchenko, and D. Giannone. 2019. “Vulnerable Growth.” American Economic Review 109(4):1263–89. https://doi.org/10.1257/aeqar.20161923.

Alessi, L., and C. Detken. 2011. “Real Time Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity.” European Journal of Political Economy 27(3):520–33. https://doi.org/10.1016/j.ejpe.2011.01.003.

Alessi, L., and C. Detken. 2014. “On Policymakers’ Loss Functions and the Evaluation of Early Warning Systems: Comment.” Economics Letters 124(3):338–40. https://doi.org/10.1016/j.econlet.2014.06.015.

Allen, F., and E. Carletti. 2013. “What Is Systemic Risk?” Journal of Money, Credit and Banking 45(1):121–27. https://doi.org/10.1111/jmcb.12038.

Allen, J., and K. Basiri. 2018. “Impact of Bankruptcy Reform on Consumer Insolvency Choice.” Canadian Public Policy/Analyse de politiques 44(2):100–11. https://doi.org/10.3138/cpp.2017-055.

Baba, Y., R.F. Engle, D. Kraft, and K.F. Kroner. 1985. “Multivariate Simultaneous Generalized ARCH.” Unpublished manuscript, Department of Economics, University of California, San Diego.

Balke, N.S. 2000. “Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks.” Review of Economics and Statistics 82(2):344–49. https://doi.org/10.1162/rest.2000.82.2.344.

Bank of Canada. 2020. “Monetary Policy Report—April 2020.” At https://www.bankofcanada.ca/2020/04/mpr-2020-04-15/.

Bauer, G., G. Pasricha, R. Sekkel, and Y. Terajima. 2018. “The Global Financial Cycle, Monetary Policies, and Macroprudential Regulations in Small, Open Economies.” Canadian Public Policy/Analyse de politiques 44(2):81–99. https://doi.org/10.3138/cpp.2017-018.

Brave, S., and A.R. Butters. 2011. “Monitoring Financial Stability: A Financial Conditions Index Approach.” Economic Perspectives, Federal Reserve Bank of Chicago 35(1):22–43.

Brave, S., and A.R. Butters. 2012. “Diagnosing the Financial System: Financial Conditions and Financial Stress.” International Journal of Central Banking 8(3):191–239.

Bruneau, G., and J. Chapman. 2017. “A Model for Financial System Risk Scenarios: The Nonlinear Macrofinancial Risk Model.” Unpublished mimeo, Bank of Canada, Ottawa.

Cardarelli, R., S.A. Elekdag, and S. Lall. 2011. “Financial Stress and Economic Contractions.” Journal of Financial Stability 7(2):78–97. https://doi.org/10.1016/j.jfs.2010.01.005.

Chatterjee, S., C.-W. (J.) Chiu, T. Duprey, and S.H. Hoke. 2017. “A Financial Stress Index for the United Kingdom.” Working Paper No. 697. London: Bank of England.

Duprey, T., and B. Klaus. 2017. “World Financial Stress Indices.” Unpublished mimeo, Bank of Canada, Ottawa.

Duprey, T., B. Klaus, and T.A. Peltonen. 2017. “Dating Systemic Financial Stress Episodes in the EU Countries.” Journal of Financial Stability 32:30–56. https://doi.org/10.1016/j.jfs.2017.07.004.

Duprey, T., and A. Ueberfeldt. 2020. “Managing GDP Tail Risk.” Staff Working Paper No. 2020–03. Ottawa: Bank of Canada.

European Central Bank. 2009. “Box 1: A Global Index of Financial Turbulence.” Financial Stability Review, December, 21–23. At https://www.ecb.europa.eu/pub/financial-stability/fsr/focus/2009/pdf/ecb~91edbc7101.fsrbox200912_01.pdf?showdebc25c52d4f23002b0447ae1db0a.

Fawcett, T. 2006. “An Introduction to ROC Analysis.” Pattern Recognition Letters 27(8):861–74. https://doi.org/10.1016/j.patrec.2005.10.010.

Galbraith, J.W., and G. Tkacz. 2013. “Analyzing Economic Effects of September 11 and Other Extreme Events Using Debit and Payments System Data.” Canadian Public Policy/Analyse de politiques 39(1):119–34. https://doi.org/10.3138/cpp.39.1.119.

Hakkio, C.S., and W.R. Keeton. 2009. “Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?” Economic Review, Federal Reserve Bank of Kansas City 2:5–50.

Hollo, D., M. Kremer, and M.L. Duca. 2012. “CISS—a Composite Indicator of Systemic Stress in the Financial System.” Working Paper No. 1426. Frankfurt am Main: European Central Bank.

Huang, R., and L. Ratnovski. 2009. “Why Are Canadian Banks More Resilient?” Working Paper 09/152. Washington, DC: International Monetary Fund.
Hubrich, K., and R.J. Tetlow. 2015. “Financial Stress and Economic Dynamics: The Transmission of Crises.” Journal of Monetary Economics 70(1):100–15. https://doi.org/10.1016/j.jmoneco.2014.09.005.

Illing, M., and Y. Liu. 2006. “Measuring Financial Stress in a Developed Country: An Application to Canada.” Journal of Financial Stability 2(3):243–65. https://doi.org/10.1016/j.jfs.2006.06.002.

International Monetary Fund. 2017. “Article IV Consultation.” IMF Country Report No. 17/210. Washington, DC: International Monetary Fund.

Kaminsky, G., S. Lizondo, and C.M. Reinhart. 1998. “Leading Indicators of Currency Crises.” IMF Staff Papers 45(1):1–48. https://doi.org/10.2307/3867328.

Kartashova, K., and X. Zhou. 2020. “How Do Mortgage Rate Resets Affect Consumer Spending and Debt Repayment? Evidence from Canadian Consumers.” Staff Working Paper No. 2020–18. Ottawa: Bank of Canada.

Kliesen, K.L., M.T. Owyang, and K.E. Vermann. 2012. “Disentangling Diverse Measures: A Survey of Financial Stress Indexes.” Federal Reserve Bank of St. Louis Review 94(5):369–98. https://doi.org/10.20955/r.94.369-398.

Kliesen, K.L., and D.C. Smith. 2010. “Measuring Financial Market Stress.” Economic Synopses, Federal Reserve Bank of St. Louis 2010(2). https://doi.org/10.20955/es.2010.2.

Laeven, L., and F. Valencia. 2013. “Systemic Banking Crises Database.” IMF Economic Review 61(2):225-70. https://doi.org/10.1057/imer.2013.12.

Li, F., and P. St-Amant. 2010. “Financial Stress, Monetary Policy, and Economic Activity.” Bank of Canada Review 2010(Autumn):9–18.

MacDonald, C., M. Van Oordt, and R. Scott. 2016. “Implementing Market-Based Indicators to Monitor Vulnerabilities of Financial Institutions.” Staff Analytical Note 5. Ottawa: Bank of Canada.

Oet, M.V., R. Eiben, T. Bianco, D. Gramlich, and S.J. Ong. 2011. “The Financial Stress Index: Identification of Systemic Risk Conditions.” Federal Reserve Bank of Cleveland Working Paper No. 11–30. Cleveland, OH: Federal Reserve Bank of Cleveland.

Poloz, S.S. 2016. “The Doug Purvis Memorial Lecture—Monetary/Fiscal Policy Mix and Financial Stability: The Medium Term Is Still the Message.” Canadian Public Policy/Analyse de politiques 42(3):225–36. https://doi.org/10.3138/cpp.2016-013en.

Poloz, S. 2020. “Monetary Policy in Unknowable Times.” Eric J. Hanson Memorial Lecture, University of Alberta, 25 May. At https://www.bankofcanada.ca/2020/05/monetary-policy-in-unknowable-times/.

Reinhart, C.M., and K.S. Rogoff. 2011. “From Financial Crash to Debt Crisis.” American Economic Review 101(5):1676–706. https://doi.org/10.1257/aer.101.5.1676.

Schularick, M.H., and A.M. Taylor. 2012. “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008.” American Economic Review 102(2):1029–61. https://doi.org/10.1257/aer.w15512.

Traclet, V., and C. MacDonald. 2018. “The Framework for Risk Identification and Assessment.” Technical Report No. 113. Ottawa: Bank of Canada.
## Appendix A

### Table A.1: List of Time Series Used in the Computation of the Index of Financial Stress

| Market Segment | Ticker | Data Type | Frequency | Source | Short Name | Transformation Details | Illing and Liu (2016) |
|----------------|--------|-----------|-----------|--------|------------|------------------------|-----------------------|
| EQU (equity)   | TOTMKCN(PI) | TSX stock index | Daily | Datastream | ABS_EQU | Monthly average of the absolute value of daily log real returns | CMAX of the TSX index over a 1 y window |
| GOV (government) | TRCN10T | 10-y Government of Canada bond | Daily | Datastream | ABS_GOV | Monthly average of the absolute value of daily change in real bond yields | Inverted slope of the yield curve; covered CA/US treasury bill spread; treasury bills bid-offer spread |
| TRUS10T | 10-year US bond | Daily | Datastream | CDIFF_GOV | Difference between the real CA–US bond spread and its minimum over the previous 5 y |
| FOR (foreign exchange) | B156XRN@BIS | Narrow real effective exchange rate | Monthly | BIS | ABS_FOR | Absolute value of the log rate | CMAX of the CA–US exchange rate |
| RESTLM | Canada’s Official International Reserves | Monthly | Famemart | CMAX_FOR | Cumulated maximum loss of official reserves over a 5 y window |
| MON (money market) | CIDOR3M | 3 month interbank rate | Daily | Datastream | ABS_MON | Monthly average of the absolute value of the overnight repo rate | Corporate paper minus treasury bill spread |
| CNTBB3M | 3 month treasury bills | Daily | Datastream | SPR1_MON | Interbank rate over the 3 mo treasury bill |
| CP.CDN.90D.OPER | Prime corporate 3 month paper rate | Daily | Famemart | SPR2_MON | 3-mo corporate paper rate over the 3 mo treasury bill |
| BAN (banking) | BANKSCN(PI) | Datastream banks price index | Daily | Datastream | IDIO_BAN | Idiosyncratic banking shocks: inverse of the residual from regressing real log bank stock returns over the real log stock market return, estimated on a 2 y rolling window |
| F0C2 | Minus distance-to-default (higher means more stress) Merrill Lynch option-adjusted spread on AA-rated businesses | Monthly | MacDonald et al. (2016) | IND_BAN | Average distance to default of Canadian financial institutions |
| | | Daily | ICE Bank of America | CDIFF_BAN | Difference between the funding spread of AA banks and its minimum over the previous 5 y |

(Continued)
### Table A.1: Continued

| Market Segment | Ticker | Data Type | Frequency | Source | Short Name | Transformation Details | Illing and Liu (2016) |
|----------------|--------|-----------|-----------|--------|------------|------------------------|-----------------------|
| COR (corporate)| F0C3   | Merrill Lynch option-adjusted spread on A-rated businesses | Daily | ICE Bank of America | CDIFF_COR | Difference between the funding spread of A-rated corporations and its minimum over the previous 5 y | Corporate bond spread |
| d.wcc          |        | WCS oil price | Monthly | Famemart | CMAX_COR | Cumulated maximum drop of the WCC oil price over a 5 y window |                      |
| F0C4           |        | Merrill Lynch option-adjusted spread on A-rated businesses | Daily | ICE Bank of America | SPR_COR | Spread between the funding cost of A- and BBB-rated corporations |                      |
| HOU (housing)  | CACERPUM@CREA | Housing price deflated using CPI | Monthly | Famemart | CMAX_HOU | Cumulated maximum drop of the real housing price over a 5 y window |                      |
| BROKER_ AVERAGE_SYRMO RT | v122540 | Average 5 y fixed mortgage rate among national mortgage | Monthly | Famemart | SPR_HOU | Spread between the 5 y mortgage rate and the 5 y Government of Canada bond |                      |
| NCBI           |        | Index of Consumer Confidence | Quarterly | Conference Board of Canada | IND_HOU | Negative of the consumer confidence index interpolated at monthly frequency |                      |

Notes: The EQU, GOV, and FOR indicators are similar to those used by Duprey et al. (2017), with the addition of the foreign reserves. The Canadian financial stress index is composed of measures of volatility (ABS), large variations (CMAX, CDIFF, CUMUL), spreads (SPR), and other, more complex indicators (IND, IDIO). For the formula used for ABS, CMAX, CDIFF, and CUMUL, refer to Duprey et al. (2017). The last column refers to the input used by Illing and Liu (2006). BIS = Bank of International Settlement; CPI = Consumer Price Index; WCS = Western Canadian Select.

Source: Datastream; BIS; Famemart; MacDonald et al. (2016); ICE Bank of America; Conference Board of Canada.
Table A.2: List of Time Series When Weighting Each Market Segment

| Market   | Ticker       | Definition                                                                                                                                                                                                 |
|----------|--------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| EQU (equity) | V122642   | Equity and warrants                                                                                                                                         |
|          | V36846      | Minus foreign currency securities to Canadian residents from chartered banks                                                                            |
| GOV (government) | V37342   | Government of Canada direct and guaranteed securities and loans, total unmatured direct and guaranteed securities (excluding non-marketable)              |
|          | V37319      | Minus Government of Canada direct and guaranteed securities and loans, marketable bonds, and notes payable in foreign currencies                           |
|          | V37331      | Minus Government of Canada direct and guaranteed securities and loans, treasury bills                                                                   |
|          | V122256     | Minus provincial governments and their enterprises, treasury bills, and other short-term paper                                                              |
|          | V122257     | Minus municipal governments, treasury bills, and other short-term paper                                                                                   |
| FOR (foreign exchange) | V37319   | Government of Canada direct and guaranteed securities and loans, marketable bonds and notes in foreign currencies                                      |
|          | V122478     | Plus provincial bonds delivered abroad                                                                                                                   |
|          | V122269     | Plus municipal bonds delivered abroad                                                                                                                     |
|          | V122255     | Plus short-term commercial paper issued in US dollars, includes instruments with an original term of £1 y                                                  |
|          | V122272     | Plus corporate bonds placed abroad, includes instruments with an original term to maturity of >1 y                                                       |
|          | V36877      | Plus foreign currency loans to Canadian residents from chartered banks                                                                               |
|          | V36846      | Plus foreign currency securities to Canadian residents from chartered banks                                                                            |
|          | V36937–V36884 | Plus foreign currency liabilities minus foreign currency assets held by chartered banks                                                   |
| MON (money market) | V122241 | Total corporate short-term paper                                                                                                                       |
|          | V37331      | Plus Government of Canada direct and guaranteed securities and loans, treasury bills                                                                   |
|          | V122256     | Plus provincial governments and their enterprises, treasury bills, and other short-term paper                                                              |
|          | V122257     | Plus municipal governments, treasury bills, and other short-term paper                                                                                   |
|          | V36864      | Plus interbank loans                                                                                                                                          |
| BAN (bank loans) | V36717   | Total personal loans (including credit cards, lines of credit)                                                                                          |
|          | V36863      | Plus business loans                                                                                                                                          |
|          | V36719      | Plus leasing receivables                                                                                                                                       |
|          | V36718      | Plus non-residential mortgages                                                                                                                                   |
|          | V36864      | Minus interbank loans                                                                                                                                 |
|          | V36877      | Minus foreign currency loans to Canadian residents from chartered banks                                                                               |
|          | V36937–V36884 | Minus foreign currency liabilities minus foreign currency assets held by chartered banks                                                   |
| COR (corporate) | V122640   | Bonds and debentures                                                                                                                                 |
|          | V122255     | Minus short-term commercial paper issued in US dollars; includes instruments with an original term of £1 y                                                  |
|          | V122272     | Minus corporate bonds placed abroad; includes instruments with an original term to maturity of >1 y                                                       |
| HOU (housing) | V36724     | Total charted banks assets: residential mortgage                                                                                                         |
|          | V1404824    | Plus non-depository credit intermediation: residential mortgage                                                                                           |
|          | V122577     | Plus local credit unions and caisses populaires: residential mortgage                                                                                     |
|          | V37050      | Plus trust and mortgage loan companies excluding bank trust and mortgage subsidiaries: residential mortgage                                                |

Notes: The weights for each market segment are normalized to sum to unity at each point in time. Data are monthly or monthly interpolation of quarterly data.

Source: Bank of Canada credit statistics.
Appendix B: Extension of the Canadian Financial Stress Index

The benchmark Canadian financial stress index (CFSI) starts in 1981. For any of these indexes of financial stress, the trade-off is between data quality and data coverage. The constraining variable is the Merton-type banking stress, but a few other variables are not available in the 1970s either. However, the CFSI can be extended backward by using proxies for missing variables or simply ignoring missing values. For banking stress, I back-cast the distance to default of MacDonald et al. (2016) by eight years using the marginal expected shortfall computed on the Datastream bank stock index returns for Canada, conditional on a large daily loss of the Toronto Stock Exchange. I also back-cast the corporate bond spreads by three years using the spreads of other bond grades. Other variables are missing without proper substitutes, and I simply drop them when computing the average stress per sector. Interbank spreads, bank funding spreads, corporate spreads, and households’ mortgage spreads are not available in the first few years. Before 1981, the market segments reflecting stress for money markets, banks, corporations, and households encompass only one or two individual inputs instead of three to four.

Before 1973, data that capture stress on those markets are more limited, and one could use the Country-Level Index of Financial Stress (CLIFS) index of Duprey and Klaus (2017), who extend the country coverage of Duprey et al. (2017) to further back-cast the CFSI until 1964. The construction method of the CLIFS index for Canada shares similarities with that of the CFSI, but it uses only three to five main time series to reflect stress on three to five market segments. The back-casted time series are presented in Figure B.1, and the episodes of high financial stress are consistent with the narrative of stressful episodes, such as the monetary crisis of 1971 or the oil price shocks of the 1970s.

![Figure B.1: Backward Extension of the CFSI](image-url)

**Notes:** The CFSI is the plain black curve and starts in 1981. The backward extended CFSI follows the same construction as the CFSI, but a few time series are missing from 1973 to 1981 for four of the seven sectors covered. Before 1973, a few sectors have no available data, and the CFSI cannot be computed. I extend the stress index back to 1964 using the CLIFS metric of Duprey et al. (2017), which follows a simplified (but similar) construction procedure but focuses only on equity, government, foreign exchange, banking, and housing stress. CFSI = Canadian financial stress index; CLIFS = Country-Level Index of Financial Stress index.

Source: Author’s calculations.

doi:10.3138/cpp.2020-047
Appendix C: CFSI with Alternative Correlation Methods

Figure C.1: Robustness CFSI with Different Correlation Methods

Notes: The benchmark CFSI specification computes correlations using an exponentially weighted moving average with a parameter $\lambda = 0.85$ (solid line). Alternatively, a higher parameter $\lambda = 0.99$ is associated with a slower update of the correlations as new information becomes available. The CFSI can also be computed using a multivariate diagonal BEKK GARCH. Using a cross-country dataset of 27 European financial stress indexes, Duprey et al. (2017) found that a parameter $\lambda = 0.85$ generates a financial stress index that is closest to the multivariate GARCH. BEKK = Baba–Engle–Kraft–Kroner (Baba et al. 1985); CFSI = Canadian financial stress index; GARCH = generalized autoregressive conditional heteroskedasticity.

Source: Author’s calculations.
Appendix D: CFSI with Principal Components

Figure D.1: Comparison CFSI with Principal Components: (a) First Principal Component, (b) Second Principal Component, (c) Third Principal Component, (d) Fourth Principal Component, (e) Fifth Principal Component, and (f) Sixth Principal Component

Note: The Canadian financial stress index (CFSI) is displayed in solid line (left scale). The alternative index is displayed in dashed line (right scale). The principal-components analysis is conducted on the same normalized input as the ones used in the CFSI. I report each of the first to the sixth principal component and their correlation with the CFSI.

Source: Author's calculations.

doi:10.3138/cpp.2020-047

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Table D.1: Contemporaneous Signalling of the CFSI Versus Principal Components

| Event Description                                      | AUROC | pAUROC | T1 | T2 | U   | AUROC | pAUROC | T1 | T2 | U   | AUROC | pAUROC | T1 | T2 | U   |
|--------------------------------------------------------|-------|--------|----|----|-----|-------|--------|----|----|-----|-------|--------|----|----|-----|
| Illing and Liu's (2006) dates + 2008 global financial crisis + 2015 oil price shock + 1990 housing market correct – LTCM crisis – dot-com bubble burst |       |        |    |    |     |       |        |    |    |     |       |        |    |    |     |
| CFSI                                                   | 0.86  | 0.82   | 0.17 | 0.27 | 0.57 | 0.17  | 0.27   | 0.48 | 0.38 | 0.09 | 0.47  |        |    |    |     |
| First principal component                              | 0.81  | 0.76   | 0.33 | 0.20 | 0.47 | 0.04  | 0.61   | 0.34 | 0.53 | 0.05 | 0.40  |        |    |    |     |
| Second principal component                             | 0.59  | 0.58   | 0.42 | 0.22 | 0.36 | 0.38  | 0.26   | 0.16 | 0.42 | 0.22 | 0.25  |        |    |    |     |
| Third principal component                               | 0.61  | 0.58   | 0.22 | 0.57 | 0.21 | 0.10  | 0.70   | 0.15 | 0.48 | 0.35 | 0.00  |        |    |    |     |
| Fourth principal component                              | 0.58  | 0.57   | 0.43 | 0.31 | 0.26 | 0.38  | 0.38   | 0.05 | 0.52 | 0.22 | 0.15  |        |    |    |     |
| Fifth principal component                               | 0.67  | 0.64   | 0.40 | 0.36 | 0.25 | 0.01  | 0.75   | 0.23 | 0.49 | 0.26 | 0.12  |        |    |    |     |
| Sixth principal component                               | 0.52  | 0.51   | 0.07 | 0.80 | 0.13 | 0.07  | 0.80   | 0.09 | 0.96 | 0.00 | 0.04  |        |    |    |     |
| Average first to second component                      | 0.79  | 0.82   | 0.25 | 0.18 | 0.57 | 0.25  | 0.18   | 0.45 | 0.25 | 0.18 | 0.48  |        |    |    |     |
| Average first to third component                        | 0.81  | 0.78   | 0.27 | 0.18 | 0.55 | 0.27  | 0.18   | 0.41 | 0.27 | 0.18 | 0.45  |        |    |    |     |
| Average first to fourth component                       | 0.83  | 0.82   | 0.33 | 0.13 | 0.54 | 0.25  | 0.22   | 0.41 | 0.35 | 0.12 | 0.48  |        |    |    |     |
| Average first to fifth component                        | 0.88  | 0.88   | 0.09 | 0.27 | 0.64 | 0.09  | 0.27   | 0.60 | 0.25 | 0.15 | 0.53  |        |    |    |     |
| Average first to sixth component                        | 0.87  | 0.88   | 0.26 | 0.14 | 0.60 | 0.10  | 0.31   | 0.54 | 0.26 | 0.14 | 0.53  |        |    |    |     |

Notes: This table displays summary statistics that show how well different Canadian financial stress indexes contemporaneously signal the stressful events identified in the 2003 survey used in Illing and Liu (2006). It consists of the following events: August 1981 spike in interest rates, Latin American debt crises (early 1980s), Canadian commercial bank and Northland failures (1985), October 1987 stock market crash, early 1990s bank losses, Mexican crisis (1994–1995), Asian crisis (1997–1998), Russian debt default and LTCM bailout (1998), the burst of the dot-com bubble (2000), and 11 September 2001 terrorist attacks. The 1998 and 2000 events were assessed as only somewhat stressful by most of the respondents and are thus removed. We added the following events that were not part of the survey: the 2008 crisis, the 2015 oil crisis, and the 1990 housing crisis. AUROC is associated with an informative signal when it is above 0.5, whatever the preferences of the regulator; pAUROC is restricted to assess the informativeness of a signal under a subset of preferences of the regulator, in the range $\mu = [0.3; 0.7]$. $\mu$ is the cost associated with T1 (i.e., the share of missed crises). Conversely, $1 - \mu$ is the cost associated with T2 (i.e., the share of false signals). A higher $\mu$ is associated with an aversion to missing crises (thus a lower T1). When computing the different measures, the 12 month after a stressful event are removed unless another stress event starts during this period. Otherwise, the assessment could be biased by the behaviour of the stress indexes during the recovery period. CFSI = Canadian financial stress index; LTCM = Long-Term Capital Management; AUROC = area under the receiver characteristic curve; pAUROC = partial area under the receiver characteristic curve; T1 = type 1 errors; T2 = type 2 errors; U = Alessi and Detken’s (2011) usefulness indicator that measures the signal’s ability to be informative under certain preferences $\mu$.

Source: Author’s calculations.

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