Credit, Asset Prices, and Financial Stress*

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Historical narratives typically associate financial crises with credit expansions and asset price misalignments. The question is whether some combination of measures of credit and asset prices can be used to predict these events. Borio and Lowe (2002) answer this question in the affirmative for a sample of thirty-four countries, but the question is surprisingly difficult to answer for individual developed countries that have faced very few, if any, financial crises in the past. To circumvent this problem, we focus on financial stress and ask whether credit and asset price movements can help predict it. To measure financial stress, we use the financial stress index (FSI) developed by Illing and Liu (2006). Other innovations include the estimation and forecasting using both linear and endogenous threshold models, and a wide range of asset prices (stock and housing prices, for example). The exercise is mainly performed for Canada, but in our robustness checks we also consider data for Japan and the United States. Our sample also includes the financial crisis of 2007–08.

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1. Introduction

Despite the apparent uniqueness of each financial cycle—from the conditions that lead to boom times, to triggers that result in reversals—historical narratives (e.g., Kindleberger and Aliber 2005)

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suggest that most cycles display common features: boom times are typically associated with periods of credit expansion and persistent increases in asset prices, often followed by rapid reversals.

These commonalities, confirmed by recent empirical work (e.g., Borio and Lowe 2002, Kaminsky and Reinhart 1999), suggest that developments in the credit and asset markets of individual countries may provide an early-warning indicator of vulnerability in the financial system that would be useful in assessing the current situation and in discussions of possible policy actions. In light of this, it is somewhat surprising that the empirical work in this area is scarce (Borio and Lowe 2002, 11). Whatever reasons there may be at a general level, the problem in doing this type of analysis for developed countries is compounded by the scarcity of events that would qualify as financial crises in those countries.[1] Absence of financial crises does not, however, mean that financial systems of developed countries have not, or cannot, come under stress, but it does raise the issue of the best way to proceed.

In this work we propose a methodology that can be used to assess the role of credit and asset prices as early-warning indicators of vulnerability in the financial system of countries that have experienced very few or no financial crises over the sample period of interest. A typical example is Canada, which will be the basis of our empirical work in this paper: in Bordo et al. (2001) dating, Canada has not experienced any "twin crises" (banking and currency crises) since the beginning of their sample in 1883, and has experienced only four currency crises since 1945.[2] These features of the sample preclude a meaningful country-level analysis based on binary indicators of crises. Instead, we suggest that in such circumstances one focuses on incidences of financial stress. In our work we use the financial stress index (FSI), a continuous measure of financial stress developed by Illing and Liu (2006). The measure was originally developed for Canada, but the underlying approach can be applied to any country. In our examination of the role of credit and

[1]Bordo et al. (2001, 55) define financial crises as episodes of financial market volatility marked by significant problems of illiquidity and insolvency among financial market participants and/or by official intervention in order to contain such consequences.

[2]For details and dating of crises, see the appendix to Bordo et al. (2001).

asset price in episodes of financial stress we consider both linear and nonlinear models, since the latter may be more suitable in capturing any behavioral asymmetries of financial market participants.

It is important to emphasize that the objective of this type of work is not to forecast idiosyncratic events that cause reversals (an impossible task using any econometric model), but rather to assess whether, historically, there has been a relationship between the various measures of movements in credit and asset prices at time t and the FSI k periods ahead. The working hypothesis is that movements in credit and asset prices are indicators of the health of the system and its ability to withstand various types of shocks. Since the impact of a shock depends not only on the state of the system but also on the magnitude of the shock, one would expect that, everything else being the same, excessive growth of credit and persistent increases in asset prices reduce the ability of the system to withstand the shocks.

To preview the main results, we find that within a linear framework, domestic credit growth is the best predictor of the FSI at all horizons, resulting in marginally lower prediction errors relative to our base-case model, although we do not observe the combination of credit and asset prices observed by Borio and Lowe (2002). Our results suggest that asset prices tend to be better predictors of stress when we allow for nonlinearities, suggesting that extreme asset price movements have disproportionate impact on financial stress. Finally, at the two-year horizon, business credit and real estate prices emerge as important predictors of financial stress, confirming the general findings of Borio and Lowe.

The presentation is organized as follows. In section 2 we review the related literature and describe the nature of the problem addressed in this paper. Section 3 discusses in detail the data used. In section 4, we describe the model and present our results. Section 5 contains the results of our robustness checks, including the application of our approach to the United States and Japan. The last section concludes.

2. Related Literature

Broadly speaking, the present work forms part of the literature attempting to arrive at a set of early-warning indicators. The general problem in this literature has been to identify a subset of macroeconomic and other relevant variables that would help predict the probability of a financial crisis.[3]

Borio and Lowe (2002) investigate the usefulness of asset prices as indicators of financial crises. The authors establish some stylized facts regarding the behavior of asset prices over the last thirty years and conclude that there is a relationship between asset price movements, credit cycles, and developments in the real economy. Given this, they asked whether a useful indicator of financial crises can be constructed. The exercise performed is to assess whether credit, asset prices, and investments—either separately or in some combination—can predict financial crises.[4] The methodology used is that of Kaminsky and Reinhart (1999), and it is based on threshold values of each series. The dating of crises is taken from Bordo et al. (2001). The key finding is that some combination of asset prices and credit gap can help predict crises.

Hanschel and Monnin (2005) focus on the banking sector and propose an index that can be used to measure stress in the Swiss banking sector. The paper then investigates whether the values of the index can be predicted by a set of macro variables. In assessing the latter, the authors follow Borio and Lowe (2002), focusing on the imbalances rather than levels of variables.

This paper is related to Hanschel and Monnin's work since it focuses on a single country and investigates the predictive ability of a set of variables for financial stress rather than as indicators of

[3]There have been a variety of papers that have explored a range of indicators for different types of crises. Recent work has tended to cluster around specific financial crises. For example, following the Mexican Crisis in 1994, papers such as Sachs, Tornell, and Velasco (1996) and Frankel and Rose (1996) explored whether a variety of variables—such as bank credit growth, currency reserves, capital inflows, and level of the exchange rate—affect the likelihood of a crisis. Following the Asian crisis in 1997, there were more efforts, such as Goldstein and Hawkins (1998) and Rodrik and Velasco (1999). Berg and Pattillo (1998) test whether crisis prediction measures constructed after the Mexican crisis would have predicted the Asian crisis. Sorge (2004) provides an excellent survey of stress-testing literature and its relationship to macroeconomic forecasting and early-warning-signals literature.

[4]The idea that credit expansions may lead to imbalances and eventual crises is certainly not new. Hayek (1932) is an early example in the twentieth century, but the views go further back. Schumpeter (1954) contains a historical survey of the key ideas by period, and their proponents.

crises. In our work, however, the indicator of financial stress used is the one developed by Illing and Liu (2006). This indicator is broader based than in Hanschel and Monnin, since it tries to capture stress in the financial system rather than only focusing on the banking sector.

In exploring the forecasting ability of credit and asset prices for financial stress, we look at both linear and nonlinear (threshold) specifications. In the latter, we follow Borio and Lowe (2002) but, rather than specifying the threshold exogenously, in our work the thresholds are determined endogenously.

3. Data

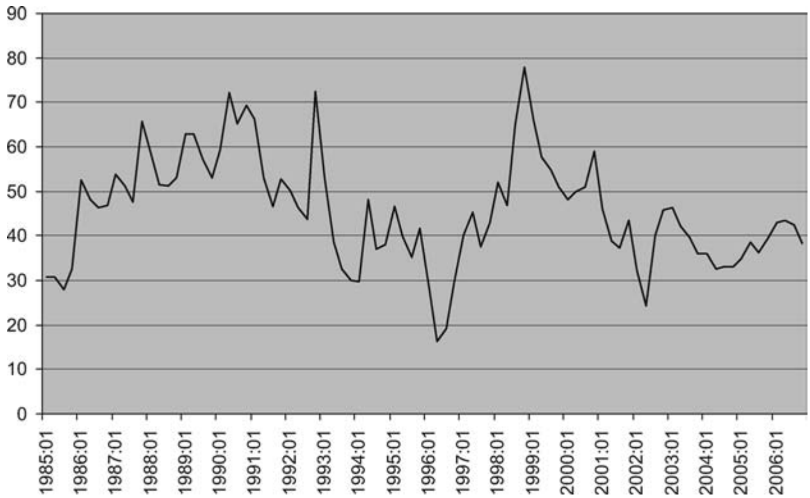
3.1 A Measure of Financial Stress

Financial stress can be characterized as a situation in which large parts of the financial sector face the prospects of large financial losses. These situations are usually accompanied by an increased degree of perceived risk (a widening of the distribution of probable losses) and uncertainty (decreased confidence in the shape of that distribution).

To capture these features of financial stress, Illing and Liu (2006) constructed a weighted average of various indicators of expected loss, risk, and uncertainty in the financial sector. The resulting financial stress index (FSI) is a continuous, broad-based measure that includes the following indicators from equity, bond, and foreign exchange markets, as well as indicators of banking-sector performance:

- the spread between the yields on bonds issued by Canadian financial institutions and the yields on government bonds of comparable duration
- the spread between yields on Canadian nonfinancial corporate bonds and government bonds
- the inverted term spread (i.e., the ninety-day Treasury bill rate minus the ten-year government yield)
- the beta derived from the total return index for Canadian financial institutions
- Canadian trade-weighted dollar GARCH volatility
- Canadian stock market (TSX) GARCH volatility

Figure 1. Financial Stress Index



- the difference between Canadian and U.S. government short-term borrowing rates
- the average bid-ask spread on Canadian Treasury bills
- the spread between Canadian commercial paper rates and Treasury bill rates of comparable duration

In constructing the FSI, Illing and Liu considered several weighting options and settled on weights that reflect relative shares of credit for particular sectors in the economy. The resulting index, shown in figure 1, was most effective in correctly signaling events that are widely associated with high financial stress (e.g., the stock market crash in October 1987, the peso crisis in 1994, the long-term capital management crisis in 1998, etc.). This is not surprising, given that Canada is a small open economy whose markets are well integrated internationally. As such, it is not insulated from international financial developments. Turmoil in international financial markets will be reflected in increased stress in Canadian markets. This does not mean that financial stress is not or cannot be domestically generated, but it may indicate that the level of "internal" stress is secondary to the level of "external" stress that spills over into Canadian financial markets. To assess the importance of external factors in predicting financial stress in Canada, we include a set of international explanatory variables described below.

3.2 Explanatory Variables

Because Canada is a small open economy, its financial stress will necessarily be impacted by international events—the 1994 peso and 1997 Asian crises being well-known recent examples. For this reason, our data set incorporates, in addition to a broad set of domestic variables, several foreign variables. However, international developments will also be felt in many domestic variables. For example, Canadian stock prices move in response to expected future earnings of Canadian firms, which in turn are largely dependent on international factors such as the economic health of Canada's trading partners or on world commodity prices. In addition, real estate prices follow similar patterns across major international cities (e.g., see Shiller 2005, 19). As a result, many of our variables will necessarily move in response to the ultimate source of the stress, be it domestic or international factors.

The explanatory variables are divided into four major categories:[5]

(i) Credit measures: the growth rate of total household credit (HouseCR), total business credit (BusCR), and total credit/GDP (CR/Y)
(ii) Asset prices (growth rates): stock prices (TSX), commercial real estate indices (real (ComREI) and nominal (real Com REI)), residential real estate indices ("New house price" and existing (RoyalLePage)), average price to personal disposable income ratio (AvgP/PDI), and Canadian dollar price of gold (GoldC$)
(iii) Macroeconomic variables: Investment/GDP (I/Y), GDP growth rate, money (M1++ and M2++), and inflation (Total CPI and Core CPI)

[5]Unless otherwise indicated, the source of the data is the Bank of Canada.

(iv) Foreign variables: crude oil, asset price indices (United States, Australia, Japan),[6] world gold price, U.S. bank credit,[7] U.S. federal funds rate, and world GDP

The data is quarterly and spans the period 1984–2006. The forecasting exercise is performed over the period 1996–2006. The last observation is 2006:Q4. The explanatory variables are converted into growth rates, so all variables are stationary.[8] We consider both quarterly and annual growth rates, since it is possible that longer-run cumulative growth rates in the explanatory variables may contain more information about financial stress than quarterly growth rates. In our output we use $d = 1$ to denote quarterly growth rates and $d = 4$ for annual (year-over-year) growth rates.

4. Models and Results

4.1 Linear Models and Forecast Evaluation

In order to evaluate the marginal contributions of the various explanatory variables, we compare all our models with a simple linear benchmark, whereby the current FSI is simply a function of the k-quarter lagged FSI:

$$FSI_t = \alpha + \beta FSI_{t-k} + \varepsilon_{1,t}. \tag{1}$$

At this time, the explanatory variables will be added to (1) in isolation and in pairs; given the multitude of horizons and variables under consideration, this alone results in several thousand models to be assessed. The augmented models are thus

$$FSI_t = \alpha + \beta_1 FSI_{t-k} + \gamma X_{t-k} + \varepsilon_{2,t}, \tag{2}$$

[6]These indices are the same ones used by Borio and Lowe (2002). In general, they are the aggregates of stock prices, bond prices, and real estate prices, but the components vary by country depending on data availability. The reader is referred to their paper for details.

[7]Source: Federal Reserve Board, H.8 Release: Assets and Liabilities of Commercial Banks in the United States. Available at http://www.federalreserve.gov/releases/h8/.

[8]Commercial real estate investment is not transformed, since it was found to be stationary.

where X is a vector containing one or two explanatory variables. Since we are primarily interested in forecast performance, we summarize the forecast performance according to the ratio of the root mean squared error (RMSE) of model (2) relative to that of (1):

$$rmr = \frac{\sqrt{\sum_{t=1996Q1}^{2006Q4} (F\hat{S}I_{2,t} - FSI_t)^2 \Big/ 44}}{\sqrt{\sum_{t=1996Q1}^{2006Q4} (F\hat{S}I_{1,t} - FSI_t)^2 \Big/ 44}}, \tag{3}$$

where $F\hat{S}I_{1,t}$, $F\hat{S}I_{2,t}$ are forecasts of the FSI originating from models (1) and (2), respectively. When the *rmr* is above 1.0, this indicates that the additional explanatory variables worsen the forecast performance relative to the base-case model; when it is below 1.0, the forecast performance is improved.[9,10]

To determine whether the ratio of mean-squared errors is statistically less than 1.0, we employ a test proposed by McCracken (2004) that can test for equality of the mean-squared errors of nested models. Let D_{t+k} denote the difference between the squared forecast errors at $t + k$ of the base-case model (i.e., the model which includes only the lagged FSI) and the alternative model (i.e., the model augmented with one or more explanatory variables):

$$D_{t+k} = \hat{\varepsilon}^2_{1,t+k} - \hat{\varepsilon}^2_{2,t+k}. \tag{4}$$

With n forecast periods, the statistic for testing the equality of mean-squared errors between the base-case and alternative model is computed as

[9] In comparisons of models that contain the same dependent variable, the above is equivalent to a comparison of the adjusted R-squared of these models. The adjustment factor for the R-squared imposes a penalty on the inclusion of additional explanatory variables. The adjusted R-squared of the resulting model will be lowered if the additional variable's contribution does not exceed the penalty factor. Consequently, the ratio of the adjusted R-squared statistics could be greater than 1.

[10] This model selection criterion gives the same weight to the errors on the upside and the downside. To the extent that the users might give more weight to increases than decreases, a selection criterion that penalizes downside errors more than the upside ones would be more appropriate. We thank the referee for bringing this point to our attention.

$$MSE - F = n \sum \frac{n^{-1} \sum_{t=R-k}^{T} \left(\hat{\varepsilon}_{1,t+k}^{2} - \hat{\varepsilon}_{2,t+k}^{2} \right)}{n^{-1} \sum_{t=R-k}^{T} \hat{\varepsilon}_{2,t+k}^{2}}, \tag{5}$$

where R represents the first out-of-sample forecast period (1996:Q1). Intuitively, note that the numerator represents the difference in mean-squared errors (MSEs) between the base-case and alternative model, and the denominator represents the MSE of the alternative. If both models produce equally accurate forecasts, then the numerator and test statistic are zero; if the base-case model has a lower MSE, then the statistic will be negative, and it will be positive if the alternative model has a lower MSE. The distribution is nonstandard due to the fact that the models are nested, and so we use the critical values computed by McCracken (2004). Results presented by McCracken show that this test has good size and power for sample sizes as small as fifty. Our own application has a sample size of forty-four (1996:Q1 to 2006:Q4), so this test should be appropriate for our purposes. Instances where the alternative model is found to have a statistically lower MSE than the base-case model are highlighted in our figures.

The details of the forecasting exercise are as follows:

- We initially estimate (1) and (2) with data from 1984 to 1996:Q1$-k$, where $k = 1$, 2, 4, 8, or 12.
- Using the estimated parameters, we produce a forecasted FSI for 1996:Q1.
- We reestimate the parameters with data from 1984 to 1996:Q2$-k$.
- We use the newly estimated parameters to obtain a forecast of the FSI for 1996:Q2.
- We continue in this fashion until forecasts have been generated for 2006:Q4, for a total of forty-four forecast periods.

Note that the above attempts to replicate actual real-time forecasts, whereby the forecaster uses data available up to time t to produce a forecast at $t + k$ (or, equivalently, data up to $t - k$ to produce forecasts at time t). The issue of data revisions does not apply in the case of most of our financial variables, as these observations are not revised. However, it is known that GDP and monetary aggregates are subject to revision, so some caution should be used in interpreting some of these forecast results, as the data that we use in these particular cases do not produce true real-time forecasts.

4.2 Threshold Specification

Equation (2) supposes that financial stress is a linear function of asset price movements and other variables. However, if one believes that unusually large movements in asset prices, credit, monetary expansion, etc., may lead to greater financial uncertainty if, for example, herding mentality replaces rational financial decisions, then the relationship between some of our explanatory variables and the FSI may be nonlinear.[11] We can approximate such relationships by allowing for threshold effects between the explanatory variables and the FSI, such that the parameters of the models are allowed to differ when the explanatory variables lie above or below their threshold values. A similar strategy was employed by Borio and Lowe (2002), but the thresholds used in that study were explicitly specified by the authors. We employ a more general approach, whereby we estimate the threshold values; these endogenous thresholds therefore maximize the probability of locating a threshold effect in the data.

The threshold models take the form

$$FSI_t = \alpha^1 + \beta^1 FSI_{t-k} + \gamma^1 X_{t-k} + \delta^1 z_{t-k} + \xi_t \quad \text{for } z_{k,t-k} \leq \tau \tag{6}$$

$$FSI_t = \alpha^2 + \beta^2 FSI_{t-k} + \gamma^2 X_{t-k} + \delta^2 z_{t-k} + \xi_t \quad \text{for } z_{k,t-k} > \tau, \tag{7}$$

where z is some variable extracted from the vector X, and τ represents the level of z that triggers a regime change. We allow for a threshold effect for each of our twenty-four explanatory variables. Superscripts denote the values taken in regimes 1 and 2, respectively.

To estimate the parameters of the threshold model (6)–(7), we follow Hansen (2000) who derives an approximation of the asymptotic distribution of the least-squares estimator of the threshold parameter $\hat{\tau}$. To understand how the parameters are estimated, we

[11] Regardless of the underlying mechanism, Misina and Tessier (2008) show that nonlinearities play the key role in capturing extreme events associated with stress, as well as in generating plausible responses to shocks.

introduce an indicator function w and can rewrite equations (6) and (7) as a single equation:

$$FSI_t = \alpha^2 + \beta^2 FSI_{t-k} + \gamma^2 X_{t-k} + \delta^2 z_{t-k} + Aw + BwFSI_{t-k} + CwX_{t-k} + Dwz_{t-k} + \xi_t, \qquad (8)$$

where

$$w = \begin{cases} 1 & z_{t-k} \leq \tau \\ 0 & z_{t-k} > \tau \end{cases},$$

$$\alpha^2 + A = \alpha^1, \beta^2 + B = \beta^1, \gamma^2 + C = \gamma^1, \text{ and } \delta^2 + D = \delta^1.$$

By assuming that $\hat{\tau}$ is bounded by the largest and smallest values of the threshold variables, we can estimate the parameters in (8) by least squares conditional on a given value of $\hat{\tau}$. By iterating through the possible values of τ in the range of available threshold values, we select the $\hat{\tau}$ that minimizes the sum of squared residuals in (8).

The forecast exercise using the threshold models proceeds in exactly the same manner as for the linear models described above, so the parameters and threshold values are reestimated each period. The *rmr* is computed as the ratio of the RMSE from (8) relative to the RMSE of a modified version of the simple base-case model (1) which allows for threshold effects in the lagged value of the FSI.

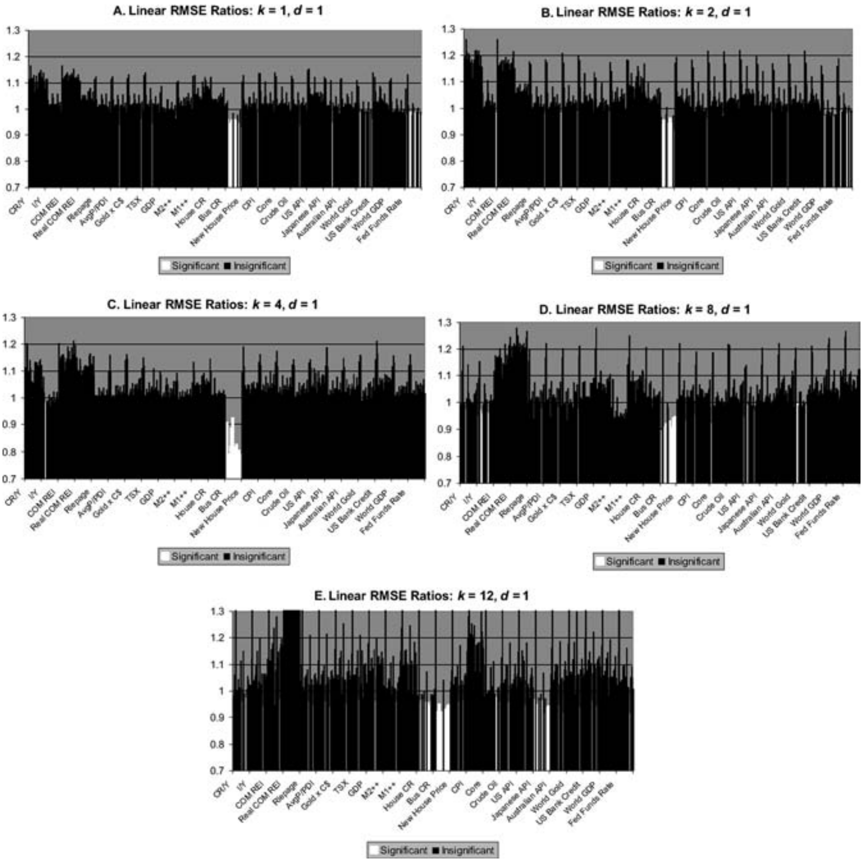
4.3 Results

Given all the combinations of variables, horizons, and specifications, we consider 11,520 models relative to the base-case model (1).[12] To summarize these results in the least cumbersome manner, we present the ratio of root mean squared errors for each horizon (k) and differencing operator (d) and model specification (linear or threshold) in twenty different graphs. This provides a simple visual approach to judge the usefulness of various variables. Since the results for $d = 1$ and $d = 4$ are very similar, we place the latter in an appendix.

The forecast performance of the linear models is summarized in figure 2. To interpret these figures, consider panel A. The horizontal axis contains labels for all the explanatory variables considered

[12] This is based on 24×24 variable combinations, five horizons, two differencing operators, and two model specifications: $576 \times 5 \times 2 \times 2 = 11{,}520$.

Figure 2. Linear Models, Forecast Performance, $d = 1$



(twenty-four variables). When a variable is listed along the horizontal axis, this indicates that it is included as the first regressor in the next twenty-four models. After each label there are twenty-four bars, corresponding to the *rmr*'s associated with models using different combinations of the labeled explanatory variable with other variables. For example, the first variable on the horizontal axis is the credit-to-GDP ratio, CR/Y. The first bar is the *rmr* for a model that includes only the CR/Y ratio as an additional explanatory variable, so that the estimated model is

$$FSI_t = \alpha + \beta_1 FSI_{t-k} + \gamma_1 (CR/Y)_{t-k} + \varepsilon_t.$$

The second bar is the *rmr* for a model including the CR/Y as well as the investment-to-GDP (I/Y) variable:

$$FSI_t = \alpha + \beta_1 FSI_{t-k} + \gamma_1 (CR/Y)_{t-k} + \gamma_2 (I/Y)_{t-k} + \varepsilon_t.$$

The third bar is the *rmr* for the model

$$FSI_t = \alpha + \beta_1 FSI_{t-k} + \gamma_1 (CR/Y)_{t-k} + \gamma_2 (ComREI)_{t-k} + \varepsilon_t,$$

etc.

The results associated with different models are assessed against the benchmark value of $rmr = 1$, which indicates that the inclusion of additional explanatory variables did not impact the forecasting performance of the base-case model. As stated earlier, $rmr > 1$ indicates that the inclusion of the variable has resulted in deterioration of the forecasting performance of the model relative to the benchmark. Finally, $rmr < 1$ indicates improved performance of the new model relative to the benchmark. Models for which the *rmr* is statistically lower than 1.0 according to the McCracken (2004) test are denoted in white.

Returning to figure 2, it is clear that the only variable that consistently helps forecast the FSI is domestic business credit, although the federal funds rate is significant at shorter horizons (up to two quarters ahead). For both these variables we find that, regardless of which variable they are paired with, they often produce mean-squared errors that are statistically lower than 1.0.

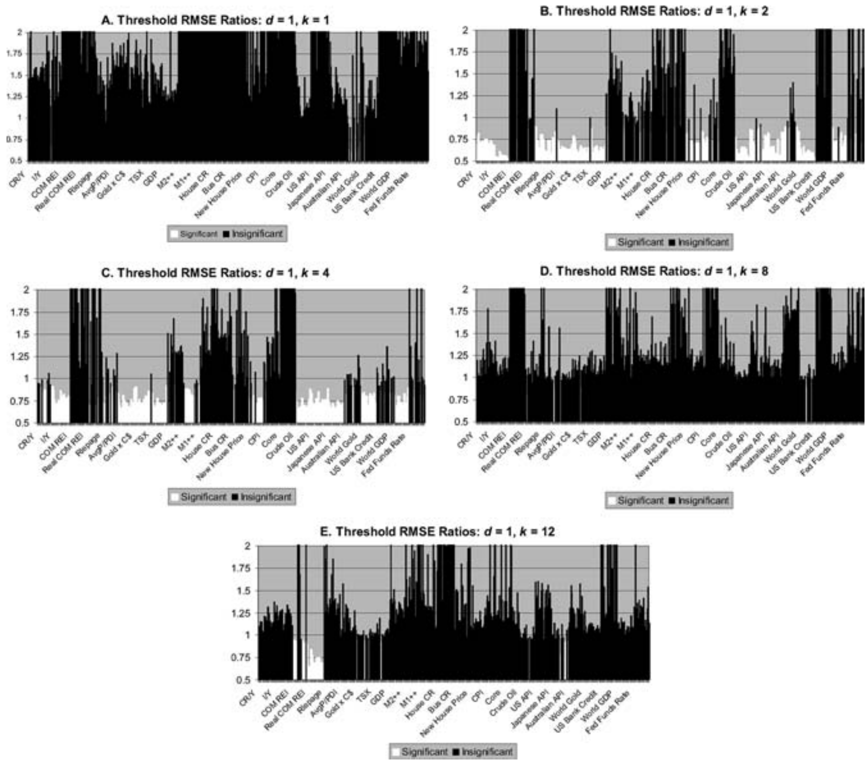
To understand the effect of business credit on the FSI, we can analyze the estimated parameters of the best forecasting models at each horizon, which are presented in table 1. We note several interesting results. First, the explanatory power of the lagged FSI decreases as the forecast horizon k increases, as evidenced by the adjusted R^2 which steadily decreases from 0.58 for $k = 1$ to 0.00 for $k = 12$. Second, the federal funds rate is retained in the best forecasting models at the shorter horizons ($k = 1$, 2), while domestic credit is retained at all horizons. Third, the parameters on the credit variables are all positive and statistically significant. This signals that a 1 percent quarterly increase in credit will cause the FSI to increase by between one and two points in the following quarters, which signals higher stress. If business credit is expanding, this could indicate that financial institutions are adding more risk to

Table 1. In-Sample Regression Results, Linear Models, Base-Case and Best Forecasting Models, $d = 1$
Sample: 1984:Q1 to 2006:Q4

Variable	$k = 1$		$k = 2$		$k = 4$		$k = 8$		$k = 12$	
Constant	7.66	11.25	14.31	21.21	19.40	28.46	30.43	40.01	45.80	52.19
	(2.27)	(3.56)	(3.77)	(5.47)	(5.62)	(7.04)	(6.32)	(7.80)	(8.27)	(10.48)
FSI_{t-k}	0.75	0.76	0.54	0.54	0.30	0.39	0.04	0.15	−0.19	−0.11
	(12.29)	(11.42)	(7.23)	(6.53)	(4.31)	(4.43)	(0.39)	(1.49)	(−2.09)	(−1.07)
Business Credit_{t-k}	0.68	—	1.13	—	2.13	—	1.34	—	1.59	—
	(2.54)		(3.32)		(7.47)		(4.08)		(4.64)	
World GDP_{t-k}	—	—	−0.01	—	—	—	—	—	—	—
			(−1.89)							
Japan API_{t-k}	—	—	—	—	—	—	—	—	0.36	—
									(2.76)	
Core CPI_{t-k}	—	—	—	—	—	—	2.29	—	—	—
							(3.11)			
Fed Funds_{t-k}	2.07	—	1.58	—	−2.32	—	—	—	—	—
	(1.99)		(5.47)		(−1.11)					
$\bar{R}^2$	0.62	0.58	0.41	0.29	0.44	0.14	0.29	0.01	0.35	0.00
RMSE Ratio	0.92		0.89		0.78		0.87		0.82	

Note: The base-case model includes only the lagged FSI. *RMSE Ratio* is the ratio of root mean squared error of the model containing exogenous regressors relative to the base-case model. t-statistics corrected for serial correlation and heteroskedasticity are in parentheses.

Figure 3. Threshold Models, Forecast Performance, $d = 1$



their balance sheets, and so results in a rise in the FSI. Conversely, when business credit falls, the opposite occurs. At shorter horizons, the federal funds rate is positively correlated with financial stress in Canada. That result is reversed at the one-year horizon, although the parameter is not statistically significant.

The results for threshold models are presented in figure 3, and the estimated coefficients for the best specifications are presented in table 2. The interpretation of these figures is similar to the linear model, except that in each model a threshold effect is allowed in the variable labeled in the figure. For example, the first variable on the horizontal axis in figure 3 is CR/Y, and the first bar is the *rmr* for the model that includes only the CR/Y ratio, with threshold effect, as an additional explanatory variable. The second bar is the *rmr* for

Table 2. In-Sample Regression Results, Threshold Models, Best Forecasting Models, $d = 1$ Sample: 1984:Q1 to 2006:Q4

Variable	$k = 1$		$k = 2$		$k = 4$		$k = 8$		$k = 12$	
Threshold Variable	Australia API		Japan API		AvgP/PDI		RLePage		Real Com REI	
$\hat{\tau}$	−3.05		−10.49		−5.79		12.93		88.22	
Regime	$\leq \hat{\tau}$	$> \hat{\tau}$	$\leq \hat{\tau}$	$> \hat{\tau}$	$\leq \hat{\tau}$	$> \hat{\tau}$	$\leq \hat{\tau}$	$> \hat{\tau}$	$\leq \hat{\tau}$	$> \hat{\tau}$
Constant	42.87	9.44	−4.22	19.25	79.88	21.29	39.65	27.37	190.02	10.72
	(2.32)	(2.97)	(−0.35)	(4.15)	(14.18)	(6.33)	(8.30)	(2.31)	(10.85)	(0.45)
FSI_{t-k}	0.47	0.73	0.22	0.56	0.06	0.24	−0.01	0.49	0.03	−0.28
	(1.95)	(10.56)	(0.91)	(6.16)	(0.79)	(3.34)	(−0.06)	(2.93)	(0.43)	(−2.39)
$CORE_{t-k}$	−1.41	0.32	—	—	—	—	—	—	—	—
	(−1.00)	(0.59)								
Australia API_{t-k}	0.98	0.20	—	—	—	—	—	—	—	—
	(1.84)	(1.83)								
Japan API_{t-k}	—	—	−2.65	0.09	—	—	—	—	—	—
			(−3.45)	(0.62)						
GDP_{t-k}	—	—	0.69	0.52	—	—	—	—	—	—
			(0.44)	(1.34)						
Business $Credit_{t-k}$	—	—	—	—	−0.22	2.03	1.09	1.63	—	—
					(−0.82)	(6.45)	(3.32)	(2.07)		
$AvgP/PDI_{t-k}$	—	—	—	—	1.79	0.36	—	—	—	—
					(13.99)	(3.07)				
$RLePage_{t-k}$	—	—	—	—	—	—	−0.50	−0.33	—	—
							(−2.25)	(−1.27)		
Real Com REI_{t-k}	—	—	—	—	—	—	—	—	−1.95	0.46
									(−8.31)	(2.05)
New House $Prices_{t-k}$	—	—	—	—	—	—	—	—	−1.18	0.86
									(−2.31)	(5.02)
Obs.	11.00	80.00	13.00	77.00	7.00	81.00	70.00	14.00	43.00	37.00
$\bar{R}^2$	0.41	0.60	0.51	0.35	0.95	0.53	0.17	0.53	0.71	0.46
RMSE Ratio	0.54		0.48		0.54		0.69		0.55	

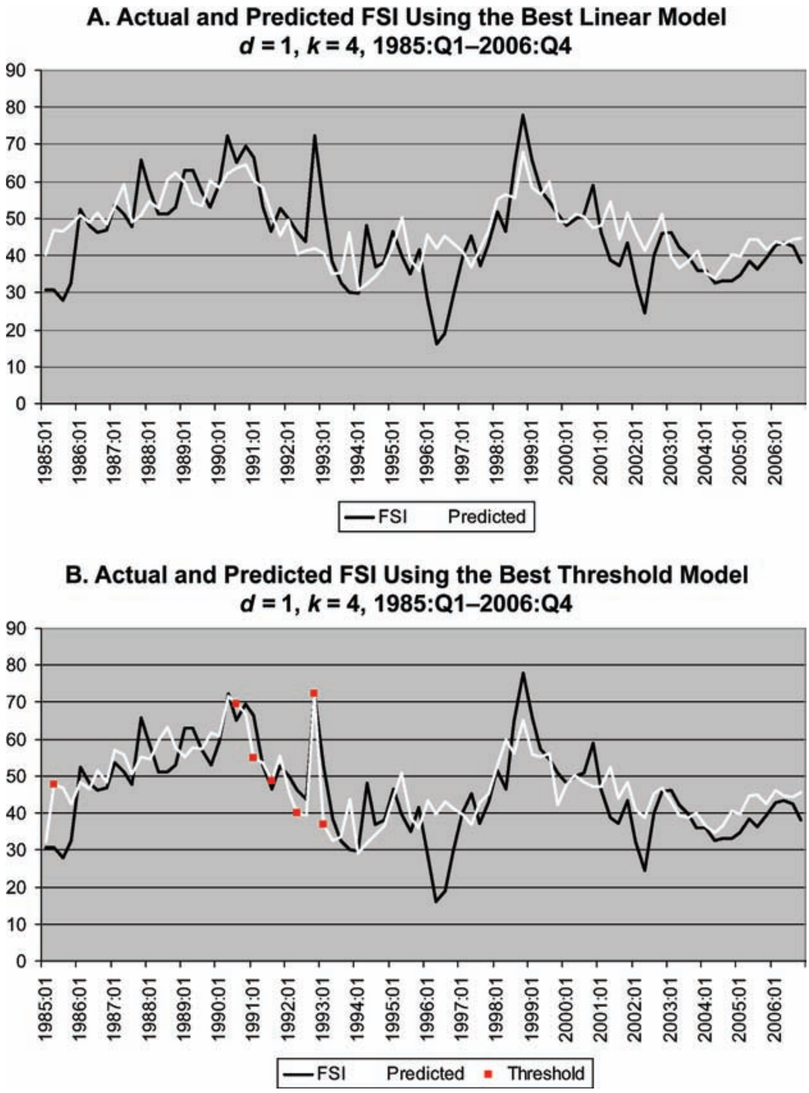
Note: The base-case model includes only the lagged FSI. *RMSE Ratio* is the ratio of root mean squared error of the model containing exogenous regressors relative to the base-case model. t-statistics corrected for serial correlation and heteroskedasticity are in parentheses.

the model that allows for the threshold effect in CR/Y and includes I/Y as an additional explanatory variable, etc.

The key features of the results at given horizon k, are as follows:

- $k = 1, 2$: No single variable appears to universally perform well at forecasting the FSI at very short horizons, as evidenced by the large number of black bars in one-quarter-ahead forecasting models. The situation improves noticeably two quarters ahead, but in both cases, the forecast performance varies according to the specific combinations of variables that are retained, as well as the choice of the threshold variable. The best forecasting equations at these horizons retain core inflation and GDP, with international asset price indices (Australia, Japan) identified as threshold variables (table 2). The *rmr* at these horizons is quite low, indicating a significant improvement in forecast performance relative to the base-case model.
- $k = 4, 8$: At these horizons, both business credit and asset prices emerge as significant predictors of financial stress (table 2). In both cases, a variable related to housing prices appears as a significant threshold variable. The *rmr* in both specifications remains quite low, indicating improvements in the forecast performance. For $k = 8$, the equation shows that when house prices rise by more than 13 percent during a quarter, the impact of additional business credit on the FSI rises from 1.1 to 1.6, so business credit expansion during a housing boom can add additional financial stress two years later.
- $k = 12$: At the longer horizons, we observe that few variables retain any forecasting power, the notable exception being the commercial real estate variable. At this horizon, commercial real estate investment is the regime-change trigger, while new house prices is retained as a significant regressor. Regime effects are quite pronounced for this equation, as the signs on both parameters actually change depending on which regime we are in. Furthermore, the number of observations in each regime are almost equal. When commercial real estate investment is low, increases in this variable and in new house prices lower stress; when commercial real estate investment is high, increases in these variables increase stress.

Figure 4. Actual and Fitted FSI



Finally, to provide a sense of how these models track the actual data, we plot in figure 4 the actual and fitted values of the best linear and threshold forecasting models for $k = 4$, a horizon which could be of interest to policymakers. In both cases, business credit is retained as a regressor and we see that, in general, both models perform reasonably well in tracking the trend and turning points of the FSI. The improvement of the threshold model relative to the linear model centers on the seven observations early in the sample, where the threshold model succeeds in picking up a few extreme movements of the FSI. One would therefore conclude that at this horizon business credit offers some hope in forecasting the FSI, regardless of the specification used.

5. Robustness Checks

To verify whether credit and asset prices are useful predictors of financial stress more generally, we first assess whether some of the more promising variables are good predictors of stress in Japan and the United States; second, we consider how these variables moved prior to the 2007–08 financial crisis.

5.1 The Crisis of 2007–08

In August 2007, the FSI increased sharply, pointing to considerable stress in the Canadian financial system. Indeed, the FSI in the recent episode reached its historical high, indicating that this is the most stressful episode since 1985. To assess the predictive power of the best forecasting model identified in the previous section, we have extended the sample to 2008:Q2 and performed a forecasting exercise along the lines described in the previous section. The results are shown in figure 5. The results show that whereas the best forecasting model does generate an increase in the FSI, the magnitude of that increase underestimates the increase in the FSI by a large margin. This is not surprising, given that the increase in stress captured by the FSI was largely triggered by exogenous events (collapse of the U.S. subprime market), but an analysis of the behavior of the explanatory variables can provide additional insights.

A look at the two key explanatory variables retained in the best threshold specification (figure 6) reveals that while both variables peaked in 2007:Q2, neither was anywhere near their historical highs. This may be an important contributing factor to the relatively good

Figure 5. 2007–08 Crisis

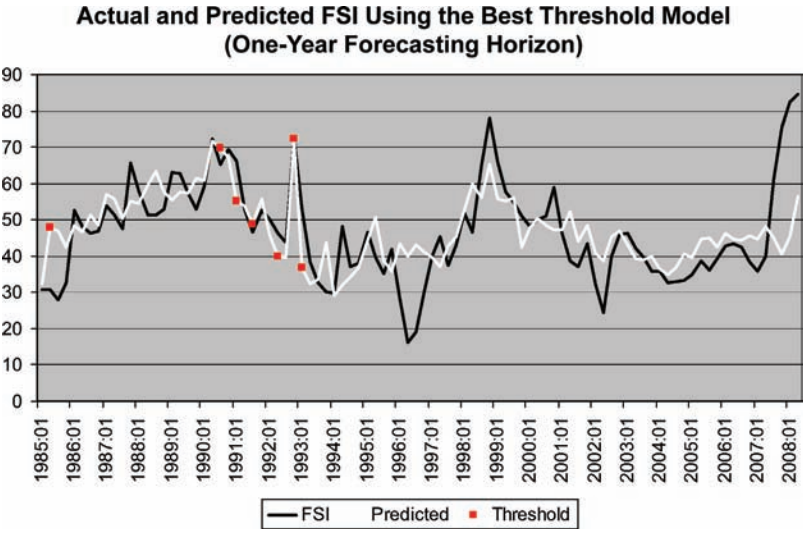
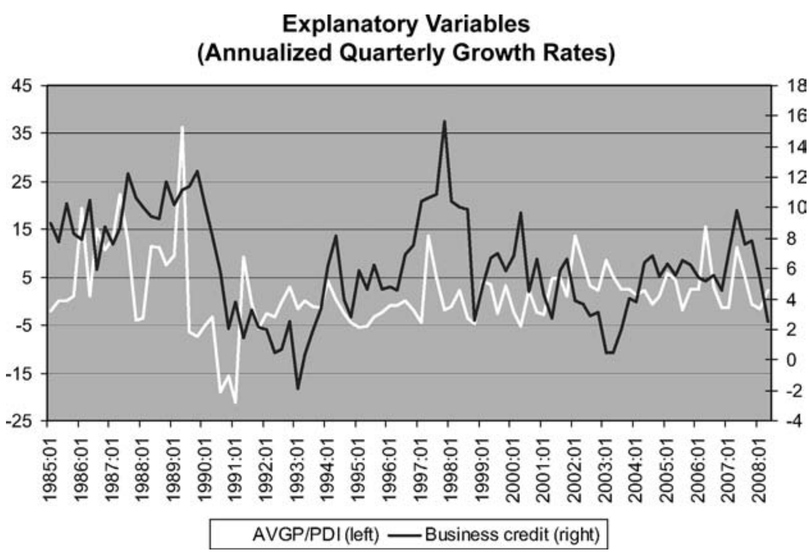


Figure 6. Behavior of the Explanatory Variables



health of the Canadian system and its resilience to date. Of course, the impact of a shock on the system is a function of the magnitude of the shock as well, and the peak in the FSI in spite of the good health of the system indicates that this is a large shock, by historical standards.

5.2 Results for Japan and the United States

We begin by constructing financial stress indexes for Japan and the United States that are as comparable as possible to the one we use for Canada.[13] We choose these two countries since their financial systems are quite different and have experienced different shocks over the last several years, so the degree of predictability of financial stress by credit and asset prices for these two countries can be informative with regard to their robustness as indicators. We notice in figures 7 and 8 that the movements in the U.S. FSI are generally similar to that of Canada's, with notable peaks in 2001 and 2008, while the Japan FSI experienced more independent movements.

To assess the usefulness of credit and asset prices in predicting the FSIs in these countries, we focus solely on the case of $d = 1$ and $k = 8$ (the eight-quarter forecast horizon). In this context, we found for Canada that the lowest forecast errors could be obtained using housing prices and business credit, with the former serving as the threshold variable. The Japan and U.S. variables that most closely matched the Canadian definitions of these variables are residential land prices[14] (from the Japanese Real Estate Institute) and total private-sector credit (from the International Monetary Fund) for Japan, and housing prices (Case-Shiller composite ten-city index) and total business credit (from the Federal Reserve bank of St. Louis's FRED database) for the United States. The threshold variable is land/housing prices. The out-of-sample forecasted values for the period 1998 to 2008 are presented in figures 7 and 8, allowing

[13] Details about the FSIs for Japan and the United States are available from the authors upon request.

[14] Land prices are the key driver of housing prices in Japan, so this is why we use this variable to capture real estate prices in Japan.

Figure 7. Forecasting the FSI for Japan

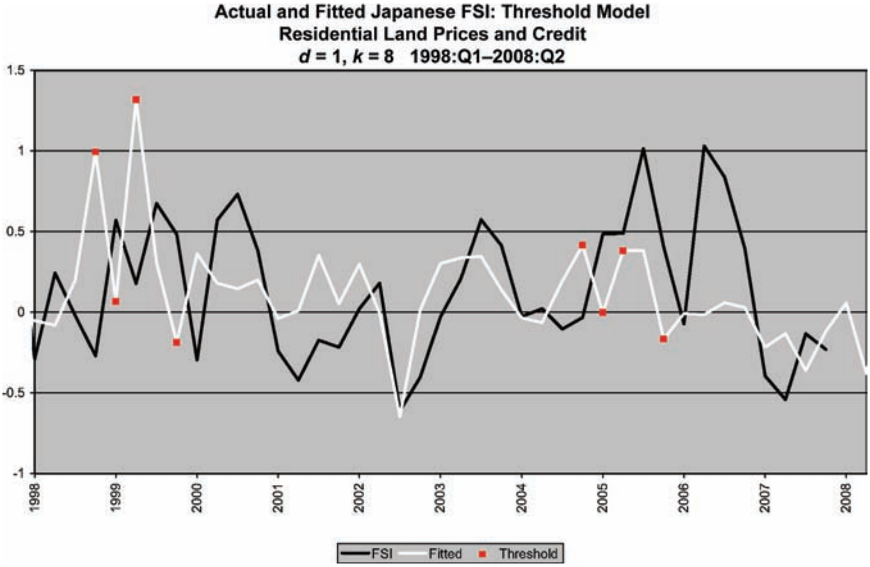
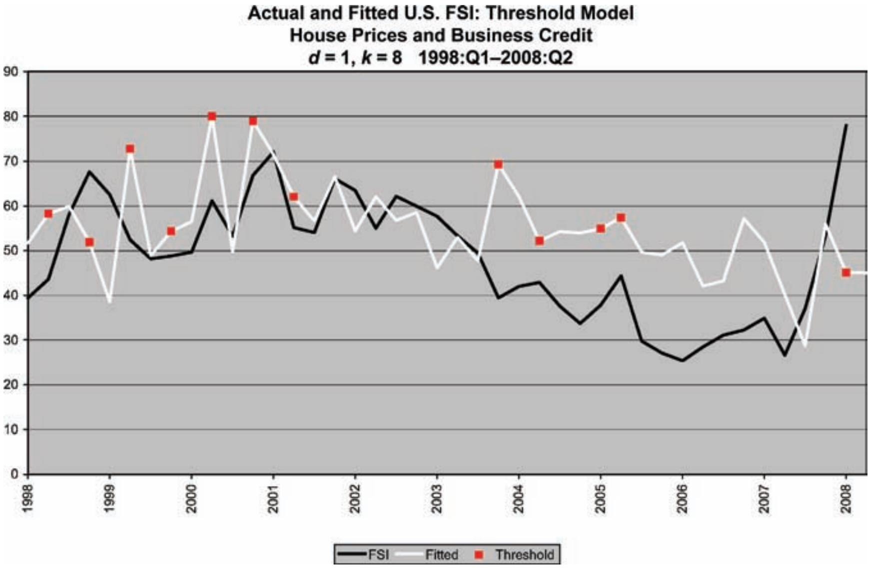


Figure 8. Forecasting the FSI for the United States



us to assess whether such variables could have predicted the recent spike in the U.S. FSI.

For Japan, although its FSI is somewhat more volatile than that of the United States and Canada, land prices and credit growth predicted some peaks and troughs relatively well; for example, the cycle from early 2002 to mid-2004 was captured quite accurately eight quarters in advance. Other episodes, such as the financial stress spike in 2006, were not captured by these variables. This suggests that financial stress was being driven by other factors in this period, so forecasters should consider additional predictors of financial stress for Japan.[15]

In the United States (figure 8) we observe that the forecasted values generally captured the level and volatility of actual FSI until about 2003, but from 2004 to 2007 it overpredicted stress, and it underpredicted stress in 2008. Most recently, housing and credit growth predicted a sharp increase in stress in late 2007, which materialized, but the subsequent stress actually overshot the predicted values. Given that housing prices are known to have increased dramatically until 2007 and then suffered a serious correction, the extent of the bubble characteristics of the U.S. housing market was only partially captured by the simple threshold relationship that we consider.

In short, credit growth and housing prices appear to predict the direction of the FSI relatively well eight quarters in advance. The challenge appears to obtain better predictions of the level of stress. To this end, although the threshold model that we use can capture some of the "bubble" features of asset prices, in future work one may wish to consider models with richer nonlinear dynamics. In the most recent episode, housing prices experienced a long and sustained buildup and then suffered a dramatic crash. Since our model overpredicted stress during the buildup phase, forecasters may wish to focus their attention on building models that more adequately capture the dynamics between asset prices and financial stress in such periods.

[15] Our last observation for the Japan FSI is 2007:Q3, so it predates the most recent global financial crisis.

6. Conclusion

The literature on financial stress typically equates financial stress with the occurrence of financial crises, and attempts to forecast the latter using different sets of macroeconomic variables. This procedure runs into difficulties when applied to countries where financial crises are rare or non-existent events, and this is evident especially when the analysis is constrained by data availability to the last twenty-five to thirty years. The absence of financial crises, however, does not imply that a country has not been subjected to financial stress in the past, or that accumulated financial imbalances could not result in financial crises in the future.

To deal with the problem of measurement of financial stress in the absence of financial crises, Illing and Liu (2006) constructed a financial stress index for Canada. The question we asked in this paper is whether a set of explanatory variables commonly considered in the macroprudential literature could help forecast financial stress. To do this we have considered both linear and threshold models and assessed their performance by comparing them with the benchmark model in which the future value of the FSI is predicted using only its lagged value.

We find that, in line with the macroprudential literature, *some* combination of credit and asset price variables are important predictors of financial stress, although the results depend on the type of model used (linear or threshold) and the forecast horizon. As a general rule, we find that these indicators offer greater value added at forecasting the FSI than the benchmark model as the forecast horizon increases. A specific indicator worthy of being highlighted is business credit, which emerges as the prominent leading indicator in both linear and nonlinear models at the one- and two-year horizons. A combination of this variable with a threshold in a housing-sector asset price leads to significant improvements in performance over the same horizon. At shorter horizons, the federal funds rate emerges as a predictor of financial stress in linear models. In general, however, international variables seem to play a smaller role than one would expect they would in a small open economy.

At the one-year horizon, which could be of interest to forward-looking policymakers, in practical terms there is little to distinguish the linear and threshold specifications, as both models track the FSI relatively well at this horizon. What matters most is the monitoring of business credit, which emerges as an important leading indicator among all variables considered in our study.

The empirical results reported here are country specific, and a more in-depth comparative study of determinants of financial stress in countries with few or no financial crises would be instructive. The methodology proposed in our work is well suited for that task.

Appendix

Figure 9. Linear Models, Forecast Performance, $d = 4$

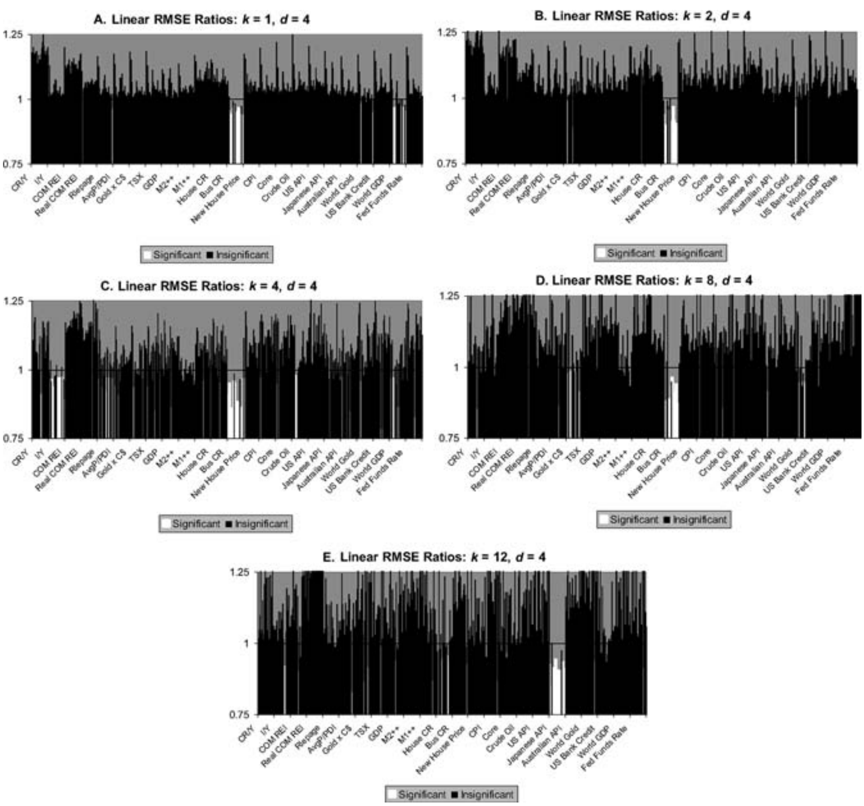
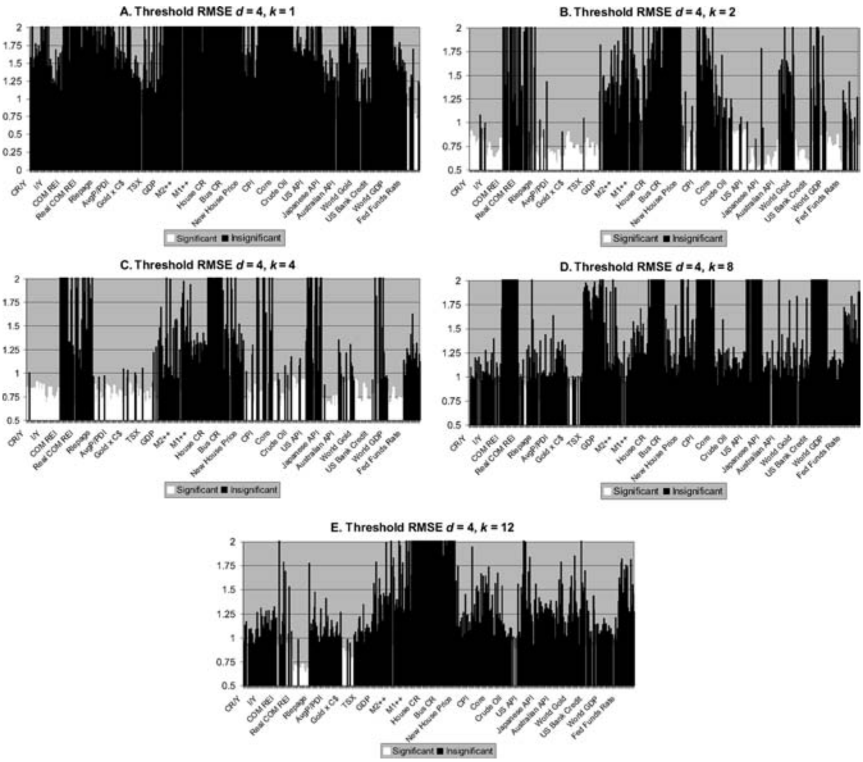


Figure 10. Threshold Models, Forecast Performance, $d = 4$



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