BANK OF CANADA
BANQUE DU CANADA

Working Paper/Document de travail
2008-10

Credit, Asset Prices, and Financial Stress in Canada

by Miroslav Misina and Greg Tkacz

www.bank-banque-canada.ca

Bank of Canada Working Paper 2008-10

April 2008

Credit, Asset Prices, and Financial Stress in Canada

by

Miroslav Misina[1] and Greg Tkacz[2]

[1]Monetary and Financial Analysis Department
[2]Research Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
mmisina@bankofcanada.ca
gtkacz@bankofcanada.ca

ISSN 1701-9397

Acknowledgements

The authors would like to thank Allan Crawford, Céline Gauthier, Mark Illing, Pierre St-Amant and Bank of Canada workshop participants for valuable comments and suggestions. Stephen Doxey provided fine research assistance.

Abstract

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 34 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 performed for Canada, but the methodology is suitable for any country that fits the above description.

JEL classification: G10, E5
Bank classification: Credit and credit aggregates; Financial stability

Résumé

Dans les analyses historiques, on associe généralement les crises financières aux périodes d'expansion du crédit et aux déséquilibres de prix sur le marché des actifs. Par conséquent, un groupe de variables réunissant à la fois des mesures du crédit et du prix des actifs pourrait-il servir à prévoir les crises? Borio et Lowe (2002) répondent à cette question par l'affirmative sur la base d'un échantillon de 34 pays. La réponse est loin d'être claire, toutefois, dans le cas isolé d'un pays développé qui a peu ou pas connu de crises financières dans le passé. Les auteurs contournent la difficulté en mettant plutôt l'accent sur le concept de tensions financières, mesurées au moyen de l'indice mis au point par Illing et Liu (2006), et examinent si les mouvements du crédit et du prix des actifs peuvent aider à prédire l'apparition de telles tensions. Entre autres innovations, ils procèdent à l'estimation de modèles linéaires et de modèles à seuils endogènes faisant intervenir un large éventail de prix d'actifs (comme ceux des actions et des maisons), de même qu'à l'élaboration de prévisions à l'aide de ces modèles. Ils étudient plus précisément le cas du Canada, mais leur méthodologie se prête à l'analyse de la situation de tout pays développé n'ayant jamais traversé de crise financière.

Classification JEL : G10, E5
Classification de la Banque : Crédit et agrégats du crédit; Stabilité financière

1 Introduction

Does a combination of credit expansions and upward movements in asset prices increase the likelihood of financial crises? In spite of the prevalence of these two factors in historical accounts of financial crises (e.g. Kindleberger and Aliber (2005)), Borio and Lowe (2002, p. 11) note that the empirical work seeking to answer this question is scarce. 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.

The objective of this work is to answer the question posed for Canada, a country that, in Bordo *et al*. (2001) dating, has not experienced any ‘twin crises’ (banking and currency crises) since the beginning of their sample in 1883, and only 4 currency crises since 1945.[2] These features of the sample, which are, broadly speaking, typical of developed countries, preclude a meaningful country-level analysis based on binary indicators of crises. Instead, we propose 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 methodology is general and can be applied to any country. In answering the main question, we consider both linear and nonlinear models, since the latter may be more apt at capturing any behavioral asymmetries of financial market participants.

Being a small open economy, financial stress in Canada 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 several foreign variables. However,

[1] Bordo *et al.* (2001, p. 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).

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, p.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.

To preview the main results, we find that within a linear framework, domestic credit growth is the best predictors of the FSI at all horizons, resulting in marginally lower prediction errors relative to our basecase 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 non-linearities, 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. 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]

[3] Sorge (2004) provides an excellent survey of stress-testing literature and its relationship to macroeconomic forecasting and early warning signals literature.

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 30 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. 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 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 non-linear (threshold) specifications. In the latter, we follow Borio and Lowe (2002) and focus on imbalances rather than levels or growth rates of variables, but, rather than specifying the threshold exogenously, in our work the thresholds are determined endogenously.

3 Data

3.1 A measure of financial stress

The Financial Stress Index (FSI) was introduced by Illing and Liu (2006), and represents an attempt to arrive at a quantitative assessment of the state of the Canadian financial system by aggregating various indicators of financial conditions. These indicators are grouped into three categories. The categories and components are as follows:[4]

- Expected loss:
    - spread between yields on bonds issued Canadian financial institutions and the yields on government bonds of comparable duration
    - yield spread on Canadian non-financial corporate bonds
    - inverted term spread (i.e., the 90-day treasury bill rate minus the 10-year government yield)
- Risk:
    - the beta derived from the total return index for Canadian financial institutions
    - Canadian trade-weighted dollar GARCH volatility
    - TSX GARCH volatility
- Uncertainty:
    - difference between Canadian and US government short-term borrowing rates
    - average bid-ask spread on Canadian treasury bills
    - spread between Canadian commercial paper rates and treasury bills rates of comparable duration.

In constructing their index, Illing and Liu consider several weighting options, and opt for credit weights. Under this approach the importance of individual components corresponds to the share of a particular market in the overall credit of the economy.

[4] See Illing and Liu (2006) for a detailed discussion of rationale behind each component.

Figure 1 plots the FSI for the sample period of interest in the present study. Higher values of the index indicate higher financial stress. It is of interest to note that even though the component parts of the FSI are based on Canadian data, the peaks of the index largely coincide with episodes of stress that are international in nature (e.g. stock market crash in October 1987, peso crisis in 1994, LTCM 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

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

- Credit measures
    - Total household credit (HouseCR)
    - Total business credit (BusCR)
    - Total credit/GDP (CR/Y)
- Asset prices
    - Stock prices (TSX)
    - Real estate
        - Commercial (nominal - ComREI; real - Real ComREI)
        - residential (new - New House Price Index; existing - Royal LePage Index; average price to personal disposable income ratio (AvgP/PDI))
    - C$ price of gold (GoldC$)

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

- Macroeconomic variables
  - Investment/GDP (I/Y)
  - GDP
  - Money (narrow (M1++), broad (M2++))
  - Inflation (Total CPI and Core CPI)
- Foreign variables
  - Crude oil
  - Asset price indices (US, Australia, Japan)[6]
  - World gold price
  - World GDP[7]
  - U.S. bank credit[8]
  - U.S. Federal Funds rate

The data is quarterly and spans the period 1984 – 2006. The forecasting exercise is performed over the period 1996 – 2006. The last observation is 2006Q4. The explanatory variables are converted into growth rates, so all variables are stationary.[9] 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.

[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: BIS.
[8] Source: Federal Reserve Board, Table H.8.
[9] Commercial real estate investment is not transformed since it was found to be stationary.

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 to 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

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

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 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.[10]

[10] 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.

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):

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

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

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

where R represents the first out-of-sample forecast period (1996Q1). Intuitively, note that the numerator represents the difference in mean squared-errors (MSEs) between the basecase 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 basecase model has a lower MSE, then the statistic will be negative, and it will be positive if the alternative has a lower MSE. The distribution is non-standard 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 50. Our own application has a sample size of 44 (1996Q1 to 2006Q4), so this test should be appropriate for our purposes. Instances where the alternative model is found to have a statistically lower MSE than the basecase 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 1996Q1 – k, where k = 1, 2, 4, 8 or 12;
- Using the estimated parameters, we produce a forecasted FSI for 1996Q1;

- We re-estimate the parameters with data from 1984 to 1996Q2 – *k*;
- We use the newly estimated parameters to obtain a forecast of the FSI for 1996Q2;
- We continue in this fashion until forecasts have been generated for 2006Q4, for a total of 44 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 non-linear. 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

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

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

where z is some variable extracted from the vector X, and □ represents the level of z that triggers a regime change. We allow for a threshold effect for each of our 24 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 introduce an indicator function w and can re-write 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

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

$\alpha^2 + A = \alpha^1$, $\beta^2 + B = \beta^1$, $\gamma^2 + C = \gamma^1$, 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 re-estimated 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

4.3.1 Linear and threshold models

Given all the combinations of variables, horizons, and specifications, we consider 11520 models relative to the base case model (1).[11] To summarize these results in the least cumbersome manner we present the ratio of root mean squared errors for each horizon (k)

[11] 24x24 variable combinations, 5 horizons, 2 differencing operators and 2 model specifications: 576 x 5 x 2 x 2 = 11520.

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 (24 variables). When a variable is listed along the horizontal axis, this indicates that it is included as the first regressor in the next 24 models. After each label there are 24 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 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 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 Fed Funds rate is significant at shorter horizons (up to 2 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 Fed 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% quarterly increase in credit will cause the FSI to increase by between 1 and 2 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 their balance sheets, and so results in a rise in the FSI. Conversely, when business credit falls the opposite occurs. At shorter horizon, the Fed funds rate is positively correlated with financial stress in Canada. That result is reversed at 1-year horizon, although the parameter is not statistically significant.

The results for threshold models are presented in Figure 3. 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 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 in Figure 3, 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 1-quarter ahead forecasting models. The situation improves noticeably 2 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. 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% 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 exceptions 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.

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 policy-makers. 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.

4.3.2 Forecasting models and recent spike in the FSI

August 2007 marks the beginning of the financial turmoil that is still under way. The increase in financial stress has been reflected in a sharp increase in the FSI in that period. The question is whether the best forecasting models identified in the previous section would have picked up the sharp spike in the index. To examine this, we considered the following models:

- Model 1 (threshold): Average house price/ disposable income, business credit
- Model 2 (threshold): TSX and business credit
- Model 3 (threshold): oil price and business credit
- Model 4 (linear): Fed funds rate and business credit
- Model 5 (linear): business credit
- Model 6 (linear): Average house price/ disposable income, business credit

Figure 7 (a) – (f) shows the results of this forecasting exercise. In all cases, the models do predict an increase in the FSI, but the increase occurs with a lag and generally does not match the peak of the FSI. Increase in the forecasted value is due largely to the inclusion of the lagged dependent variable, rather than a dramatic changes in the variables retained in these specifications.

A closer examination of the behaviour of subcomponents of the FSI[12] reveals that the sharp spike in the FSI in August is primarily due to a sharp increase in interest spreads,

[12] Figures of the subcomponents of the FSI are available from authors.

more specifically the commercial paper spread, and the average bid-ask spread on Treasury bills. None of the explanatory variables retained in our best specifications are directly related to this component of the FSI. Consequently, we would not expect our models to capture sharp increases in the FSI that are driven by non-structural factors.

More generally, one would not expect credit and asset prices to pick up sharp spikes in any measure of financial stress. In line with findings in Borio and Lowe (2002), it is the financial imbalances (overextension of credit, persistent asset price increases that are not sustained by fundamentals) that make financial system vulnerable and increase likelihood of financial crises. Each crisis has (at least ex ante) a unique trigger event, which may impact the FSI, but will not be predicted by credit and asset price variables. Indeed, it is doubtful that any econometeric model can be of much help in predicting these idiosyncratic events.

5 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 25 – 30 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. The question we asked in this paper is whether a set of explanatory variables commonly considered in the macro prudential literature could help forecast financial stress. To do this we have considered both linear and threshold models and assessed their performance by comparing them to 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 macro prudential 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 non-linear models at the 1 and 2-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 Fed 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 policy-makers, 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 specific to Canada. Whereas they do confirm Borio and Lowe's findings, on balance business credit seems to play a somewhat more important role in forecasting financial stress. A 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.

References

Bordo, M., B. Eichengreen, D. Klingebiel, and M. S. Martinez-Peria (2001) “Financial crises: Lessons from the last 120 years.” *Economic Policy*, April.

Borio, C. and P. Lowe (2002) “Asset prices, financial and monetary stability: Exploring the nexus.” BIS Working Paper No. 114, July.

Hanschel, E. and P. Monnin (2005) “Measuring and forecasting stress in the banking sector: Evidence from Switzerland.” *BIS Papers No. 22: Investigating the Relationship Between the Financial and Real Economy*, April, 431-449.

Hansen, B. (2000) “Sample splitting and threshold estimation.” *Econometrica* 68, 575-603.

Illing, M. and Y. Liu (2006) “ Measuring financial stress in a developed country: An application to Canada,” *Journal of Financial Stability* 2, 243 – 65.

Kaminsky, G. and C. Reinhart (1999) “The twin crises: The causes of banking and balance-of-payments problems.” *American Economic Review* 89, 473-500.

Kindleberger, C, and R. Aliber (2005) *Manias, Panics, and Crashes: A History of Financial Crises,* 5th Edition. John Wiley & Sons.

McCraken, M. W. (2004) Asymptotics for out-of-sample tests of Granger-causality. University of Missouri, Working Paper.

Shiller, R. J. (2005) *Irrational Exuberance*, 2nd Edition. New York: Doubleday.

Sorge, M. (2004) “Stress-testing financial systems: and overview of current methodologies.” BIS Working Paper No. 165

Table 1: In-sample Regression Results, Linear Models, Basecase and Best Forecasting Models, $d = 1$

Sample: 1984Q1 to 2006Q4

Variable	k=1		k=2		k=4		k=8		k=12	
Constant	7.66 (2.27)	11.25 (3.56)	14.31 (3.77)	21.21 (5.47)	19.40 (5.62)	28.46 (7.04)	30.43 (6.32)	40.01 (7.80)	45.80 (8.27)	52.19 (10.48)
FSI_{t-k}	0.75 (12.29)	0.76 (11.42)	0.54 (7.23)	0.54 (6.53)	0.30 (4.31)	0.39 (4.43)	0.04 (0.39)	0.15 (1.49)	-0.19 (-2.09)	-0.11 (-1.07)
Business $Credit_{t-k}$	0.68 (2.54)	--	1.13 (3.32)	--	2.13 (7.47)	--	1.34 (4.08)	--	1.59 (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 (1.99)	--	1.58 (5.47)	--	-2.32 (-1.11)	--	--	--	--	--
$\overline{R}^2$	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	

The basecase 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 basecase model. t-statistics corrected for serial correlation and heteroskedasticity are in parentheses.

Table 2: In-sample Regression Results, Threshold Models, Best Forecasting Models, d = 1

Sample: 1984Q1 to 2006Q4

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 (2.32)	9.44 (2.97)	-4.22 (-0.35)	19.25 (4.15)	79.88 (14.18)	21.29 (6.33)	39.65 (8.30)	27.37 (2.31)	190.02 (10.85)	10.72 (0.45)
FSI_{t-k}	0.47 (1.95)	0.73 (10.56)	0.22 (0.91)	0.56 (6.16)	0.06 (0.79)	0.24 (3.34)	-0.01 (-0.06)	0.49 (2.93)	0.03 (0.43)	-0.28 (-2.39)
$CORE_{t-k}$	-1.41 (-1.00)	0.32 (0.59)	--	--	--	--	--	--	--	--
Australia API_{t-k}	0.98 (1.84)	0.20 (1.83)	--	--	--	--	--	--	--	--
Japan API_{t-k}	--	--	-2.65 (-3.45)	0.09 (0.62)	--	--	--	--	--	--
GDP_{t-k}	--	--	0.69 (0.44)	0.52 (1.34)	--	--	--	--	--	--
Business $Credit_{t-k}$	--	--	--	--	-0.22 (-0.82)	2.03 (6.45)	1.09 (3.32)	1.63 (2.07)		--
$AvgP/PDI_{t-k}$	--	--	--	--	1.79 (13.99)	0.36 (3.07)	--	--	--	--
$RLePage_{t-k}$	--	--	--	--	--	--	-0.50 (-2.25)	-0.33 (-1.27)	--	--
Real Com REI_{t-k}	--	--	--	--	--	--	--	--	-1.95 (-8.31)	0.46 (2.05)
New House $Prices_{t-k}$	--	--	--	--	--	--	--	--	-1.18 (-2.31)	0.86 (5.02)
Obs.	11.00	80.00	13.00	77.00	7.00	81.00	70.00	14.00	43.00	37.00
$\overline{R}^2$	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	

The basecase 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 basecase model. t-statistics corrected for serial correlation and heteroskedasticity are in parentheses.

Figure 1

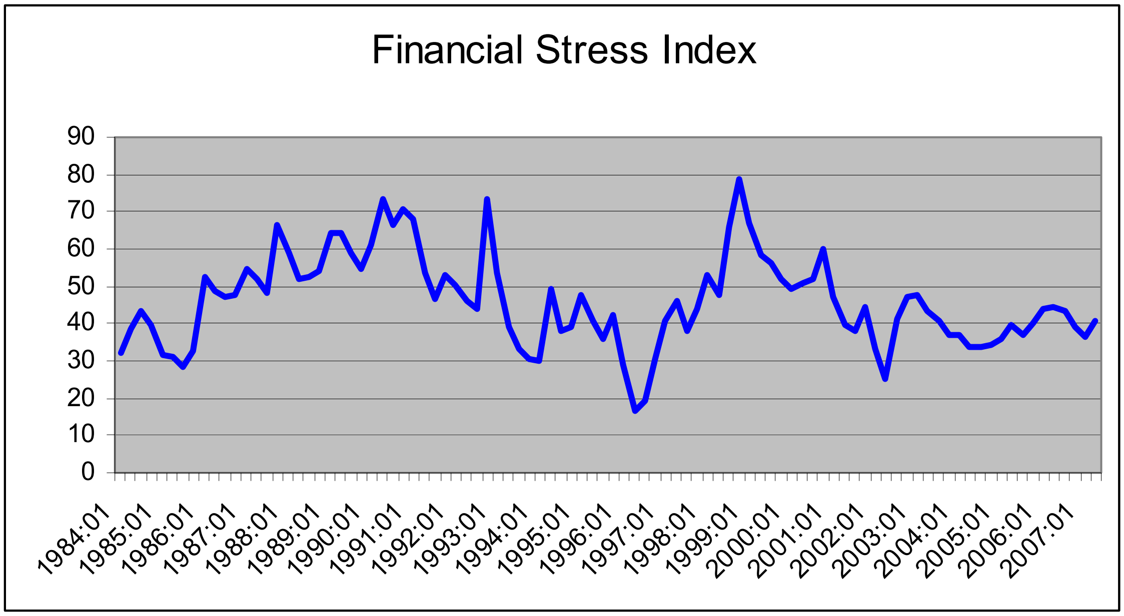

Financial Stress Index
90
80
70
60
50
40
30
20
10
0
1984:01
1985:01
1986:01
1987:01
1988:01
1989:01
1990:01
1991:01
1992:01
1993:01
1994:01
1995:01
1996:01
1997:01
1998:01
1999:01
2000:01
2001:01
2002:01
2003:01
2004:01
2005:01
2006:01
2007:01

Figure 2: Linear Models, Forecast Performance, *d*=1

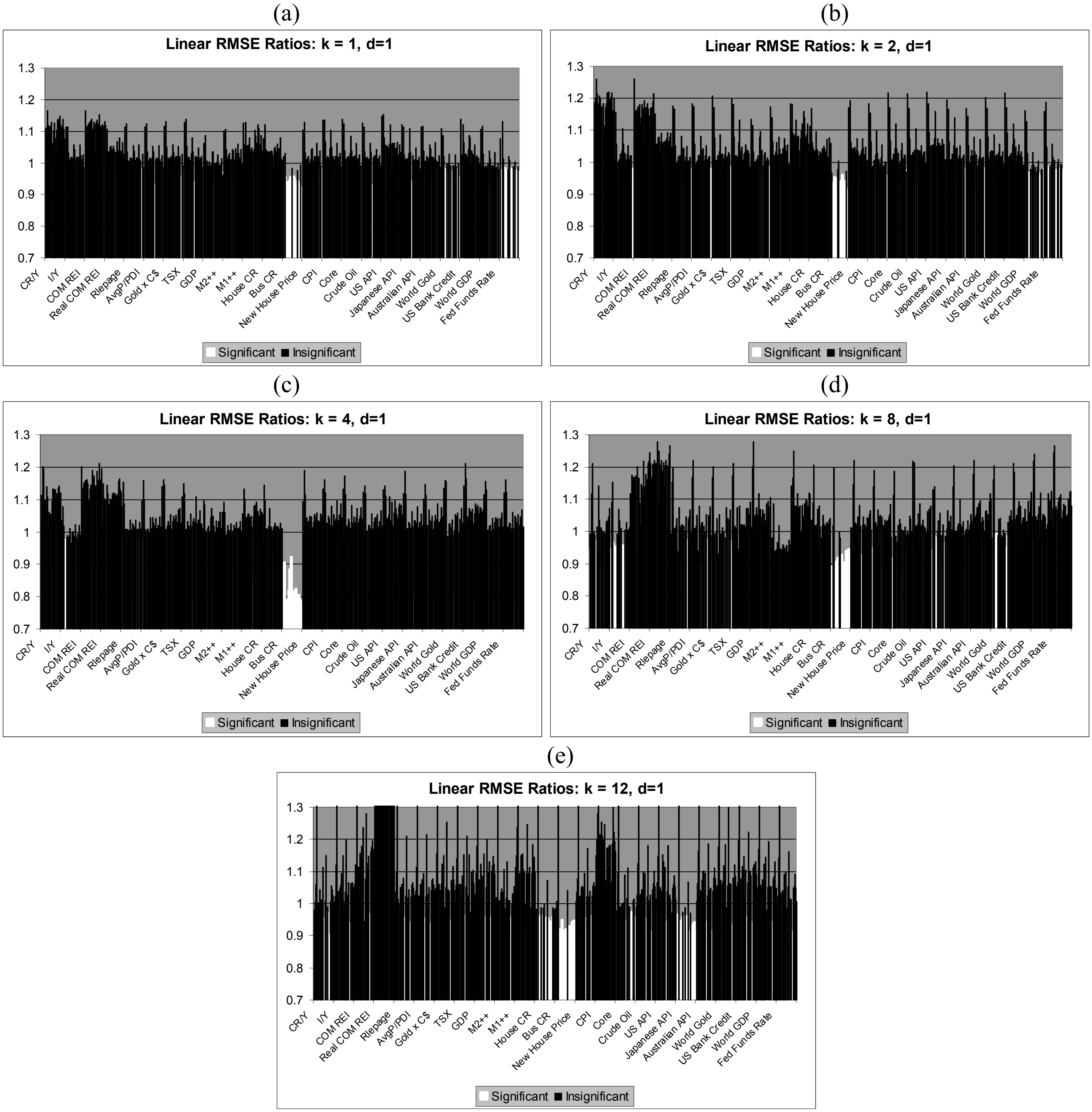
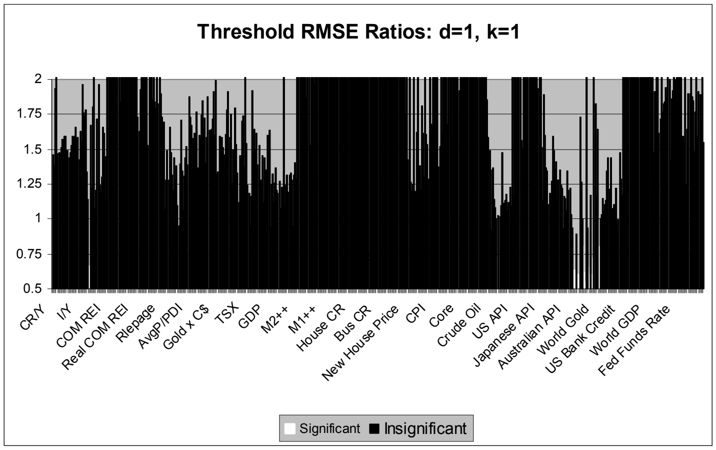
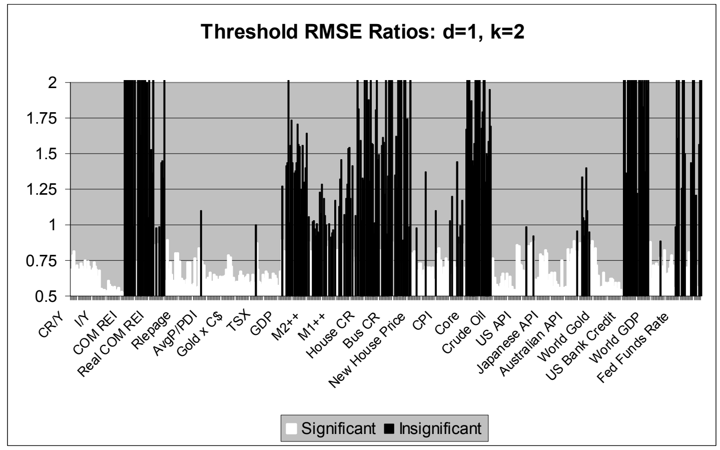


Figure 3: Threshold Models, Forecast Performance, *d*=1

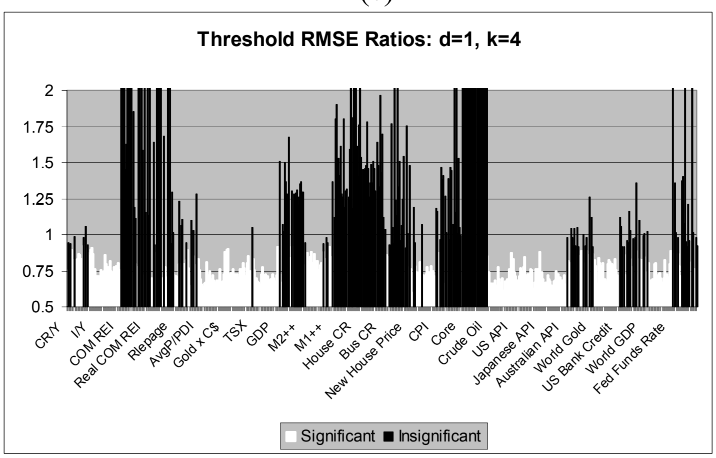
(a)



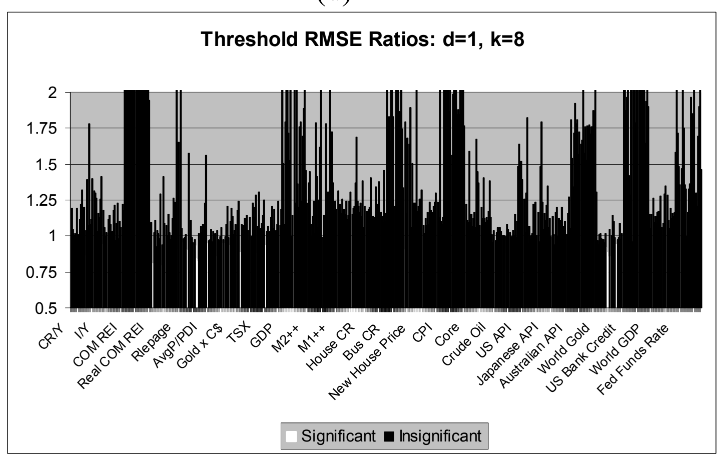
(b)



(c)



(d)



(e)

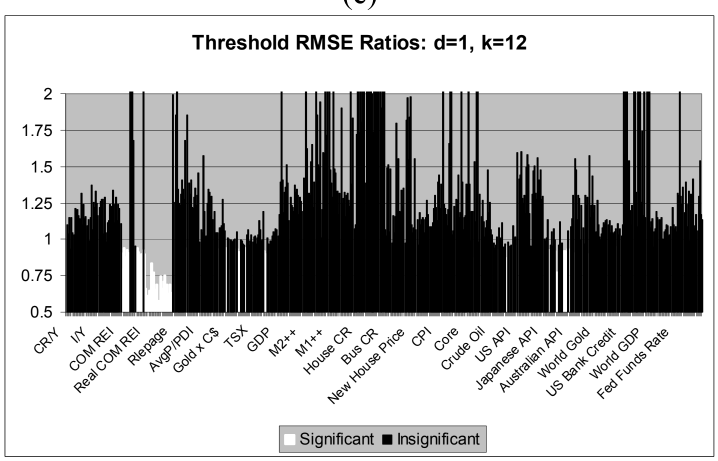
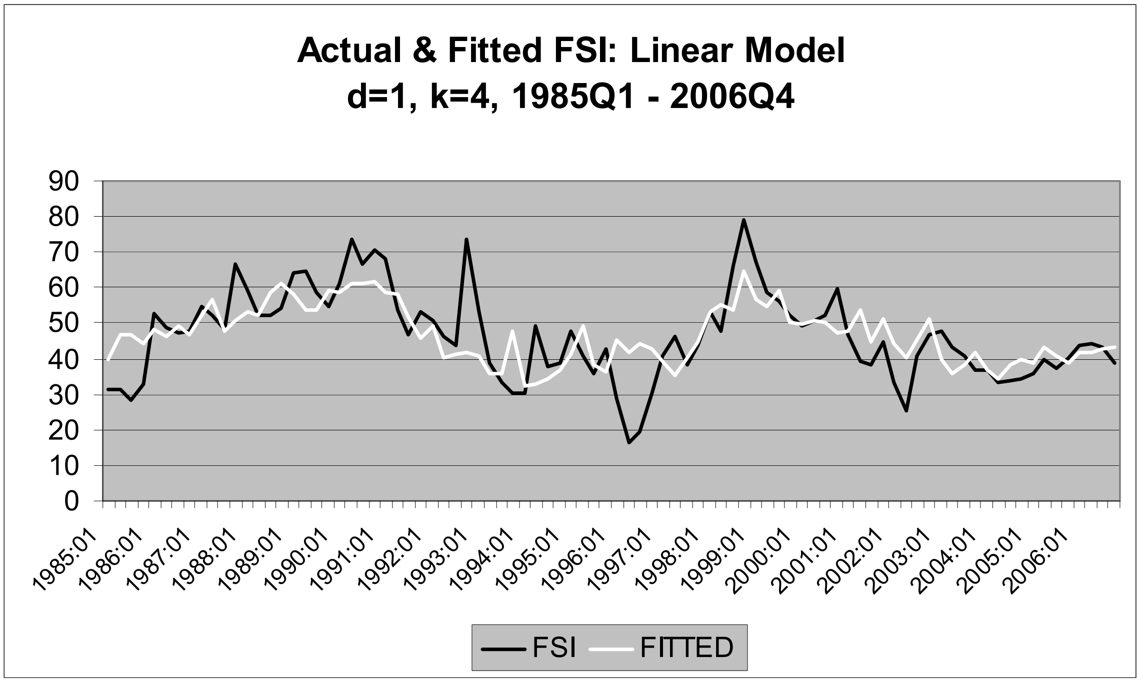
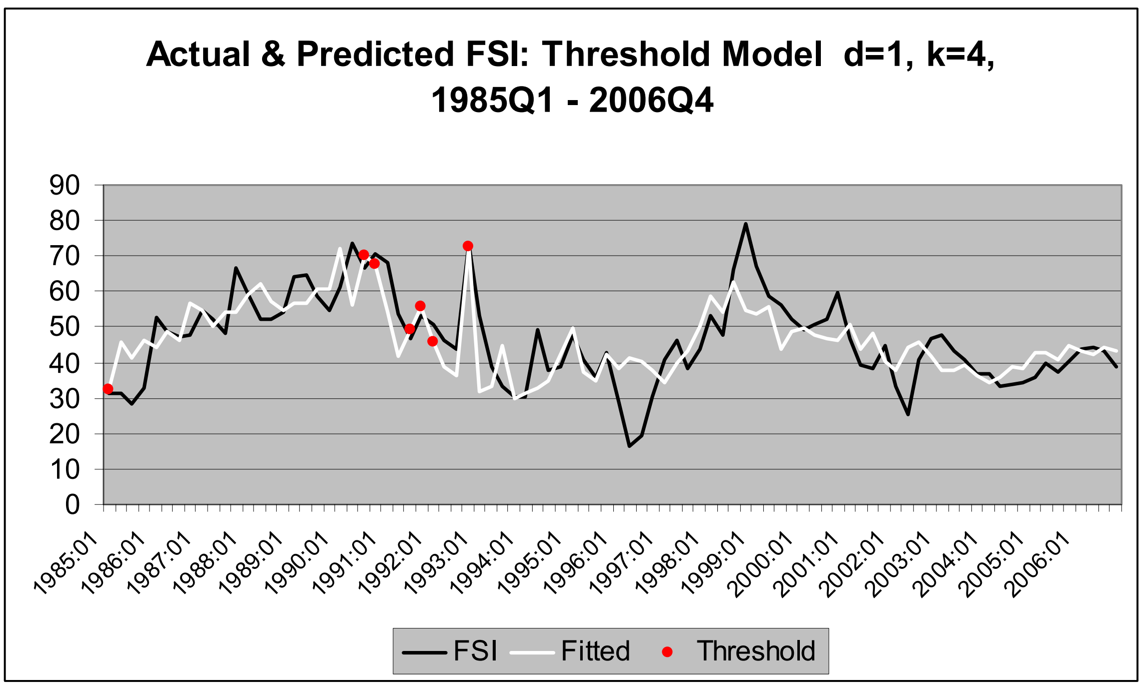


Figure 4: Actual and Fitted FSI

(a)

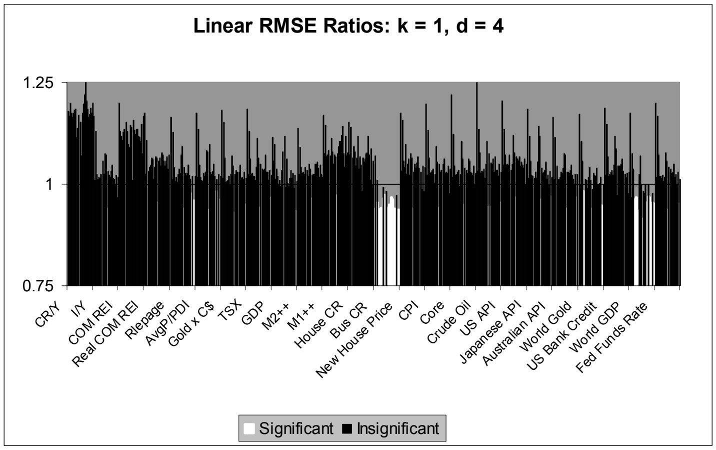


(b)

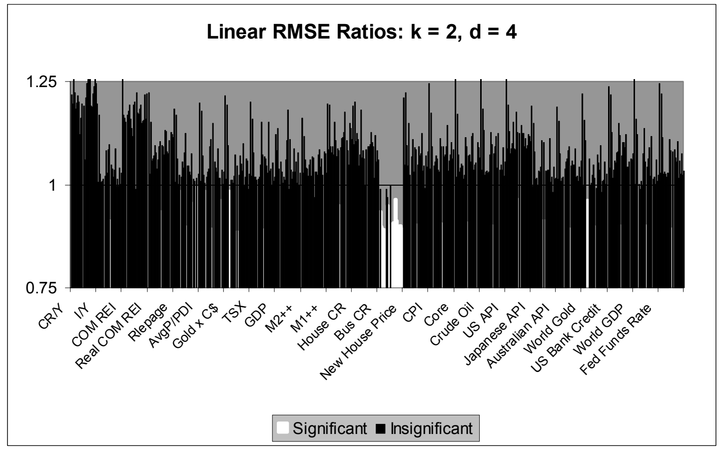


Appendix
Figure 5: Linear Models, Forecast Performance, *d*=4

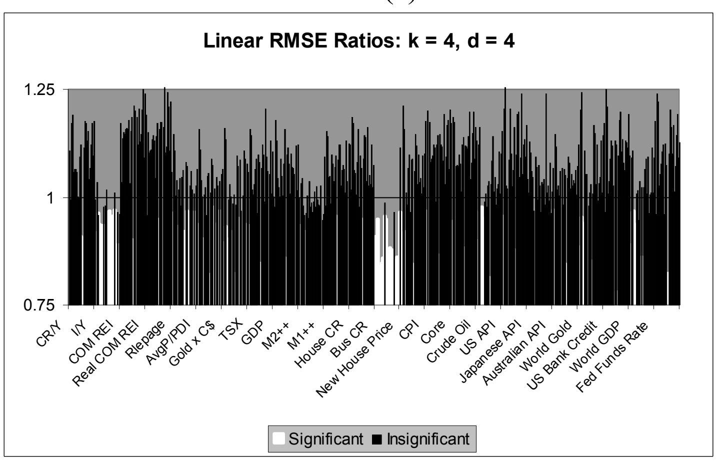
(a)



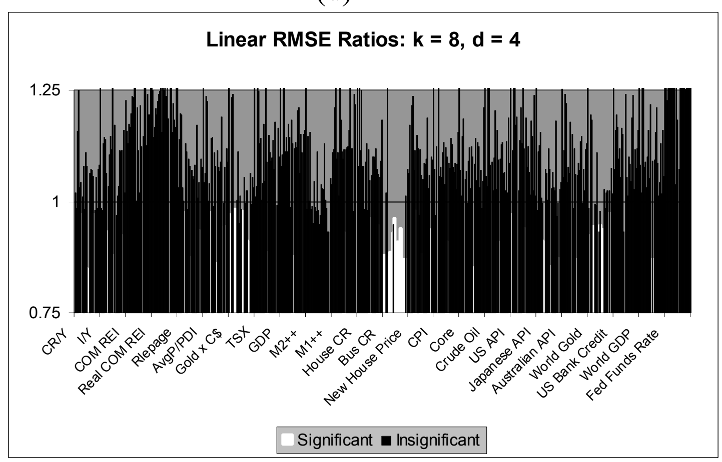
(b)



(c)



(d)



(e)

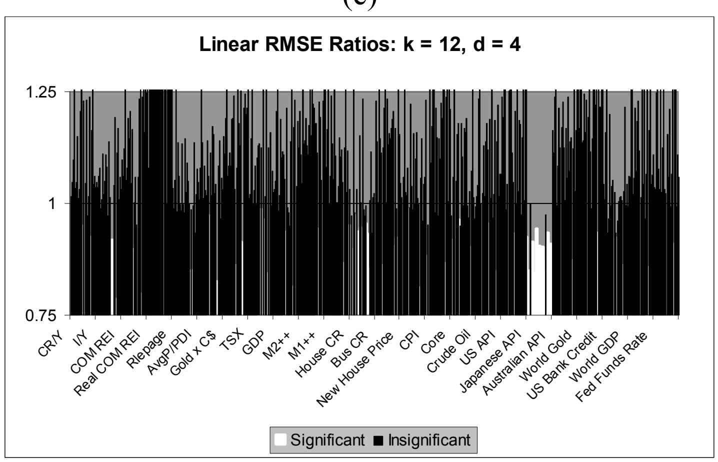


Figure 6: Threshold Models, Forecast Performance, *d*=4

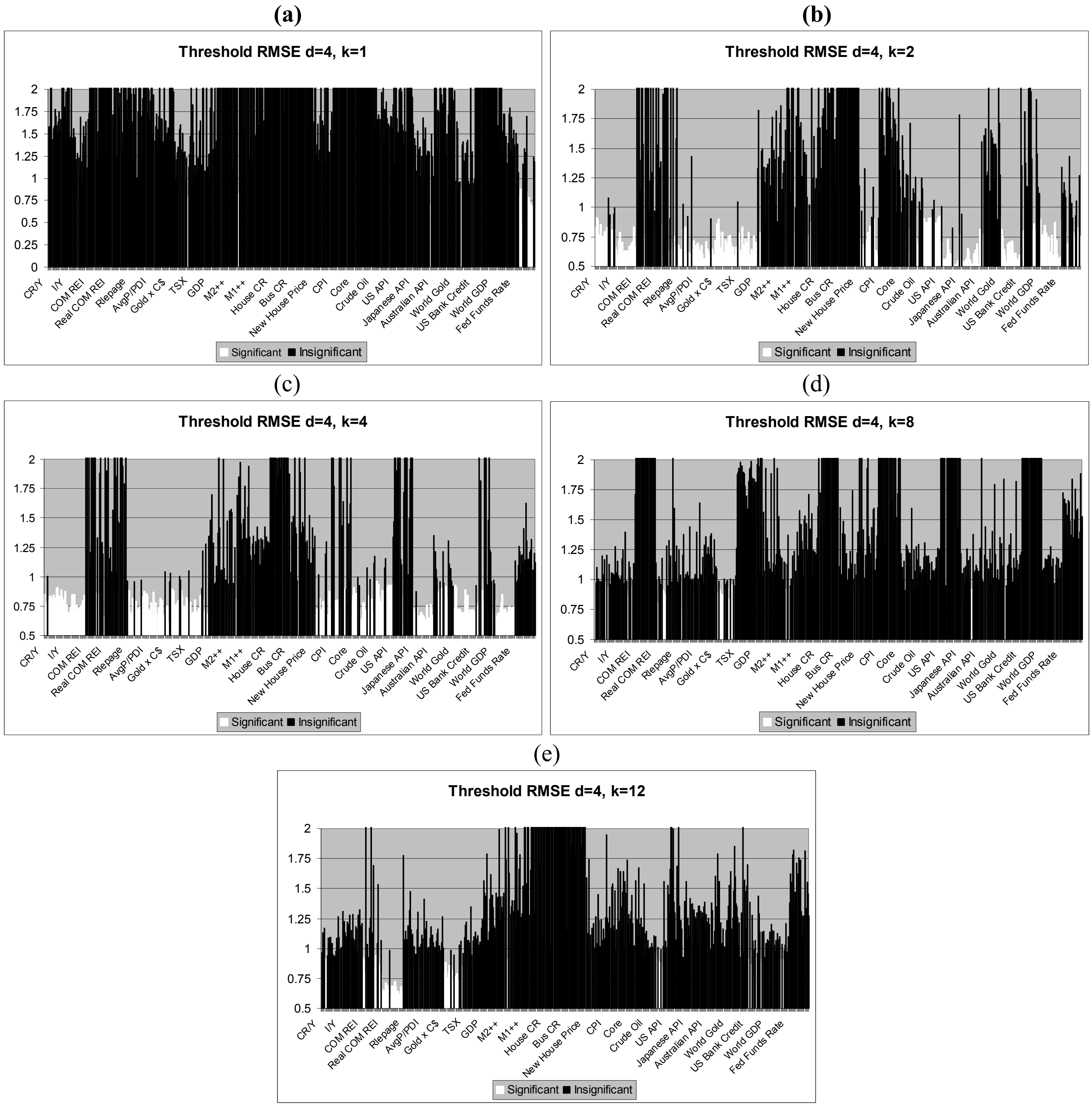
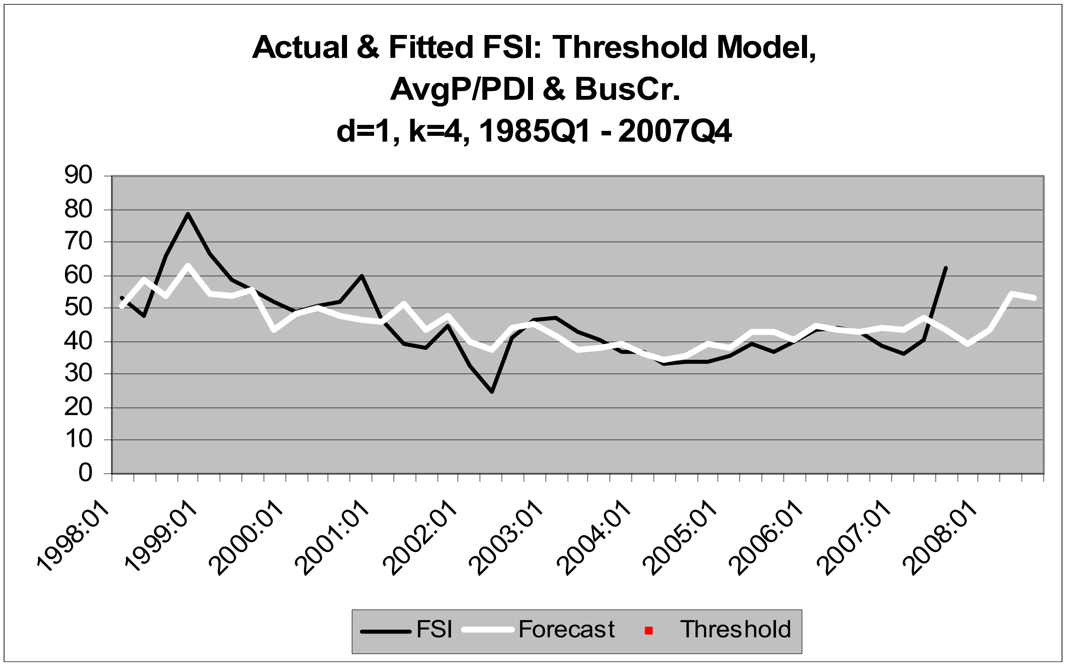
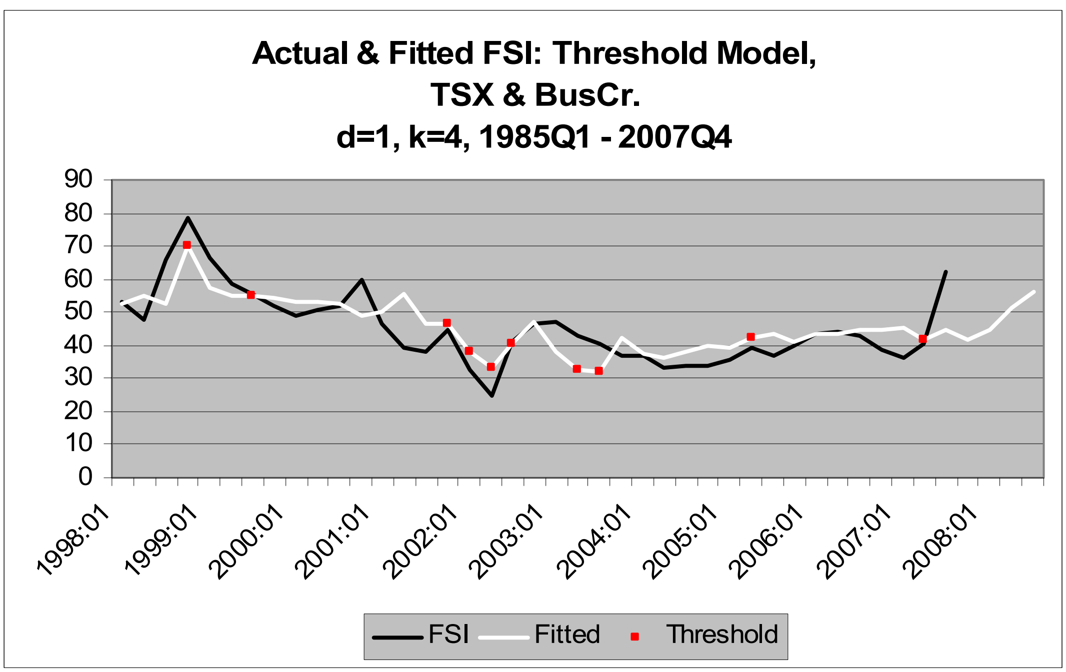


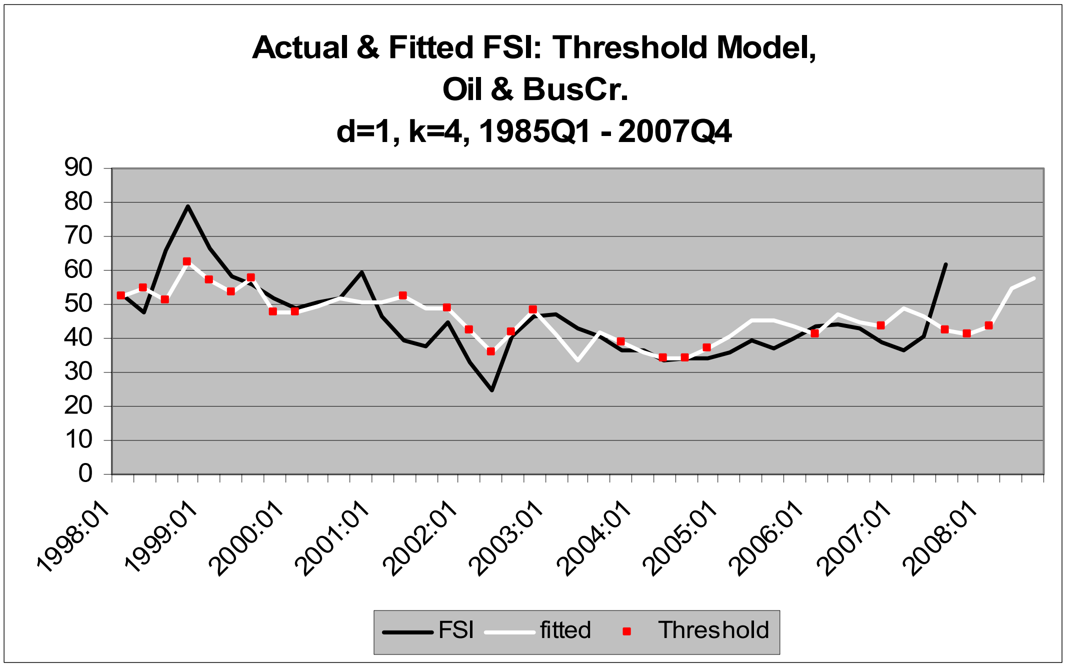
Figure 7: Forecasts of August 2007 spike in the FSI



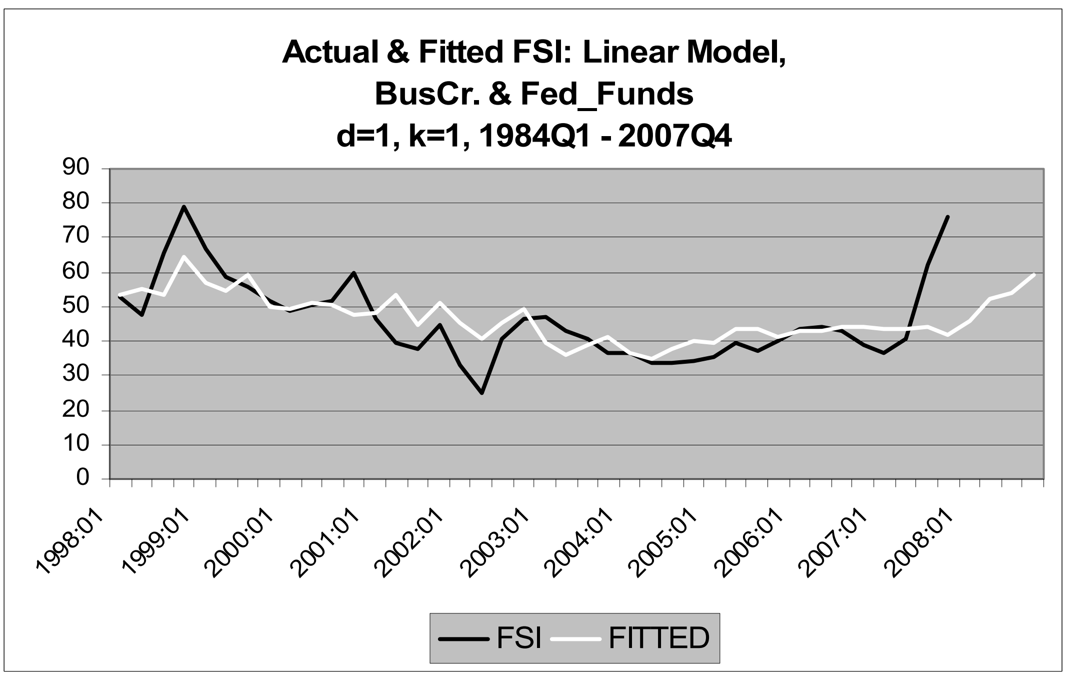
(a)



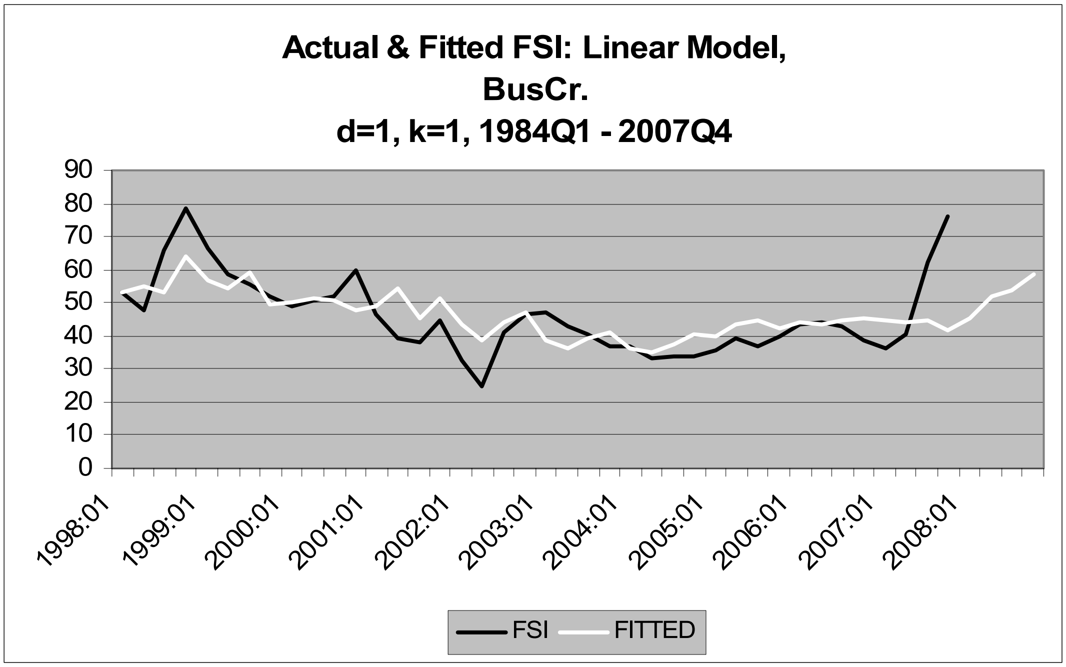
(b)


Actual & Fitted FSI: Threshold Model,
Oil & BusCr.
d=1, k=4, 1985Q1 - 2007Q4
90
80
70
60
50
40
30
20
10
0
1998:01
1999:01
2000:01
2001:01
2002:01
2003:01
2004:01
2005:01
2006:01
2007:01
2008:01
FSI
fitted
Threshold

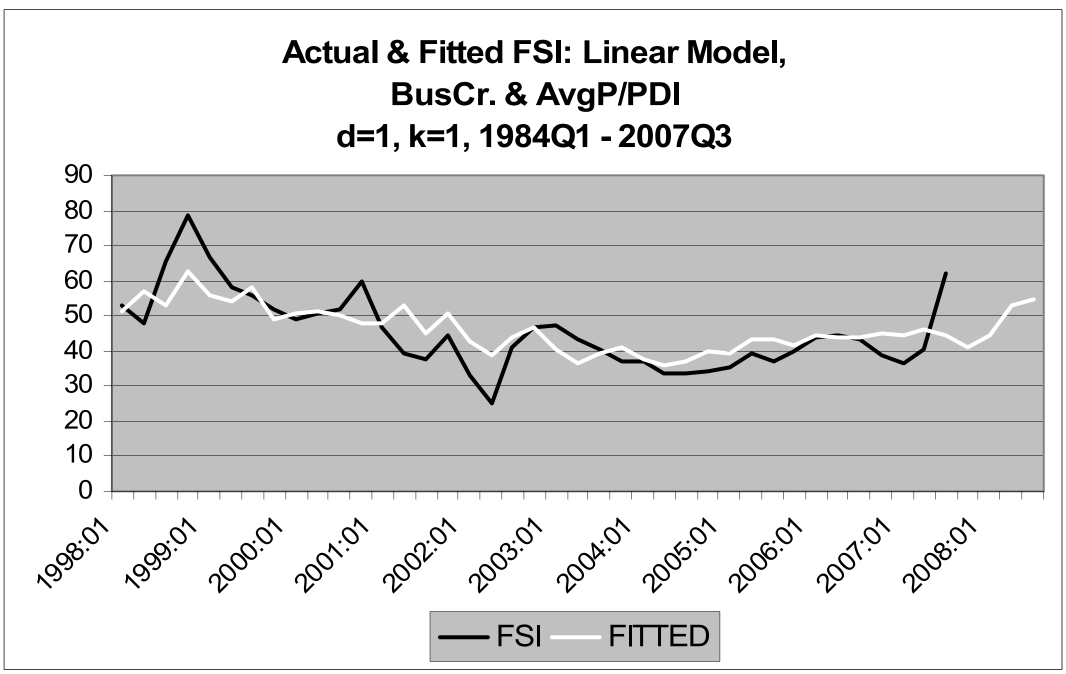
(c)


Actual & Fitted FSI: Linear Model,
BusCr. & Fed_Funds
d=1, k=1, 1984Q1 - 2007Q4
90
80
70
60
50
40
30
20
10
0
1998:01
1999:01
2000:01
2001:01
2002:01
2003:01
2004:01
2005:01
2006:01
2007:01
2008:01
FSI
FITTED

(d)


Actual & Fitted FSI: Linear Model,
BusCr.
d=1, k=1, 1984Q1 - 2007Q4
90
80
70
60
50
40
30
20
10
0
1998:01
1999:01
2000:01
2001:01
2002:01
2003:01
2004:01
2005:01
2006:01
2007:01
2008:01
FSI
FITTED

(e)


Actual & Fitted FSI: Linear Model,
BusCr. & AvgP/PDI
d=1, k=1, 1984Q1 - 2007Q3
90
80
70
60
50
40
30
20
10
0
1998:01
1999:01
2000:01
2001:01
2002:01
2003:01
2004:01
2005:01
2006:01
2007:01
2008:01
FSI
FITTED

(f)