BANK OF CANADA
BANQUE DU CANADA

Working Paper/Document de travail
2013-13

A Semiparametric Early Warning Model of Financial Stress Events

by Ian Christensen and Fuchun Li

Bank of Canada Working Paper 2013-13

May 2013

A Semiparametric Early Warning Model of Financial Stress Events

by

Ian Christensen and Fuchun Li

Financial Stability Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
Address correspondence to: fuchunli@bankofcanada.ca

ISSN 1701-9397

Acknowledgements

We are grateful to Jason Allen, James Chapman, Kim Huynh, Tatevik Sekhposyan and Norman Swanson for helpful comments and suggestions. We also thank seminar participants at the Bank of Canada, the 46th Annual Conference of the CEA and the 32nd Annual International Symposium on Forecasting.

Abstract

The authors use the Financial Stress Index created by the International Monetary Fund to predict the likelihood of financial stress events for five developed countries: Canada, France, Germany, the United Kingdom and the United States. They use a semiparametric panel data model with nonparametric specification of the link functions and linear index function. The empirical results show that the semiparametric early warning model captures some well-known financial stress events. For Canada, Germany, the United Kingdom and the United States, the semiparametric model can provide much better out-of-sample predicted probabilities than the logit model for the time period from 2007Q2 to 2010Q2, while for France, the logit model provides better performance for non-financial stress events than the semiparametric model.

JEL classification: G01, G17, C12, C14
Bank classification: Financial stability; Econometric and statistical methods

Résumé

Les auteurs s’appuient sur l’indice de tension financière créé par le Fonds monétaire international afin de prévoir le risque de matérialisation de tensions financières dans cinq pays développés : l’Allemagne, le Canada, les États-Unis, la France et le Royaume-Uni. Ils utilisent un modèle semi-paramétrique avec données sur panel et spécification non paramétrique de fonctions de lien et d’une fonction linéaire indicielle. Les résultats empiriques montrent que le prédicteur avancé constitué par leur modèle restitue des épisodes bien connus de tensions financières. Dans le cas de l’Allemagne, du Canada, des États-Unis et du Royaume-Uni, le modèle semi-paramétrique peut fournir des prévisions des probabilités hors échantillon qui sont de qualité nettement supérieure à celles du modèle logit pour la période comprise entre le 2^{e} trimestre de 2007 et le 2^{e} trimestre de 2010. Pour la France, le modèle logit produit de meilleures prévisions des tensions non financières que le modèle semi-paramétrique.

Classification JEL : G01, G17, C12, C14
Classification de la Banque : Stabilité financière; Méthodes économétriques et statistiques

1 Introduction

Due to the large costs that economies suffer in a financial crisis,[1] effective early warning tools have substantial value to policy-makers by allowing them to detect underlying economic weaknesses and vulnerabilities, and possibly take pre-emptive policy actions to head off the potential crisis or limit its effects. Recognizing this, international organizations and academics have been developing early warning models. For instance, the International Monetary Fund (IMF) has been systemically tracking, on an ongoing basis, various models by Kaminsky, Lizondo and Reinhart (1998) and Berg and Pattilo (1999). Many central banks, such as the U.S. Federal Reserve and the Bundesbank, academics, and private sector institutions (e.g., JP Morgan, Credit Suisse First Boston, Deutsche Bank), have also developed early warning models for financial crises (e.g., Davis and Karim 2008; Reinhart and Rogoff 2008).

Typically, early warning models are designed to predict financial crises. Recently, studies have started using financial stress indexes to examine which economic variables can help predict financial stress for a single country (Hakkio and Keep 2009; Misina and Tkacz 2009) or several countries (Hollo, Kremer and Lo Duca 2012; Cardarelli, Elekdag and Lall 2009; Holmfeldt et al. 2009). Financial stress is defined as an interruption of the normal functioning of a financial system (Hakkio and Keep 2009), and can have large real effects by boosting the cost of credit and making business, financial institutions and households highly uncertain about the outlook for the economy. In this paper, we use the Financial Stress Index (FSI) proposed by the IMF for developed economies as the measure of financial stress, and to predict the likelihood of occurrence of high financial stress events for five developed countries: Canada, France, Germany, the United Kingdom

[1] Financial crises have a large impact on the real economy, especially a loss in output, and frequently the effects spill over to other economies (Edison 2003).

and the United States.[2] In the literature on early warning models, logit and probit models are commonly used (Bussiere and Fratzscher 2006; Davis and Karim 2008). Although a logit model or a probit model is analytically convenient, in practice the functional form is seldom known. If the functional form is misspecified, the estimation of the coefficients and the inference based on them can be highly misleading. To relax the restrictive assumption that the functional form is known, semiparametric or nonparametric models are often employed.

In this paper, we propose a semiparametric early warning model with a nonparametric specification of the link functions and linear index function to predict the probability that a financial stress event will occur over a one-year horizon. Such a semiparametric model has the advantages that it does not require the arbitrary distributional assumptions usually invoked in parametric analysis, and overcomes the so-called curse of dimensionality that hampers nonparametric techniques in applications with high-dimensional data and standard sample sizes.

The choice of explanatory variables in our semiparametric model is based on the variables reported in Demirgüç-Kunt and Detragiache (1998) and Davis and Karim (2008). These variables are chosen based on theoretical considerations and their availability on a quarterly basis. We include ten independent variables in our model: real GDP growth rate, exchange rate, real short-term interest rate, inflation, M2/foreign exchange reserve, growth rate of private credit/GDP, bank reserve/bank asset, current account/GDP, house price index return, and stock price return.

Van den Berg, Candelon and Urbain (2008) adopt a panel data logit model to predict financial crises, and they test for poolability using a panel of 13 countries. The pooling data are rejected by the Hausman test. Therefore, although the pooling of countries increases the number of useful observations and is supposed to lead to a gain in estimation accuracy, it is first necessary to determine

[2]It is important to emphasize that the objective of our paper is not to forecast the future value of the Financial Stress Index, but rather to forecast the probability that a high financial stress event will occur within a given period of time; that is, that we try to build an early warning system of high financial stress events.

whether the data are poolable by the semiparametric model. In addition to standard parametric tests, nonparametric tests for poolability using panel data have been well developed; see Baltagi, Hidalgo and Li (1996), Criado (2008), Hall and Hart (1990), Koul and Schick (1997), Lavergne (2001), Neumeyer and Dette (2003), Vilar-Fernandez and Gonzalez-Manteiga (2004, 2007) and Jin and Su (2010), among others. A recent review of this topic is provided in Su and Ullah (2010). However, to our knowledge, the equality of the unknown link functions in the framework of semiparametric single-index panel data models has not yet been tested. We propose a new consistent test for poolability in a framework of semiparametric binary choice models (details of the test are provided in the appendix). Our results suggest that we cannot reject the hypothesis that the link functions are the same across the five countries.

Predictive ability analysis reveals that for Canada and the United Kingdom the semiparametric early warning model has better in-sample performance than the logit model, while for France and Germany the logit model outperforms the semiparametric model. Out-of-sample performance indicates that the semiparametric early warning model can capture some well-known financial stress events. Particularly for Canada, Germany, the United Kingdom and the United States, the semiparametric model can provide much better out-of-sample predicted probabilities than the logit model for the time period from 2007Q2 to 2010Q2. For France, the logit model provides better performance for non-financial stress events than the semiparametric model. It is important to mention that, since a formal specification test for whether the data are poolable by a logit model is not available, the model's predictive performance is conditional on the untested assumption that it can pool the data. However, as the most commonly used early warning model in this literature, the logit model is still chosen as a benchmark model to evaluate the predictive ability of the semiparametric model.

The paper is organized as follows. Section 2 identifies financial stress events. Section 3 presents a semiparametric early warning model of financial stress events. In section 4, we describe the forecasting results from our semiparametric single-index model, and compare them with those from the logit model. Section 5 concludes. The test statistic, the proofs of the asymptotic results of the test statistic and Monte Carlo simulation of the test statistic are reported in the appendix.

2 Identifying Financial Stress Events

There is evidence that financial stress may cause severe financial crises and recessions (Bloom 2009). Financial stresses on a financial system are frequently associated with 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, the IMF constructed a Financial Stress Index (FSI) for developed economies. The FSI is a variance-weighted average of three subindexes associated with the banking, securities and foreign exchange markets. All components in the three subindexes are originally in a monthly frequency. The FSI is constructed by taking the average of the components after adjusting for the sample mean and standardizing by the sample standard deviation. Finally, it is converted into a quarterly frequency by taking the average of the monthly data.[3]

We use the FSI as the measure of financial stress, to predict the probabilities that a financial stress event will occur in a given period of time. As a first step, for country j we define the financial stress event as occurring when the FSI rises above a threshold,

$$hfs_{j,t} = \begin{cases} 1 & \text{if } FSI_t > \mu_{FSI} + 1.5\sigma_{FSI} \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where σ_{FSI} and μ_{FSI} are the sample standard deviation and the sample mean of FSI, respectively. This definition will be used in our econometric analysis. Although the choice of 1.5 as a threshold is somewhat arbitrary, the cataloguing of financial stress events obtained by this choice tends to follow closely the chronology of financial market distress described in the literature. In particular, 1.5 standard deviations yields a reasonable number of observations for estimating the probability of a high financial stress occurring (51 financial stress events are identified by Equation (1) in-sample).

[3] The details of the components of the index are explained in Cardarelli, Elekdag and Lall (2009).

Figures 1 to 3 plot the FSI for the sample period starting from 1981Q2, to 2010Q2. Higher values of the index indicate higher financial stress. It is interesting to note that even though the component parts of the FSIs are based on individual country data, the peaks of the index largely coincide with episodes of financial stress events that are international in nature; for example, the stock market crash of October 1987, the long-Term Capital Management (LTCM) crisis in 1998 and the subprime crisis starting in the third quarter of 2007. This is not surprising, given that these economies are well-integrated internationally. As such, these financial stress events are not insulated from international financial developments. This represents a challenge if we are to use only domestic information as explanatory variables.

3 Model Specification

The objective of our early warning model is to predict whether a financial stress event will occur within a given time horizon. We transform the contemporaneous variable $hfs_{j,t}$ into a forward-looking variable $Y_{t,j}$, which is defined as,

$$Y_{t,j} = \begin{cases} 1 & \text{if } \exists\ k = 1, ..., 4 \text{ s.t. } hfs_{j,t+k} = 1 \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

In other words, we attempt to predict whether a financial stress event will occur in the coming four quarters. The length of the forecasting period is chosen by balancing two opposite requirements. On the one hand, economic variables will tend to provide more information as a financial system approaches a financial stress event. On the other hand, from a policy-maker's perspective, it is desirable to have a warning of a financial stress event as early as possible in order to take pre-emptive policy action. In the literature on early warning models, some researchers (Kaminsky, Lizondo and Reinhart 1998; Davis and Karim 2008) use the eight-quarter horizon, and others (Bussiere and Fratzscher 2006) use the four-quarter horizon. Given that our model is semiparametric, compared to the eight-quarter horizon, we prefer using the four-quarter horizon, so that we have more observations to estimate our model.

In each period, country j is either experiencing a financial stress event or it is not. The probability that a financial stress event will occur at a particular time in country j is hypothesized to be a function of a vector of m explanatory variables denoted by $X_{t,j}$. The choice of explanatory variables is discussed below. Let θ be a vector of m unknown coefficients and $F(X_{t,j}\theta)$ be the cumulative probability distribution function evaluated at $X_{t,j}\theta$.

As is standard in the early warning literature, the goal is to explain the occurrence of a financial stress event with a vector of explanatory variables, $X_{t,j}$. For example, the discrete-dependent variable model using a logistic distribution defines the logit model, $\text{Prob}(Y_{tj} = 1|X_{tj}\theta) = F(X_{tj}\theta) = \frac{e^{X_{tj}\theta}}{1+e^{X_{tj}\theta}}$. The parameters θ are obtained by maximum likelihood estimation, where each possible value of $Y_{t,j}$ contributes to the joint likelihood function. The logit model yields a predicted probability with which a financial stress event will occur within the next four quarters.

We consider the following semiparametric panel data specification:

$$E[Y_{tj}|X_{tj}\theta_j] = Pr[Y_{tj} = 1|X_{tj}\theta_j] = g_j(X_{tj}\theta_j), t = 1,2,...,n, \text{and } j = 1,2,...,J, \quad (3)$$

where $\theta_j \in \Theta \subset R^m, m \geq 1$, is an unknown $m \times 1$ constant vector and $g_j(\cdot)$ is an unknown distribution function. The semiparametric estimation problem is to estimate both θ_j and $g_j(\cdot)$ from observations on X_{tj} and Y_{tj}. Note that the semiparametric specification is more flexible than is the logit model, which is a special case obtained by assuming the logistic cumulative distribution function for $g_j(\cdot)$.

Under the assumption that the data are poolable, there exists a constant vector θ and a distribution function $g(\cdot)$ such that $g_j(x\theta) = g(x\theta)$ almost everywhere for all $1 \leq j \leq J$, where $x \in \Omega \subset R^m$.

The estimator of θ is obtained by maximizing the quasi-log-likelihood function,

$$\frac{1}{n}\sum_{j=1}^{J}\sum_{t=1}^{n}[Y_{tj}ln[\hat{g}(X_{tj}\theta)]^2+(1-Y_{tj})ln[(1-\hat{g}(X_{tj}\theta))^2]], \tag{4}$$

where $\hat{g}(X_{t,j}\theta)$ is the pooled estimator of $g(X_{tj}\theta)$ by

$$\hat{g}(X_{t,j}\theta) \equiv \frac{1}{Jnh}\sum_{i}\sum_{s}Y_{s,i}K[\frac{(X_{s,i}-X_{t,j})\theta}{h}]/\sum_{i}\sum_{s}Y_{s,i}K[\frac{(X_{s,i}-X_{t,j})\theta}{h}], \tag{5}$$

and h is the smoothing parameter used in the kernel nonparametric estimation of $g(X_{tj}\theta)$, and $K(\cdot)$ is a kernel function.

Our choice of explanatory variables is based on the variables reported in Kaminsky, Lizondo and Reinhart (1998) and Davis and Karim (2008). These variables are chosen based on theoretical considerations and their availability on a quarterly basis for all five countries and time periods. We include ten independent variables: real GDP growth, nominal exchange rate depreciation, real short-term interest rate, inflation, M2/foreign exchange reserve, the growth of private credit/GDP, the growth of bank reserve/bank asset, current account/GDP ratio, the growth of the house price index, and the stock price index return.

Table 1 provides more information on the variables used. The first column identifies the category headings and the second column provides the variable name. The third column briefly summarizes the economic rationale for the variable.

4 Predictive Ability

4.1 In-Sample Predictive Ability

Even though the semiparametric single-index model is frequently used in economics and finance, it has not been used in the literature on early warning models. In this section, we evaluate its performance as an early warning model, and we compare its predictive performance with that of the commonly used logit model.

Figures 4 to 6 show the predicted probabilities of financial stress events for the five countries from 1981Q2 to 2010Q2. In particular, the probabilities from 1981Q2 to 2007Q2 are the in-sample forecasts, and the probabilities from 2007Q3 to 2010Q2 are the out-of-sample forecasts. For a given predicted probability, the decision maker must decide whether the predicted probability is large enough to issue a warning. Taking no action is costly when a financial stress is nearing, but so is taking action when a financial event is not impending. Since the predicted probability is a continuous variable, one needs to specify a cut-off or threshold probability above which the predicted probability can be interpreted as a signal of pending high financial stress. It should be noted that the lower the threshold probability chosen, the more signals the model will send, with the drawback that the number of wrong signals will increase. By contrast, raising the threshold probability reduces the number of wrong signals, but at the expense of increasing the number of missed financial stress events; i.e., the absence of a signal when a high financial stress actually occurs within the next four quarters.[4] In practice, decision makers must choose a probability threshold that minimizes a loss function. For this purpose, we first define the following matrix.

	Financial stress event	No financial stress event
Signal issued	**A**	**B**
No signal issued	**C**	**D**

In this matrix, for a given cut-off threshold probability, A is the number of quarters in which the model issued a correct signal, B the number of quarters in which the model issued a wrong signal, C the number of quarters in which the model failed to issue a signal, and D the number of quarters in which the model correctly did not issue a signal. If an early warning model issues a signal in the quarter that is to be followed by a financial stress event (within the next four quarters), then $A > 0$

[4]The higher the probability threshold set for calling a financial stress event, the higher the probability of type I errors (failure to call a crisis) and the lower the probability of type II errors (false alarm).

and $C = 0$, and if it does not issue a signal in the quarter that is not followed by a financial stress event (within the next four quarters), then $B = 0$ and $D > 0$. A perfect model would only produce values of A and D, and $B = 0$ and $C = 0$.

In this paper, the cut-off threshold probability is calculated by minimizing the noise-to-signal ratio, which is defined as $[B/(B+D)]/[A/(A+C)]$.[5] To obtain the "optimal" threshold probability, a grid search is performed over the range of potential threshold probabilities from 0.15 to 0.50. The probability value where the noise-to-signal ratio is at a minimum is chosen as the cut-off probability.

Following Davis and Karim (2008) and Bussiere and Fratzscher (2006), the probability forecast evaluation is based on five different criteria: the signal-to-noise ratio, the probability of financial stress events correctly called, the probability of false alarms in total alarms, the conditional probability of financial stress events given an alarm, and the conditional probability of financial stress events given no alarm. The probability of financial stress events correctly called is defined as the percentage of the number of quarters in which a signal is followed by at least a financial stress event within the next four quarters$(A/(A+C))$. The probability of false alarms in total alarms is defined as the percentage of the number of quarters in which a signal is not followed by at least a financial stress event within the next four quarters $(B/(A+B))$. The conditional probability of a financial stress event given an alarm is defined as the percentage of the number of quarters in which a signal is followed by at least one financial stress event within the next four quarters given an alarm $(A/(A+B))$. The conditional probability of financial stress given no alarm is defined as

[5] Let the null hypothesis be the occurrence of a financial stress event within the next four quarters and the alternative hypothesis be the lack of occurrence of a financial stress event within the next four quarters. Then the noise-to-signal ratio is defined to be the minimum of the ratio of type II errors to one minus the size of type I errors, which is denoted as $[B/(B+D)]/[1-C/(A+C)]$. The size of a type I error is defined as the probability of rejecting the null hypothesis given that the null hypothesis is true. The type I error is then defined as $C/(A+C)$. Similarly, the size of a type II error is the probability of not rejecting the null hypothesis when it is false. This is called a false signal and is equal to $B/(B+D)$.

the percentage of the number of quarters in which a signal does not issue but at least one financial stress event occurs within the next four quarters ($C/(C+D)$).

We divide our data into two subsamples. The first, from 1981Q2 to 2007Q2 (with a total of 530 observations), is a sample used to estimate model parameters; the second, from 2007Q3 to 2010Q2 (with a total of 55 observations), is a prediction sample used to evaluate out-of-sample forecasts. We first consider the in-sample performance of our semiparametric model. For comparison, we also consider the multivariate logit model, which relates the likelihood of the occurrence or non-occurrence of a financial stress event to the ten explanatory variables by the logistic functional form.[6]

Table 2 provides the semiparametric estimation of index coefficients, indicating that the ten variables in our semiparametric model have the expected sign,[7] most of them being significant at the 5 per cent significance level. Table 3 reports the values of test statistics obtained by testing the null hypothesis whether the link functions are the same across any two different countries. The testing results cannot reject the null hypothesis. Consequently, we use the panel data across the five countries to estimate our semiparametric early warning model.

Table 4 reports these goodness-of-fit criteria for the semiparametric models and multivariate logit models for the five countries: Canada, the United States, the United Kingdom, France and Germany. Several conclusions can be drawn from Table 4. The signal-to-noise ratios for all five countries are higher than 1, suggesting that these models are informative. For Canada and the

[6]The probability that the forward-looking variable $Y_{t,i}$ takes a value of one (a financial stress event occurs) at a point in time is given by the value of the logistic cumulative distribution evaluated for the data and parameters at that point in time. Thus, $Prob(Y_{t,i}=1)=F(\theta X_{t,i})=\frac{e^{X_{t,i}\theta}}{1+e^{X_{t,i}\theta}}$, where $F(X_{t,i}\theta)$ is the cumulative logistic distribution. The parameters are obtained by maximum likelihood estimation, where each possible value of $Y_{t,i}$ contributes to the joint likelihood function so that the log likelihood becomes $logL=\sum_{i=1}^{n}\sum_{t=1}^{T}[Y_{t,i}logF(X_{t,i}\theta)+(1-Y_{t,i})log(1-X_{t,i}\theta)]$. The same explanatory variables are used in the logit model and the semiparametric model.

[7]The sign on the house price index return is negative, indicating that declining house prices are associated with subsequent financial stress. This is consistent with historical experience, where real estate prices tend to drop in advance of financial crises.

United Kingdom, the semiparametric model not only has higher signal-to-noise ratios than the logit model, but has higher probabilities of financial stress events correctly called, higher conditional probabilities of financial stress events given an alarm, lower probabilities of false alarms in total alarms, and lower conditional probabilities of financial stress events given no alarm, indicating that the predicted probabilities from the semiparametric model can provide a more accurate early warning for an upcoming financial stress event than the multivariate logit models for these countries. For the United States, even if the semiparametric model has a higher signal-to-noise ratio than the logit model, it has worse performance than the logit model in terms of its higher probability of false alarms and higher probability of financial stress events given no alarm. A noticeable feature is that the probabilities obtained from the logit model are quite low for France immediately after the exchange rate mechanism (ERM) crisis. Since France did not experience a financial stress event after the less-developed-countries (LDC) crisis, the low predicted probabilities indicate that in-sample prediction of non-financial stress events performs well.

In summary, the in-sample analysis reveals that the semiparametric single-index model for Canada and the United Kingdom has better in-sample performance for early warning financial stress events than the logit model, while the logit models for France and Germany outperform the semiparametric model. A formal specification test for whether the data are poolable by logit distribution is not available; we cannot exclude the possibility that the logit model can be used to pool the data.

4.2 Out-of-Sample Predictive Ability

In-sample predictive ability is important and can reveal useful information about possible sources of model misspecification. However, in general, there is no guarantee that a model that fits historical data well will also perform well out-of-sample. Obviously, the value of the early warning model of financial stress events lies in its ability to forewarn policy-makers of impending trouble: its out-of-sample predictive ability.

Table 5 reports the out-of-sample performance of predicted probabilities for both the semiparametric model and the logit model from 2007Q3 to 2010Q2. For Canada, the United States, the United Kingdom and Germany, the semiparametric model has much better out-of-sample performance than the logit model across all five criteria, although the semiparametric model for France has worse out-of-sample performance than the semiparametric model. For Canada, moving from the logit model to the semiparametric model increases the probability of correctly predicted financial stress events from 0.13 to 1 and increases the conditional probability of experiencing a financial stress event given an alarm from 0.5 to 0.73.

Notably, the signal-to-noise ratios from the logit model for Canada, the United States and the United Kingdom are less than one, indicating that the logit models for these three countries are not informative. For France and Germany, the signal-to-noise ratios are not available, because the number of quarters in which the logit models issued a good signal (A) and a bad signal (B) is zero. As Figure 5 shows, for France the predicted probabilities from the logit model were considerably lower such that they do not issue any signals. Given that France did not experience financial stress events throughout the out-of-sample period (Figure 2), this suggests that the out-of-sample prediction of non-financial stress episodes is good. On the other hand, as Figure 3 indicates, Germany experienced financial stress events, but the logit model did not predict them. The results suggest that the semiparametric models have better out-of-sample performance than the logit model for Canada, Germany, the United Kingdom and the United States.

5 Conclusion

This paper proposes a semiparametric early warning model of financial stress events for five developed countries: Canada, France, Germany, the United Kingdom and the United States. To determine whether the data for the five countries are poolable by the semiparametric model, we propose a new consistent test for poolability in a framework of semiparametric binary choice models. Monte Carlo simulations show that the test has good finite-sample performance. The test suggests that we cannot reject the null hypothesis that the data for the five countries are poolable by the semiparametric model.

The semiparametric early warning model performs well in capturing well-known financial stress events. In particular, for Canada, Germany, the United Kingdom and the United States, the semiparametric model provides much better out-of-sample results than the logit model. But for France, the logit model provides better performance for non-financial stress events than the semiparametric model.

It should be emphasized that the semiparametric early warning model proposed in this paper certainly does not constitute the final step toward a comprehensive early warning model of financial stress events. We would like to add explanatory variables to the model, such as the volatility of the stock market index, the volatility of interest rates and the variables that capture contagion. We continue to explore these and other improvements to the early warning system.

References

[1] Baltagi, B.H., J. Hidalgo and Q. Li (1996) "A nonparametric test for poolability using panel data." *Journal of Econometrics 75, 345-367.*

[2] Berg, A. and C. Pattillo (1999) "Predicting currency crises: the indicators approach and an alternative." *Journal of International Money and Finance, Elsevier 18 , 561-586.*

[3] Bloom, N. (2009) "The impact of uncertainty shocks." *Econometrica 77, 4, 623-685.*

[4] Bussiere, M. and M. Fratzscher (2006) "Towards a new early warning system of financial crises." *Journal of International Monetary and Finance, 25, 953-973.*

[5] Cardarelli, R., S. Elekdag and S. Lall (2009) "Financial stress, downturns, and recoveries." *IMF working paper, Wp 09/100.*

[6] Criado, C.O. (2008) "Temporal and spatial homogeneity in air pollutants panel EKC estimations: two nonparametric tests applied to Spanish Provinces." *Environmental and Resource Economics 40, 265-283.*

[7] Davis, E.P. and D. Karim (2008) "Comparing early warning systems for banking crises." *Journal of Financial Stability 4, 89-120.*

[8] Demirgüç-Kunt, A. and E. Detragiache (1998) "The determinants of banking crises in developed and developing countries." IMF Staff Paper, 45, 1. International Monetary Fund, Washington.

[9] Edison, H. (2003) "Do indicators of financial crisis work? an evaluation of an early warning system." *International Journal of Finance and Economics 8, 11-53.*

[10] Fan, Y. and Q. Li (1999) "Central limit theorem for degenerate U-statistic of absolute regular processes with application to model specification testing." *Journal of Nonparametric Statistics 10, 245-271.*

[11] Hall, P. and J.D. Hart (1990) "Bootstrap test for difference between means in nonparametric regression." *Journal of the American Statistical Association 85, 1039-1049.*

[12] Hakkio, C. and W. Keep (2009) "Financial stress: what is it, how can it be measured, and why does it matter?" *Federal Reserve Bank of Kansas City, Economic Review, Second Quarter, 5-50.*

[13] Härdle, W. and T. Stoker (1989) "Investigating smooth multiple regression by the method of average derivatives." *Journal of the American Statistical Association, 84, 408, 986-995.*

[14] Hollo, D., M. Kremer and M. Lo Duca (2012) "CISS - A composite indicator of systemic stress in the financial system." *ECB Working paper, No 1426.*

[15] Holmfeldt, M., A. Ryden, L. Stromberg and M. Stromqvist (2009) "How has the stress on the financial markets developed?-an index-based discussion." *Riksbank Economic Commentaries 13.*

[16] Jin, S. and L. Su (2010) "A nonparametric poolability test for panel data models with cross section dependence." School of Economics, Singapore Management University, Singapore.

[17] Kaminsky, G., S. Lizondo and C. Reinhart (1998) "Leading indicators of currency crises." *IMF Staff Paper 45 (1), 1-48.*

[18] Klein, R.W. and R. Spady (1993) "An efficient semiparametric estimator for binary response models. " *Econometrica 61, 2, 387-421.*

[19] Koul, H.L. and A. Schick (1997) "Testing for the equality of two nonparametric regression curves." *Journal of Statistical Planning and Inference 65, 293-314.*

[20] Lavergne, P. (2001) "An equality test across nonparametric regressions." *Journal of Econometrics 103, 307-344.*

[21] Li, Q. (1999) "Consistent model specification tests for time series econometric models." *Journal of Econometrics 92, 101-1047.*

[22] Misina, M. and G. Tkacz (2009) "Credit, asset prices, and financial stress" *International Journal of Central Banking 5, 4, 95-12.*

[23] Neumeyer, N. and H. Dette (2003) "Nonparametric comparison of regression curves: an empirical process approach." *Annals of Statistics 31, 880-920.*

[24] Ramberg, J.S. and B.W. Schmeiser (1974) "An approximate method for generating asymmetric random variables." *Communications of the Association for Computing Machinery 17, 78-82.*

[25] Reinhart, C.M. and K. Rogoff (2008) "Is the 2007 U.S. subprime crisis so different? An international historical comparison." *American Economic Review 98, 2, 339-344.*

[26] Su, L. and A. Ullah (2010) "Nonparametric and semiparametric panel econometric models: estimation and testing." School of Economics, Singapore Management University.

[27] Van den Berg, J., B. Candelon and J-P. Urbain (2008) "A cautious note on the use of panel models to predict financial crises." *Economics Letters 101, 1, 80-83.*

[28] Vilar-Fernandez, J.M. and W. Gonzalez-Manteiga (2004) "Nonparametric comparison of curves with dependent errors." *Statistics 38, 81-99.*

[29] Vilar-Fernandez, J.M. and W. Gonzalez-Manteiga (2007) "Bootstrap tests for nonparametric comparison of regression curves with dependent errors." *Test 16, 123-144.*

Appendix

The appendix consists of sections A and B. In section A, we provide the test statistic, the assumptions under which the asymptotic results of the test statistic can be derived and the proofs of the asymptotic results. The Monte Carlo simulations of the test statistic are reported in section B.

Section A: Testing for Poolability in a Framework of Semiparametric Binary Response Models

A panel data framework is mainly motivated by an efficiency argument, since pooling countries increases the number of useful observations, which is supposed to improve accuracy when estimating the underlying discrete choice models. However, in a framework of semiparametric binary response models, a major concern for panel data is whether the data are poolable; i.e., $g_i(x\theta_0) = g_j(x\theta_0)$ almost surely for $1 \leq i, j \leq J$ on the joint support of $g_i(\cdot)$ and $g_j(\cdot)$. More precisely, we have the following null and alternative hypotheses:

$$H_0 : g_i(x\theta_0) = g_j(x\theta_0) \text{ for all } i \text{ and } j \text{ almost surely on the joint support of } g_i(\cdot) \text{ and } g_j(\cdot). \quad \text{(A.1)}$$

The alternative hypothesis is

$$H_1 : g_i(x\theta) \neq g_j(x\theta) \text{ for some } i \neq j \text{ for any } \theta \in \Theta \text{ with positive measure.} \quad \text{(A.2)}$$

Let $f_j(\cdot)$ be the density function of $X_{tj}\theta_j$. For any $x \in R^m$ and $\theta \in \Theta$, we define $f(x\theta) \equiv \frac{1}{J}\sum_{j=1}^{J} f_j(x\theta)$, and $g(x\theta) \equiv \frac{1}{J}\sum_{j=1}^{J} g_j(x\theta)\frac{f_j(x\theta)}{f(x\theta)}$. Then, the equivalent null hypothesis is that there exists some $\theta_0 \in \Theta$ such that

$$H_0 : g_j(x\theta_0) = g(x\theta_0) \text{ for all } j \text{ almost surely,} \quad \text{(A.3)}$$

and the equivalent alternative hypothesis is

$$H_1 : g_j(x\theta) \neq g(x\theta) \text{ for some } j \text{ and for any } \theta \in \Theta \text{ almost surely.} \quad \text{(A.4)}$$

We define

$$\theta_n^* \equiv argmin_{\theta\in\Theta}\frac{1}{n}\sum_{j=1}^{J}\sum_{t=1}^{n}[Y_{tj}ln[\hat{g}(X_{tj}\theta)]^2+(1-Y_{tj})ln[(1-\hat{g}(X_{tj}\theta))^2]], \tag{A.5}$$

and $\theta^* = \text{limit}_{n\to\infty}\theta_n^*$.

Let $U_{tj} \equiv Y_{tj} - g(X_{tj}\theta^*), f(x\theta^*) \equiv \frac{1}{J}\sum_{j=1}^{J} f_j(x\theta^*)$, and $\varepsilon_{tj} \equiv U_{tj}f(X_{tj}\theta^*)$.

We construct our test statistic based on the following distance measure between the probability functions $g_j(X_{tj}\theta_j)$ and $g(X_{tj}\theta^*)$:

$$I_j \equiv E[\varepsilon_{tj}E[\varepsilon_{tj}|X_{tj}\theta^*]f_j(X_{tj}\theta^*)]. \tag{A.6}$$

Define $I \equiv \frac{1}{J}\sum_{j=1}^{J} I_j$. First note that, under H_0, we have $E[Y_{tj}|X_{tj}\theta^*] = g_j(X_{tj}\theta_0) = g(X_{tj}\theta_0)$ for all j, that is $I = 0$. If $I = 0$, then we have that $E[[(E[Y_{tj}|X_{tj}\theta^*] - g(X_{tj}\theta^*))f(X_{tj}\theta^*)]^2 f_j(X_{tj}\theta^*)] = 0$ for any j, which indicates that $E[Y_{tj}|X_{tj}\theta^*] = E[Y_{tj}|X_{tj}\theta_0] = g_j(X_{tj}\theta_0)$ and $g_j(x\theta_0) = g(x\theta_0)$ almost surely. Therefore, we have $I = \frac{1}{J}\sum_{j=1}^{J} E[[(E[Y_{tj}|X_{tj}\theta^*] - g(X_{tj}\theta^*))f(X_{tj}\theta^*)]^2 f_j(X_{tj}\theta^*)] \geq 0$ and the equality holds if and only if H_0 is true.

Define the pooled kernel estimator of $g(X_{tj}\theta^*)$ by

$$\hat{g}(X_{tj}\theta^*) = (Jnh)^{-1}\sum_{i=1}^{J}\sum_{s=1}^{n} K_{si,sj}Y_{si}/\hat{f}(X_{tj}\theta_n^*), \tag{A.7}$$

where $\hat{f}(X_{tj}\theta_n^*) \equiv (Jnh)^{-1}\sum_{i=1}^{J}\sum_{s=1}^{n} K_{si,tj}$ is the pooled kernel estimator of the density function of $f(x\theta^*)$, $K_{ti,sj} = K[(\frac{X_{ti}-X_{sj}}{h})\theta_n^*]$ is the kernel function used for the pooled estimator, and h is the smoothing parameter associated with the kernel $K(\cdot)$.

We estimate ε_{tj} by $\hat{\varepsilon}_{tj} \equiv Y_{tj} - \hat{g}(X_{tj}\theta_n^*)$, and $E[\hat{\varepsilon}_{tj}|X_{tj}\theta^*]f_j(X_{tj}\theta^*)$ by $(\frac{1}{(n-1)h})\sum_{s\neq t}\hat{\varepsilon}_{sj}K_{sj,tj}$. Hence, the estimator of I is

$$I_n = \frac{1}{J}\sum_{j=1}^{J}\sum_{t=1}^{n}\frac{1}{n(n-1)h}\sum_{s\neq t}(Y_{sj} - \hat{g}(X_{sj}\theta_n^*))\hat{f}(X_{sj}\theta_n^*)(Y_{tj} - \hat{g}(X_{tj}\theta_n^*))\hat{f}(X_{tj}\theta_n^*)K_{tj,sj}. \tag{A.8}$$

Our test statistic is defined as

$$J_n \equiv nh^{1/2} I_n / v_n, \tag{A.9}$$

where

$$v_n = \sqrt{\frac{1}{J^2 n(n-1)h} \sum_{j=1}^{J} \sum_{t=1}^{n} \sum_{s \neq t} \hat{\varepsilon}_{tj}^2 \hat{\varepsilon}_{sj}^2 K_{sj,tj}^2}. \tag{A.10}$$

We define

$$I_n^j = \sum_{t=1}^{n} \frac{1}{n(n-1)h} \sum_{s \neq t} (Y_{sj} - \hat{g}(X_{sj}\theta_n^{**})) \hat{f}(X_{sj}\theta_n^*)(Y_{tj} - \hat{g}(X_{tj}\theta_n^*)) \hat{f}(X_{tj}\theta_n^*) K_{tj,sj}, \tag{A.11}$$

and

$$J_n^j \equiv nh^{1/2} I_n^j / v_n^j, \tag{A.12}$$

where

$$v_n^j = \sqrt{\frac{1}{n(n-1)h} \sum_{t=1}^{n} \sum_{s \neq t} \hat{\varepsilon}_{tj}^2 \hat{\varepsilon}_{sj}^2 K_{sj,tj}^2}. \tag{A.13}$$

We specify the following assumptions, under which the asymptotic validity of this test statistic, J_n, can be established.

Assumption A1.

(i) *The data consist of a random sample* (Y_{tj}, X_{tj}), $j = 1, \ldots, n$. *The random variable* Y_{tj} *is binomial with realizations* 1 *and* 0.

(ii) *The model satisfies an index restriction:* $E[Y_{tj}|X_{tj}] = E[Y_{tj}|X_{tj}\theta_j] = Pr[Y_{tj} = 1|X_{tj}\theta_j]$, *where the parameter vector* θ_j *(*$\neq 0$*) lies in a compact parameter space* Θ.

(iii) *For each* j, *the model is identified in this sense that if* $P[Y_{tj} = 1|X_{tj}\theta_j^1] = P[Y_{tj} = 1|X_{tj}\theta_j^2]$, *then we have* $\theta_j^1 = \theta_j^2$, *where* $\theta_j^i \in \Theta$, *for i=1, 2.*

Assumption A2.

(i) ε_{tj}, X_{tj} *is a strictly stationary and absolutely regular process with the mixing coefficient* $\theta_m = O(\rho^m)$ *for some* $0 < \rho < 1$. *With probability one,* $E[\varepsilon_{tj}|A^t_{-\infty}(X_{tj}), A^{t-1}_{-\infty}(Y_{tj})] = 0$. $E[|\varepsilon^{4+\eta}_{tj}|] < \infty$ *and* $E[|\varepsilon^{i_1}_{t_1 j}\varepsilon^{i_2}_{t_2 j}, \ldots, |, \ldots, \varepsilon^{i_l}_{t_l j}|^{1+\zeta}] < \infty$ *for some arbitrarily small* $\eta > 0$ *and* $\zeta > 0$, *where* $2 \leq l \leq 4$ *is an integer,* $0 \leq i_j \leq 4$ *and* $\sum_{j=1}^{l} i_j \leq 8$.

(ii) *Let* $\sigma^2_j(x) = E[\varepsilon^2_{tj}|X_{tj} = x], \mu_j(x) = E[\varepsilon^4_{tj}|X_{tj} = x]$. $\sigma^2_j(x)$ *and* $\mu_j(x)$ *satisfy some Lipschitz conditions:* $|\sigma^2_j(u+v) - \sigma^2_j(u)| \leq D(u)||v||$ *and* $|\mu_j(u+v) - \mu_j(u)| \leq D(u)||v||$ *with* $E[|D(X_{tj})|^{2+\eta'}] < \infty$ *for some small* $\eta' > 0$.

(iii) *Let* $f_{\tau_1,\ldots,\tau_l}$ *be the joint probability density function of* $(X_{1,j}\theta^*, X_{1+\tau_1,j}\theta^*, \ldots, X_{1+\tau_l,j}\theta^*)(1 \leq l \leq 3)$. *Then* $f_{\tau_1,\ldots,\tau_l}$ *exists and satisfies a Lipschitz condition :* $|f_{\tau_1,\ldots,\tau_l}(x_1\theta^* + u_1, x_2\theta^* + u_2, \ldots, x_l\theta^* + u_l) - f_{\tau_1,\ldots,\tau_l}(x_1\theta^*, x_2\theta^*, \ldots, x_l\theta^*)| \leq D_{\tau_1,\ldots,\tau_l}(x_1, x_2, \ldots, x_l)||u||$, *where* $D_{\tau_1,\ldots,\tau_l}(x_1, x_2, \ldots, x_l)$ *is integrable and satisfies the condition that* $\int D_{\tau_1,\ldots,\tau_l}(x, x, \ldots, x)||x||^{2\xi}dx < M < \infty$, *and*

$\int D_{\tau_1,\ldots,\tau_l} f_{\tau_1,\ldots,\tau_l}(x_1\theta^*, \ldots, x_l\theta^*)dx < M < \infty$ *for some* $\xi > 1$.

(iv) *The kernel function* $K(\cdot)$ *is symmetric and bounded with* $\int K(u)du = 1$, *and* $\int u^2K(u)du < \infty$. $|D^r_x K(x)| < c$ *and* $\int |D^r_x K(x)|dx| < c$, *where* $r = 0, 1, 2, 3, 4$.

(v) *The smoothing parameter* $h_n = O(n^{-\bar{\alpha}})$ *for some* $1/8 < \bar{\alpha} < 1/6$. *The trimming function used to downweight observations has the form* $\tau \equiv \{1 + exp[(h_n^{\delta/5} - t')/h_n^{\delta/4}]\}^{-1}$, *where* $\delta > 0$ *and* t' *is to be interpreted as a density estimate.*

We now briefly comment on the above assumptions. (i)-(ii) in Assumption A1 state the model by which the data are generated. In particular, (ii) in Assumption A1 allows us to aggregate a multidimensional X_{tj} into a single-index case. (iii) in Assumption A1 can be interpreted as the parameter restrictions that are necessary for identification. Klein and Spady (1993, Theorem 1 and Theorem 2) provide sufficient conditions for identification for a general case where the index function is specified as a nonlinear function. (i) in Assumption A2 requires that X_{tj} be a stationary absolutely regular process with a geometric decay rate, and imposes some moment conditions on $\{\varepsilon_{tj}\}$. (ii) in Assumption A2 contains some smoothness conditions on the second and fourth conditional moment functions of ε_{tj}. (iii) in Assumption A2 contains some Lipschitz-type conditions and moment conditions. (iv) in Assumption A2 is a standard assumption on the kernel function. (v) in Assumption A2 implies that $\log(n)h^{\eta_1} \to 0$ and $n^{7/8}h/(\log n)^{\eta_2} \to \infty$ for arbitrary positive constants η_1 and η_2. It allows the choice of a wide range of smoothing parameter values and is stronger than the usual conditions of $h \to 0$ and $nh \to \infty$.

The following result describes the asymptotic properties of the test statistic.

Theorem 1. *Under the Assumptions (A1) and (A2), we have*

(i) under H_0, for any $j \in \{1,2,...,J\}$, $J_n^j \to N(0,1)$ in distribution as $n \to \infty$, and v_n^j is a consistent estimator of v^j, where $v^j = \sqrt{2\int K^2(u)du\{\int f_j^2(x)\sigma_j^4(x)dx\}}$, and $\sigma_j^2(x) = E[U_{tj}^2 f^2(X_{tj}\theta_0)| X_{tj}\theta_0 = x]$. Under $H_1, Pr[J_n^j \geq B_n] \to 1$ as $n \to \infty$, for any nonstochastic sequence $B_n = o(nh_n^{1/2})$.

(ii) if (X_{tj}, Y_{tj}) are independently and identically distributed in the i subscript, then under H_0, $J_n \to N(0,1)$ in distribution as $n \to \infty$, and v_n is a consistent estimator of v, where $v = \sqrt{2\int K^2(u)du\{\frac{1}{J}\sum_{j=1}^J \int f_j^2(x)\sigma_j^4(x)dx\}}$, and $\sigma_j^2(x) = E[U_{tj}^2 f^2(X_{tj}\theta)|X_{tj}\theta = x]$. Under $H_1, Pr[J_n \geq B_n] \to 1$ as $n \to \infty$, for any nonstochastic sequence $B_n = o(nh_n^{1/2})$.

Proof of Theorem 1:

Throughout the appendix, we will use the short-hand notation $K_{tj,sj} = K[\frac{(X_{tj}-X_{sj})\theta^*}{h}], \hat{K}_{tj,sj} = K[\frac{(X_{tj}-X_{sj})\theta_n^*}{h}]$, and $K_{tj,sj}^{(s)} = K^{(s)}[\frac{(X_{tj}-X_{sj})\theta^*}{h}]$, for $s = 1,2$.

$$\begin{aligned} J_n &= \frac{1}{J}\sum_{j=1}^{J}\sum_{t=1}^{n}\frac{1}{n(n-1)h}\sum_{s\neq t}\{(g_j(X_{sj}\theta^*) - \hat{g}(X_{sj}\theta_n^*))\hat{f}(X_{sj}\theta_n^*)(g_j(X_{tj}\theta^*) - \hat{g}(X_{tj}\theta_n^*))\hat{f}_c(X_{tj}\theta_n^*) \\ &\quad + U_{tj}U_{sj}\hat{f}_c(X_{sj}\theta_n^*)\hat{f}_c(X_{tj}\theta_n^*) + 2U_{tj}\hat{f}_c(X_{tj}\theta_n^*)(g_j(X_{sj}\theta^*) - \hat{g}(X_{sj}\theta_n^*))\hat{f}_c(X_{sj}\theta_n^*)\}\hat{K}_{tj,sj} \\ &\equiv J_{n1} + J_{n2} + 2J_{n3}. \qquad \text{(A.14)} \end{aligned}$$

We shall complete the proof of the part (i) in Theorem 1 by showing that $J_{ni} = o_p(nh^{1/2})$ for $i = 1,3$ and $nh^{1/2}J_{n2}$ converges to normal in distribution.

$$\begin{aligned}
E|J_{n1}| &= E|\frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}(g_j(X_{sj}\theta)-\hat{g}(X_{sj}\theta_n^*))\hat{f}(X_{sj}\theta_n^*) \\
&\quad \times(g_j(X_{tj}\theta)-\hat{g}(X_{tj}\theta_n^*))\hat{f}_c(X_{tj}\theta_n^*)\hat{K}_{tj,sj}| \\
&\leq \frac{1}{2Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}E\{[(g_j(X_{sj}\theta)-\hat{g}(X_{sj}\theta_n^*))^2\hat{f}^2(X_{sj}\theta_n^*) \\
&\quad +(g_j(X_{tj}\theta)-\hat{g}(X_{tj}\theta_n^*))^2\hat{f}^2(X_{tj}\theta_n^*)]\hat{K}_{tj,sj}\} \\
&= \frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}E[(g_j(X_{sj}\theta)-\hat{g}(X_{sj}\theta_n^*))^2\hat{f}(X_{sj}\theta_n^*)\hat{K}_{tj,sj}] \\
&= \frac{1}{Jn}\sum_{j=1}^{J}\sum_{t=1}^{n}E[(g_j(X_{tj}\theta)-\hat{g}(X_{tj}\theta_n^*))^2\hat{f}^2(X_{tj}\theta_n^*)\hat{f}_j(X_{tj}\theta_n^*)] \\
&= \frac{1}{Jn}\sum_{j=1}^{J}\sum_{t=1}^{n}E[(g_j(X_{tj}\theta)-\hat{g}(X_{tj}\theta_n^*))^2\hat{f}^2(X_{tj}\theta_n^*)f_j(X_{tj}\theta_0)] \\
&\quad +\frac{1}{Jn}\sum_{j=1}^{J}\sum_{t=1}^{n}E[(g_j(X_{tj}\theta)-\hat{g}(X_{tj}\theta_n^*))^2\hat{f}^2(X_{tj}\theta_0)(\hat{f}_j(X_{tj}\theta_n^*)-f_j(X_{tj}\theta_0))] \\
&\equiv J_{n11}+J_{n12} = o_p((nh^{1/2})^{-1}), \qquad \text{(A.15)}
\end{aligned}$$

where $J_{n11} = o_p((nh^{1/2})^{-1})$ and $J_{n12} = o_p((nh^{1/2})^{-1})$ are derived by similar argument as in lemmas C.3(i) and C.4 (i) in Li (1999), respectively. Now we consider J_{n2} :

$$\begin{aligned}
J_{n2} &= \frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}f(X_{sj}\theta_n^*)f(X_{tj}\theta_n^*)\hat{K}_{tj,sj} \\
&\quad +\frac{2}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}(\hat{f}(X_{tj}\theta_n^*)-f(X_{tj}\theta_n^*))f(X_{sj}\theta_n^*)\hat{K}_{tj,sj} \\
&\quad +\frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}(\hat{f}(X_{tj}\theta_n^*)-f(X_{tj}\theta_n^*))((\hat{f}(X_{sj}\theta_n^*)-f(X_{sj}\theta_n^*))\hat{K}_{tj,sj} \\
&\equiv J_{n21}+J_{n22}+J_{n23}. \qquad \text{(A.16)}
\end{aligned}$$

For J_{n21}, we have

$$\begin{aligned}
J_{n21} &= \frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}f(X_{sj}\theta)f_c(X_{tj}\theta)\hat{K}_{tj,sj} \\
&+\frac{2}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}[f(X_{sj}\theta_n^*)-f(X_{sj}\theta)]f(X_{tj}\theta)\hat{K}_{tj,sj} \\
&+\frac{1}{Jn(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}[f(X_{sj}\theta_n^*)-f(X_{sj}\theta)][f(X_{tj}\theta_n^*)-f(X_{tj}\theta)]\hat{K}_{tj,sj} \\
&\equiv J_{n21}^1+J_{n21}^2+J_{n21}^3. \qquad \text{(A.17)}
\end{aligned}$$

We are going to prove that J_{n21}^1 converges to a normal distribution in distribution and $J_{n21}^i = o_p((nh^{1/2})^{-1})$ for $i=2$ and 3. Let $J_{n21,j}^1 = \frac{2}{n(n-1)h}\sum_{1\le s<t\le n}U_{tj}U_{sj}f(X_{sj}\theta)f_c(X_{tj}\theta)\hat{K}_{tj,sj}$, then $J_{n21}^1=\frac{1}{J}\sum_{j=1}^{J}J_{n21,j}^1$. Applying a Taylor series expansion to $\hat{K}_{tj,sj}$, we have $\hat{K}_{tj,sj}=K_{tj,sj}+K_{tj,sj}^{(1)}(X_{tj}-X_{sj})(\theta_n^*-\theta_0)+\frac{1}{2}\bar{K}_{tj,sj}^{(2)}[(X_{tj}-X_{sj})(\theta_n^*-\theta_0)]^2$. Therefore, for $1\le j\le J$ we have

$$\begin{aligned}
J_{n21,j}^1 &= \frac{2}{n(n-1)h}\sum_{1\le s<t\le n}U_{tj}U_{sj}f(X_{sj}\theta)f(X_{tj}\theta)K_{tj,sj} \\
&+\frac{1}{n(n-1)h}\sum_{1\le s<t\le n}U_{tj}U_{sj}f(X_{sj}\theta)f(X_{tj}\theta)K_{tj,sj}^{(1)}[(X_{tj}-X_{sj})/h](\theta_n^*-\theta_0) \\
&+\frac{1}{2n(n-1)h}\sum_{1\le s<t\le n}U_{tj}U_{sj}f(X_{sj}\theta)f(X_{tj}\theta)K_{tj,sj}^{(2)}[(X_{tj}-X_{sj})/h]^2[\theta_n^*-\theta_0]^2 \\
&\equiv J_{n21,j}^1(1)+J_{n21,j}^1(2)(\theta_n^*-\theta_0)+J_{n21,j}^1(3)(\theta_n^*-\theta_0)^2. \qquad \text{(A.18)}
\end{aligned}$$

Now we consider $J_{n21,j}^1(2)$.

Let (a) denote the case of $min\{|s-s'|,|s-t|,|s-t'|\}>m$ and (b) the case of $min\{|s-s'|,|s-t|,|s-t'|\}\le m$. We have

$$
\begin{aligned}
E(||J^1_{n21,j}(2)||^2) &= n^{-2}(n-1)^{-2}h^{-2}\sum_t\sum_{s\neq t}\sum_{t'}\sum_{s'\neq t'}E[\varepsilon_{tj}\varepsilon_{sj}\varepsilon_{t'j}\varepsilon_{s'j} \\
&\quad \times K^{(1)}_{tj,sj}[(X_{tj}-X_{sj})/h]K^{(1)}_{t'j,s'j}[(X_{t'j}-X_{s'j})/h]] \\
&= n^{-2}(n-1)^{-2}h^{-2}\{\sum_{(a)}+\sum_{(b)}\} \\
&\quad \times E[\varepsilon_{tj}\varepsilon_{sj}\varepsilon_{t'j}\varepsilon_{s'j}K^{(1)}_{tj,sj}[(X_{tj}-X_{sj})/h]K^{(1)}_{t'j,s'j}[(X_{t'j}-X_{s'j})/h]] \\
&\leq n^{-2}(n-1)^{-2}h^{-2}\{cn^4\theta_m^{\delta/(1+\delta)}+mn^3\} \\
&\quad \times max_{t\neq s,t'\neq s'}E[\varepsilon_{tj}\varepsilon_{sj}\varepsilon_{t'j}\varepsilon_{s'j}K^{(1)}_{tj,sj}[(X_{tj}-X_{sj})/h]K^{(1)}_{t'j,s'j}[(X_{t'j}-X_{s'j})/h]] \\
&= (n^2h)^{-2}(o(1)+mn^3O(h^{2/\eta})) \qquad \text{(A.19)}
\end{aligned}
$$

for $1<\eta<2, m=[Clog(n)]$ and

$$
\begin{aligned}
& max_{t\neq s,t'\neq s'}E[\varepsilon_{tj}\varepsilon_{sj}\varepsilon_{t'j}\varepsilon_{s'j}K^{(1)}_{tj,sj}[(X_{tj}-X_{sj})/h]K^{(1)}_{t'j,s'j}[(X_{t'j}-X_{s'j})/h]] \\
& \leq cmax_{t\neq s,t'\neq s'}\{[E|\varepsilon_{tj}\varepsilon_{sj}\varepsilon_{t'j}\varepsilon_{s'j}|^{\xi}]^{1/\xi}E[|K^{(1)}_{tj,sj}[||(X_{tj}-X_{sj})/h||]K^{(1)}_{t'j,s'j}[||(X_{t'j}-X_{s'j})/h||]^{\eta}]^{1/\eta}\} \\
= \;& O(h^{2/\eta}) \qquad \text{(A.20)}
\end{aligned}
$$

where $\eta=(1-\xi^{-1})^{-1}, \xi>2, 1<\eta<2$. Hence $E(||J^1_{n21}(2)||^2)=o((n^2h)^{-2})+O(m(nh^{2(\eta-1)/\eta})^{-1})$, which indicates that $J^1_{n21,j}(2)(\theta_n^*-\theta_0)=o_p((nh^{1/2})^{-1})$.

It remains to evaluate the order of $J^1_{n21,j}(3)$. We have

$$
\begin{aligned}
E||J^1_{n21,j}(3)|| &\leq n^2(n-1)^{-1}n^2max_{s\neq t}E|\varepsilon_{tj}\varepsilon_{sj}H_{tj,sj}||(X_{tj}-X_{sj})/h||^2| \\
&\leq max_{s\neq t}\{[E|\varepsilon_{tj}\varepsilon_{sj}|^{\xi}]^{1/\xi}[E[H_{tj,sj}||(X_{tj}-X_{sj})/h||^2]^{\eta}]^{1/\eta}\} \\
&= O(h^{-(\eta-1)/\eta})
\end{aligned}
$$

for some $1<\eta<2$. Hence $J^1_{n21,j}(3)(\theta_n^*-\theta_0)^2=O(n^{-1}h^{-(\eta-1)/\eta})=o_p((nh^{1/2})^{-1})$. Summarizing the above, we have shown that $J^1_{n21,j}=J_{n21,j}(1)^1+o_p((nh^{1/2})^{-1})$. Therefore, $J^1_{n21,j}$ has the same distribution as $J^1_{n21,j}(1)$.

Let $Z_t = (X_{tj}\theta, U_{tj})$ and $H_n(Z_s, Z_t) = U_{tj}U_{sj}f_c(X_{sj}\theta)f_c(X_{tj}\theta)K_{tj,sj}$; then, $H_n(Z_s, Z_t)$ is symmetric and $E[H_n(Z_s, Z_t)|Z_s = z] = 0$. Thus, the central limit theorem of Fan and Li (1999) for a degenerate $U-$statistic will be used to derive the asymptotic normality distribution of $J^1_{n21,j}$. It is easy to check that the Assumptions A1 and A2 in this paper imply (D1)-(D2) in Li (1999). Hence, by lemma 2.1 in Li (1999), we have $nh^{1/2}J^1_{n21,j}(1) \to N(0, \sigma^2_{j0})$, where $\sigma^2_{j0} = 2\int K^2(u)du \int f^2_j(x)\sigma^4_j(x)dx$ and $\sigma^2_j(x) = E[U^2_{tj}f^2_c(X_{tj}\theta)|X_{tj}\theta = x]$.

Using $f_c(X_{sj}\theta^*_n) - f_c(X_{sj}\theta) = \nabla f_c(X_{sj}\theta_0)(\theta^*_n - \theta_0) + 1/2(\theta^*_n - \theta_0)'\nabla^2 f_c(X_{sj}\bar{\theta})(\theta^*_n - \theta_0)$, where $\bar{\theta}$ is between θ^*_n and θ_0, we get

$$\begin{aligned} J^2_{n21} &= \frac{2}{n(n-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n}\sum_{s\neq t}\{(\theta^*_n - \theta_0)'U_{tj}U_{sj}\triangledown f_c(X_{sj}\theta_0)f_c(X_{tj}\theta)\hat{K}_{tj,sj} \\ &\quad +(\theta^*_n - \theta_0)'U_{tj}U_{sj}\triangledown^2 f_c(X_{sj}\bar{\theta}_0))f_c(X_{tj}\theta)/2(\theta^*_n - \theta_0)\hat{K}_{tj,sj}\} \\ &\equiv (\theta^*_n - \theta_0)'\sum_{j=1}^{J}A_{nj} + (\theta^*_n - \theta_0)'\sum_{j=1}^{J}B_{nj}(\theta^*_n - \theta_0). \end{aligned} \tag{A.21}$$

For any $j, 1 \le j \le J$, we have

$$\begin{aligned} A_{nj} &= \frac{1}{n(n-1)h}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}\nabla f_c(X_{sj}\theta_0)f_c(X_{tj}\theta_0)\hat{K}_{tj,sj} \\ &= \frac{1}{n(n_j-1)h}\sum_{t=1}^{n_j}\sum_{s\neq t}U_{tj}U_{sj}\nabla f_c(X_{sj}\theta_0)f_c(X_{tj}\theta_0)K_{tj,sj} \\ &\quad +\frac{1}{n(n-1)h}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}\nabla f_c(X_{sj}\theta_0)f_c(X_{tj}\theta_0)K^{(1)}_{tj,sj}[\frac{(X_{tj}-X_{sj})'}{h}](\theta^*_n - \theta_0) \\ &\quad +\frac{1}{2n(n-1)h}\sum_{t=1}^{n}\sum_{s\neq t}U_{tj}U_{sj}\nabla f_c(X_{sj}\theta_0)f_c(X_{tj}\theta_0)K^{(2)}_{tj,sj}[\frac{(X_{tj}-X_{sj})}{h}]^2(\theta^*_n - \theta_0)^2 \\ &\equiv A_{nj1} + A_{nj2}(\theta^*_n - \theta_0) + A_{nj3}(\theta^*_n - \theta_0)'(\theta^*_n - \theta_0). \end{aligned} \tag{A.22}$$

Let $W_t \equiv \nabla f_c(X_{tj}\theta_0)$. We have

$$\begin{aligned}
E(||A_{nj1}||^2) &= n^{-2}(n-1)^{-2}h^{-2}\sum_{t=1}^{n}\sum_{s\neq t}\sum_{t'=1}^{n_j}\sum_{s'\neq t'} E[W_t' U_{sj}U_{s'j}W_{t'}K_{tj,sj}K_{t'j,s'j}] \\
&= n^{-2}(n-1)^{-2}h^{-2}\{\sum_a + \sum_b\} max_{t\neq t',s\neq s'} E[W_t' U_{sj}U_{s'j}W_{t'}K_{tj,sj}K_{t'j,s'j}] \\
&\leq cn^{-2}(n-1)^{-2}h^{-2}\{cn^4\theta_m^{\delta/(\delta+1)} + mn^3\} max_{t\neq t',s\neq s'}\{[E(|U_{sj}U_{s'j}|^{\xi})]^{1/\xi} \\
&\quad \times [E(M(X_t)M(X_{t'})K_{tj,sj}K_{t'j,s'j})^{\eta}]^{1/\eta}\} \\
&= n^{-2}(n-1)^{-2}h^{-2}\{o(1) + n^3 O(h^{2/\eta})\} \qquad \text{(A.23)}
\end{aligned}$$

for some $\eta = (1-\xi^{-1})^{1/\xi}$ ($\xi > 2, 1 < \eta < 2$). Hence, $A_{nj1} = o_p((n^2h^p)^{-1}) + O_p(m^{1/2}(n^{-1/2}h^{-(\eta-1)/\eta}))$, which implies that $(\theta_n^* - \theta_0)' A_{nj1} = o_p((nh^{1/2})^{-1})$ because of $1 < \eta < 2, m = [Clog(n)]$ and $h = O(n^{-\alpha})$. For A_{nj2}, we have

$$\begin{aligned}
E||A_{nj2}|| &\leq cn^{-1}(n_j-1)^{-1}h^{-1}n^2 max_{s\neq t} E||M(X_{tj})M(X_{sj})U_{tj}U_{sj}K'_{tj,sj}(\frac{X_{tj}-X_{sj}}{h})|| \\
&\leq cn^{-1}(n_j-1)^{-1}h^{-1}n^2 max_{s\neq t}\{[E|U_{tj}U_{sj}|^{\xi}]^{1/\xi} \\
&\quad \times [E||(M(X_{tj})M(X_{sj})K'_{tj,sj}(\frac{X_{tj}-X_{sj}}{h})||^{\eta})]^{1/\eta}\} \\
&= O(h^{-1+1/\eta}), \qquad \text{(A.24)}
\end{aligned}$$

where $1 < \eta < 1/2$, which leads to $(\theta_n^* - \theta_0)' A_{nj2}(\theta_n^* - \theta_0) = O_p(n^{-1}h^{-1+1/\eta}) = o_p((nh^{1/2})^{-1})$.

$$E|A_{nj3}| \leq cn^{-1}(n_j-1)^{-1}h^{-1}\sum_{t=1}^{n_j}\sum_{s\neq t} E|U_{tj}U_{sj}\nabla f_c(X_{sj}\theta_0) f_c(X_{tj}\theta_0)[\frac{(X_{tj}-X_{sj})'(X_{tj}-X_{sj})}{h^2}]|.$$

We consider J_{n21}^3.

$$\begin{aligned}
J_{n23}^1 &= \frac{1}{n(n_j-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n_j}\sum_{s\neq t} U_{tj}U_{sj}\hat{K}_{tj,sj}\nabla f_c(X_{tj}\theta_0)\nabla f_c'(X_{sj}\theta_0)(\theta_n^*-\theta_0)'(\theta_n^*-\theta_0) \\
&\quad +2\frac{1}{n(n_j-1)h}\sum_{j=1}^{J}\sum_{t=1}^{n_j}\sum_{s\neq t} U_{tj}U_{sj}\hat{K}_{tj,sj}\nabla f_c(X_{tj}\theta_0)(\theta_n^*-\theta_0)(\theta_n^*-\theta_0)'\nabla^2 f_c(X_{sj}\theta_0)(\theta_n^*-\theta_0) \\
&\quad +\frac{1}{4n(n_j-1)h}(\theta_n^*-\theta_0)'\sum_{j=1}^{J}\sum_{t=1}^{n_j}\sum_{s\neq t} U_{tj}U_{sj}\hat{K}_{tj,sj}\nabla^2 f_c(X_{tj}\tilde{\theta})(\theta_n^*-\theta_0)(\theta_n^*-\theta_0)'\nabla^2 f_c(X_{sj}\tilde{\theta})(\theta_n^*-\theta_0) \\
&\equiv J_{n23}^1(1) + J_{n23}^1(2) + J_{n23}^1(3). \qquad \text{(A.25)}
\end{aligned}$$

Using the same way in which we prove $J^1_{n21,j}(3)(\theta^*_n - \theta_0)^2 = o_p((nh^{1/2})^{-1})$, we can prove $J^1_{n23}(i) = o_p((nh^{1/2})^{-1})$ for $i = 1,2,3$.

Now we consider J_{n3}. Under the null hypothesis, we have $g_j(X_{sj}\theta) = g_j(X_{sj}\theta)$. We have

$$|g_j(X_{sj}\theta) - \hat{g}(X_{sj}\theta^*_n)| \leq |g(X_{sj}\theta) - g(X_{sj}\theta^*_n)| + |g(X_{sj}\theta^*_n) - \hat{g}(X_{sj}\theta^*_n)| \tag{A.26}$$

By Theorem 3.3 in Härdle and Stoker (1989), we have $|g(X_{sj}\theta^*_n) - \hat{g}(X_{sj}\theta^*_n)| = O_p(n^{-2/5})$, and $|g(X_{sj}\theta) - g(X_{sj}\theta^*_n)| = |g'(X_{sj}\bar{\theta})X_{sj}(\theta^*_n - \theta)| = O_p(n^{-1/2})$. Hence, we have $g(X_{sj}\theta^*_n) - \hat{g}(X_{sj}\theta^*_n) = O_p(n^{-2/5})$, which implies that $J_{n3} = O_p(n^{-2/5}J_{n2}) = o_p((nh^{1/2})^{-1})$.

Section B: Monte Carlo Simulations of the Test Statistic

We examine the finite-sample performance of the test using Monte Carlo simulations. We use the following data-generating processes for $X_{tj} = (X^1_{t,j}, X^2_{t,j})$, where $j = 1$ and $j = 2$ represent country 1 and country 2, respectively.

$$X^1_{t,1} = 1 + 0.2X^1_{t-1,1} + \varepsilon_{t,1}, \tag{B.1}$$

$$X^2_{t,1} = 1 + 0.5X^1_{t-1,2} + \varepsilon_{t,2} \tag{B.2}$$

and

$$X^1_{t,2} = 1 + 0.2X^1_{t-1,2} + \eta_{t,1}, \tag{B.3}$$

$$X^2_{t,2} = 1 + 0.5X^2_{t-1,2} + \eta_{t,2} \tag{B.4}$$

where $\varepsilon_{t,1}$ and $\varepsilon_{t,2}$ are independently and identically distributed as $N(0,1)$, and $\eta_{t,1}$ and $\eta_{t,2}$ are independently and identically distributed as $t(3)$. Let $X_{t,1} = (X^1_{t,1}X^2_{t,1})$ and $X_{t,2} = (X^1_{t,2}X^2_{t,2})$. We generate the discrete observations $Y_{t,1}$ and $Y_{t,2}$ as follows:

$$Y_{t,1} = \begin{cases} 1 & \text{if } \zeta_{t,1} < \beta' X_{t1} \\ 0 & \text{if } \zeta_{t,1} \geq \beta' X_{t1} \end{cases} \tag{B.5}$$

and

$$Y_{t,2} = \begin{cases} 1 & \text{if } \zeta_{t,2} < \beta' X_{t2} \\ 0 & \text{if } \zeta_{t,2} \geq \beta' X_{t2} \end{cases} \tag{B.6}$$

To examine the test's size performance, we simulate the $Y_{t,1}$ and $Y_{t,2}$ by specifying $\zeta_{t,1}$ and $\zeta_{t,2}$ following the standard normal distribution and logistic distribution, respectively. To study the test's power performance, we generate $\zeta_{t,1}$ from the logistic distribution. We then select three other distributions from the generalized lambda family proposed in Ramberg and Schmeiser (1974). The distribution in this family is defined in terms of the inverse of the cumulative distribution functions: $F^{-1}(u) = \lambda_1 + [u^{\lambda_3} - (1-u)^{\lambda_4}]/\lambda_2$ for $0 < u < 1$. In this simulation, each experiment is based on $1,000$ replications. The critical values for the test are from the standard normal distribution; i.e., $z_{0.01} = 2.33, z_{0.05} = 1.645$ and $z_{0.1} = 1.28$.

Table 6 reports the estimated sizes and powers of our test. The results suggest that as n increases, the estimated sizes converge to their nominal sizes although at a fairly slow rate. For a given alternative distribution, our test detects the misspecification of the link functions quite well in the logistic distribution. For a given alternative, the test's power always increases rapidly with respect to the sample size, in line with the test's consistency property. It should be noted that the power of our test is quite stable over different choices of c, which is particularly true for large samples.

Table 1: **Interpretation of Variables**

Category	Variable	Comments
Macroeconomic indicator	Real GDP growth	Economic recession often precedes crises
	Nominal depreciation	Financial crises could be driven by excessive foreign exchange risk exposure
	Real short-term interest rate	High short-term real interest rates affect bank balance sheets adversely and are often associated with capital outflows
	Inflation	Inflation is likely to be associated with high nominal interest rates; it may proxy macroeconomic mismanagement and adversely affect the financial sector through various channels
Financial indicator	M2/foreign exchange reserve	Expansionary monetary policy and/or a sharp decline in reserves are associated with the onset of a crisis
	Growth rate of private credit/GDP	This indicator captures the extent to which financial liberalization has progressed; financial liberalization may increase financial fragility due to increased opportunities for excessive risk taking and fraud
	Bank reserve/bank asset	Adverse macroeconomic shocks should be less likely to lead to crises when the banking sector is liquid; we use the ratio to capture liquidity
	Current account/GDP	Large current account deficits are associated with imbalances that may lead to a crisis
	House price index return	Real estate market downturns are associated with crises
	Stock price index return	Stock market downturns are associated with crises

This table reports the indicators used in the paper. The first column shows the category headings and the second column provides the name of the variable. The third column briefly summarizes the economic rationale for the variable.

Table 2: **Estimation Results of the Parameters in the Semiparametric Model**

Variable	Coefficient	Standard error
Constant	-0.1021*	0.0119
Real GDP	-0.1002*	0.0056
Depreciation	0.0982	0.4016
Real interest rate	0.0985*	0.0039
Inflation	0.0989*	0.0024
M2/foreign exchange reserve	-0.0924*	0.1307
Growth rate of private credit/GDP	0.0980*	0.0613
Bank reserve/bank asset	-0.4755*	0.0037
Current account/GDP	0.1022*	0.0621
House price index return	-0.1026*	0.0278
Stock price index return	1.1416*	0.0051

This table reports the estimations of the coefficients. The standard errors are obtained by a jackknife simulation approach. The star, $*$, indicates that the estimation is significant at the 5 per cent level.

Table 3: **Testing for Poolability by a Semiparametric Model**

	Canada	France	Germany	United Kingdom	United States
Canada		0.045	1.076	0.199	1.093
France			0.047	0.023	0.015
Germany				0.047	0.015
United Kingdom					0.018

This table reports values of the test statistic, J_n^j, in equation (17). The null hypothesis is there exists $\theta_0 \in \Theta$, such that $g_i(x'\theta_0) = g_j(x'\theta_0)$ for $i \neq j$ almost surely on the joint support of $g_i(\cdot)$ and $g_i(\cdot)$; the alternative hypothesis is $g_i(x'\theta) \neq g_j(x'\theta)$ for any $\theta \in \Theta$ with positive measure. The critical value at 5 per cent significance level is 1.645. For example, the value 0.045 in row "Canada" and column "France" indicates that we cannot reject the null hypothesis of poolability of the link function between Canada and France.

Table 4: **In-Sample Performance**

	Semiparametric Model			Binomial Logit Model		
Canada: Cut-off Probability $= 0.35$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	27	1	28	20	8	28
$Y_{it} = 0$	55	23	78	47	31	78
Total	82	24	106	67	39	106
Signal-to-noise ratio:			1.37			1.18
Probability of financial stress events correctly called:			0.96			0.71
Probability of false alarms in total alarms:			0.67			0.71
Probability of financial stress events given an alarm:			0.33			0.29
Probability of financial stress events given no alarm:			0.04			0.21
U.S.: Cut-off Probability $= 0.40$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	10	13	23	15	8	23
$Y_{it} = 0$	15	68	83	26	57	83
Total	25	81	106	41	65	106
Signal-to-noise ratio:			3.28			2.08
Probability of financial stress events correctly called:			0.44			0.65
Probability of false alarm of total alarms:			0.52			0.64
Probability of financial stress events given an alarm:			0.48			0.36
Probability of financial stress events given no alarm:			0.15			0.12
U.K.: Cut-off Probability $= 0.25$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	23	6	29	23	6	29
$Y_{it} = 0$	18	59	77	24	53	77
Total	41	65	106	27	59	106
Signal-to-noise ratio :			3.39			2.54
Probability of financial stress events correctly called:			0.79			0.78
Probability of false alarm of total alarms:			0.43			0.59
Probability of financial stress events given an alarm:			0.56			0.48
Probability of financial stress events given no alarm:			0.09			0.10
France: Cut-off Probability $= 0.20$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	8	3	11	11	0	11
$Y_{it} = 0$	47	48	95	31	64	95
Total	55	51	106	42	64	106
Signal-to-noise ratio:			1.47			3.06
Probability of financial stress events correctly called :			0.73			1.00
Probability of false alarm of total alarms:			0.85			0.73

Continued on next page...

...table 5 continued

Semiparametric Model				Binomial Logit Model		
Probability of financial stress events given an alarm:			0.15			0.26
Probability of financial stress events given no alarm:			0.05			0.00
Germany: Cut-off Probability $= 0.20$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	4	15	19	7	12	19
$Y_{it} = 0$	12	75	87	8	79	87
Total	16	90	106	15	91	106
Signal-to-noise ratio :			1.53			4.00
Probability of financial stress events correctly called:			0.22			0.36
Probability of false alarm of total alarms:			0.75			0.53
Probability of financial stress events given an alarm:			0.25			0.47
Probability of financial stress events given no alarm:			0.16			0.13

This table reports the in-sample performance of the semiparametric model in terms of five different criteria: signal-to-noise ratio, probability of financial stress events correctly called, probability of false alarm of total alarms, probability of financial stress events given an alarm, and probability of financial stress events given no alarm, which are defined as $[B/(B+D)]/[A/(A+C)], A/(A+C), B/(A+B), A/(A+B)$, and $C/(C+D)$, respectively. For comparison, the results for the multivariate logit model are also reported in this table. The sample period is from 1981Q2 to 2007Q2.

Table 5: **Out-of-Sample Performance**

	Semiparametric Model			Binomial Logit Model		
Canada: Cut-off Probability $= 0.35$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	8	0	8	1	7	8
$Y_{it} = 0$	3	0	3	1	2	3
Total	11	0	11	2	9	11
Signal-to-noise ratio:			1.00			0.38
Probability of financial stress events correctly called:			1.00			0.13
Probability of false alarm of total alarms:			0.27			0.50
Probability of financial stress events given an alarm:			0.73			0.50
Probability of financial stress events given no alarm:			*NaN*			0.78
U.S.: Cut-off Probability $= 0.40$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	6	2	8	2	6	8
$Y_{it} = 0$	1	2	3	2	1	3
Total	7	4	11	4	7	11
Signal-to-noise ratio :			2.25			0.37
Probability of financial stress events correctly called:			0.75			0.25
Probability of false alarm of total alarms:			0.14			0.50
Probability of financial stress event given an alarm:			0.86			0.50
Probability of financial stress event given no alarm:			0.50			0.86
U.K.: Cut-off Probability $= 0.25$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	4	3	7	4	3	7
$Y_{it} = 0$	2	2	4	3	1	4
Total	6	5	11	7	4	11
Signal-to-noise ratio			1.14			0.76
Probability of financial stress events correctly called:			0.57			0.57
Probability of false alarm of total alarms:			0.33			0.43
Probability of financial stress event given an alarm:			0.67			0.57
Probability of financial stress event given no alarm:			0.60			0.75
France: Cut-off Probability $= 0.20$				**Cut-off Probability** $= 0.20$		
	$S_{it} = 1$	$S_{it} = 0$	Total	$S_{it} = 1$	$S_{it} = 0$	Total
$Y_{it} = 1$	0	0	0	0	0	0
$Y_{it} = 0$	4	7	11	0	11	11
Total	4	7	11	0	11	11

Continued on next page...

...table 6 continued

	Semiparametric Model			Binomial Logit Model		
Signal-to-noise ratio:			*NaN*			*NaN*
Probability of financial stress events correctly called:			*NaN*			*NaN*
Probability of false alarm of total alarms:			1.00			*NaN*
Probability of financial stress events given an alarm:			0.00			*NaN*
Probability of financial stress events given no alarm:			0.00			0.00
Germany: Cut-off Probability = 0.20				**Cut-off Probability** = 0.20		
	$S_{it}=1$	$S_{it}=0$	Total	$S_{it}=1$	$S_{it}=0$	Total
$Y_{it}=1$	7	0	7	0	7	7
$Y_{it}=0$	4	0	4	0	4	4
Total	11	0	11	0	11	11
Signal-to-noise ratio:			1.00			*NaN*
Probability of financial stress events correctly called:			1.00			0.00
Probability of false alarm of total alarms:			0.36			*NaN*
Probability of financial stress events given an alarm:			0.64			*NaN*
Probability of financial stress events given no alarm:			*NaN*			0.64

This table reports the out-of-sample performance of the semiparametric model in terms of five different criteria: signal-to-noise ratio, probability of financial stress events correctly called, probability of false alarm of total alarms, probability of financial stress events given an alarm, and probability of financial stress events given no alarm, which are defined as $[B/(B+D)]/[A/(A+C)], A/(A+C), B/(A+B), A/(A+B)$, and $C/(C+D)$, respectively. For comparison, the results for the multivariate logit model are also reported in this table. The sample period is from 1981Q3 to 2010Q2. *NaN* indicates that there is no definition of the criterion, since the denominator in the criterion is zero.

Table 6: **Percentage of Rejections of H_0**

	$c=0.5$			$c=1.0$			$c=1.5$		
n	1%	5%	10%	1%	5%	10%	1%	5%	10%
				Percentage of Rejections of the true H_0					
				Probit Model					
50	0.009	0.018	0.031	0.001	0.007	0.010	0.001	0.003	0.003
100	0.005	0.019	0.029	0.000	0.002	0.008	0.001	0.002	0.003
200	0.006	0.017	0.031	0.003	0.008	0.011	0.001	0.004	0.005
500	0.007	0.021	0.043	0.004	0.008	0.015	0.000	0.002	0.007
1000	0.006	0.035	0.054	0.004	0.021	0.029	0.003	0.015	0.037
				Logit Model					
50	0.002	0.011	0.024	0.004	0.008	0.015	0.001	0.006	0.008
100	0.006	0.013	0.021	0.002	0.004	0.009	0.002	0.005	0.012
200	0.007	0.015	0.025	0.002	0.005	0.013	0.004	0.004	0.010
500	0.001	0.008	0.024	0.002	0.005	0.013	0.005	0.011	0.031
1000	0.005	0.025	0.047	0.004	0.012	0.032	0.004	0.037	0.042
				Percentage of rejections of the false H_0					
				$\lambda_1=3.586508, \lambda_2=0.04306, \lambda_3=0.025213, \lambda_4=0.094029$					
50	0.604	0.714	0.773	0.751	0.843	0.877	0.761	0.845	0.890
100	0.911	0.958	0.977	0.975	0.989	0.992	0.977	0.993	0.997
200	0.998	0.999	0.999	1.000	1.000	1.000	1.000	1.000	1.000
500	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
				$\lambda_1=9.7726, \lambda_2=0.0151878, \lambda_3=-0.001, \lambda_4=-0.13$					
50	0.124	0.195	0.257	0.225	0.331	0.385	0.233	0.345	0.430
100	0.307	0.423	0.504	0.491	0.607	0.689	0.551	0.679	0.752
200	0.721	0.827	0.874	0.867	0.933	0.961	0.922	0.965	0.978
500	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
				$\lambda_1=3.586508, \lambda_2=0.04306, \lambda_3=0.025213, \lambda_4=0.094029$					
50	0.596	0.713	0.767	0.720	0.813	0.866	0.786	0.866	0.906
100	0.908	0.946	0.970	0.976	0.987	0.994	0.984	0.993	0.996
200	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
500	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
1000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

This table reports the finite-sample performance of the size and the power of the test J_n^j. For each sample size we simulate 1,000 samples. The null models are the probit model and the logit model. Three other distributions from the generalized lambda family proposed in Ramberg and Schmeiser (1974) are selected as alternative models under the null hypothesis that the data come from a logit model.

Figure 1: **Financial Stress Index for Canada and the United States**

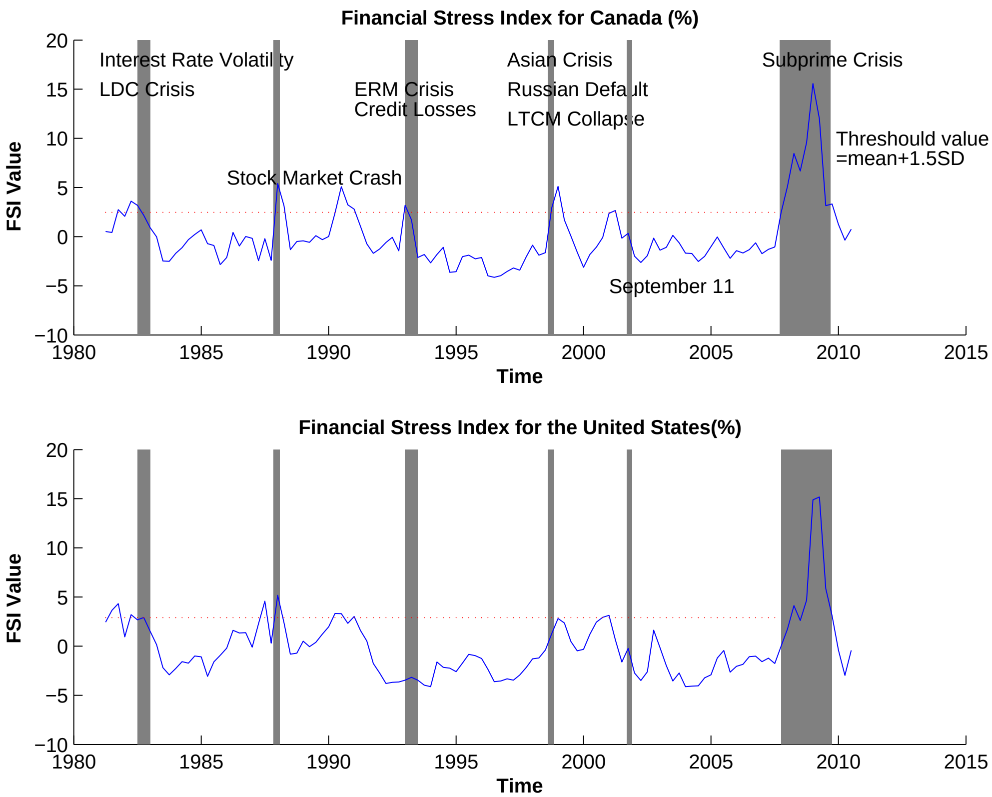


Figure 1 plots the FSI, created by the IMF for developed countries, for Canada and the United States. Each shaded region in this figure represents a financial crisis, and the width of each shaded region indicates the period that the crisis lasts. The sample period is from 1981Q2 to 2010Q2.

Figure 2: **Financial Stress Index for the United Kingdom and France**

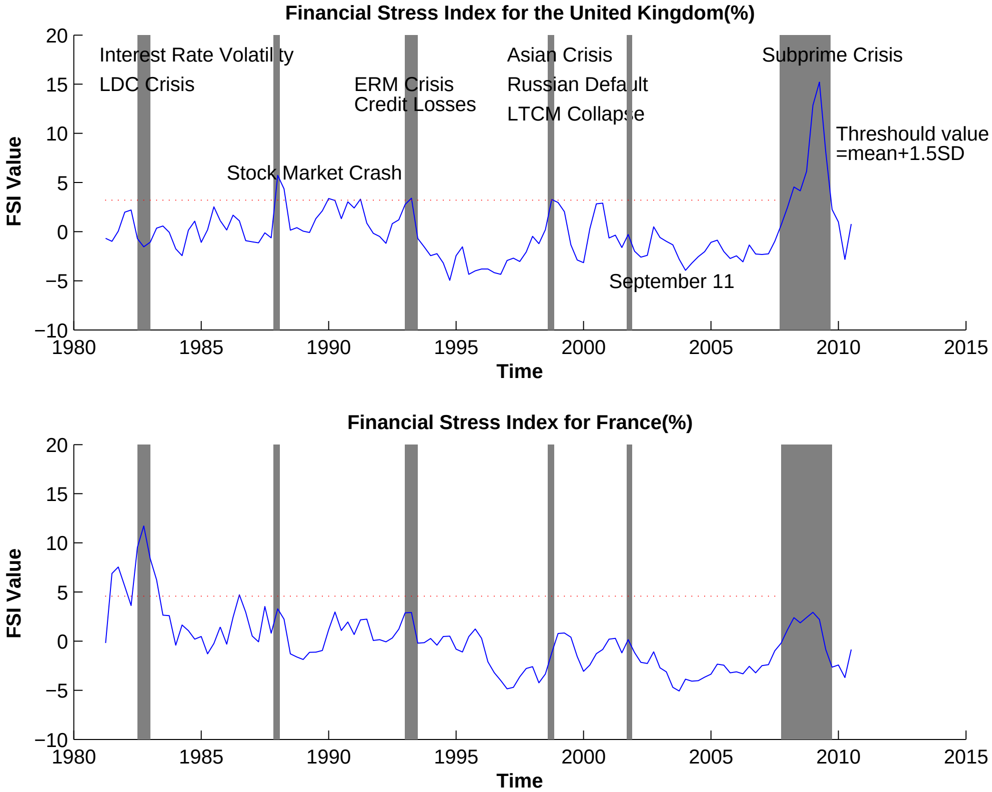


Figure 2 plots the FSI, created by the IMF for developed countries, for the United Kingdom and France. Each shaded region in this figure represents a financial crisis, and the width of each shaded region indicates the period that the crisis lasts. The sample period is from 1981Q2, to 2010Q2.

Figure 3: **Financial Stress Index for Germany**

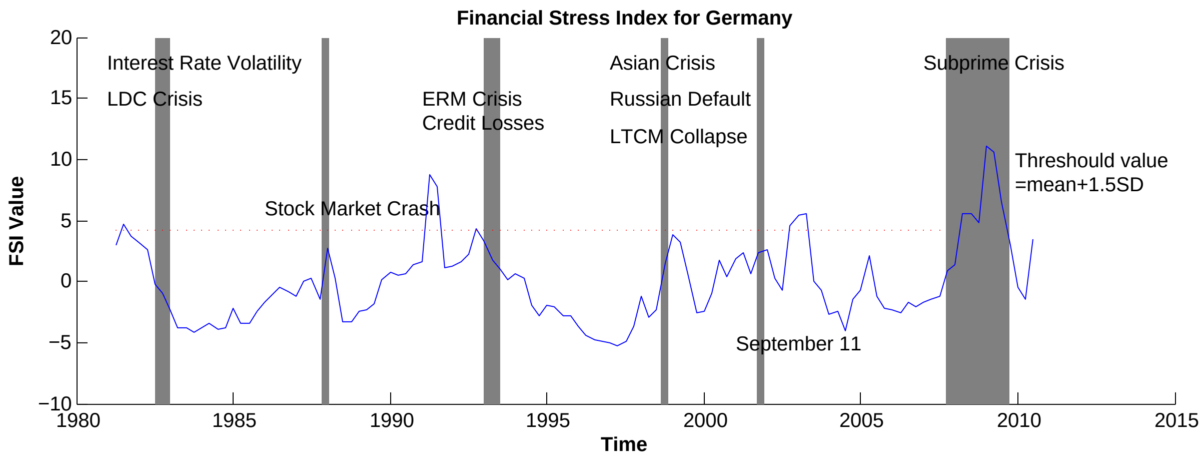


Figure 3 plots the FSI, created by the IMF for developed countries, for Germany. Each shaded region represents a financial crisis, and the width of each shaded region indicates the period that the crisis lasts. The sample period is from 1981Q2 to 2010Q2.

Figure 4: **Probability Forecasts for Financial Stress Events**

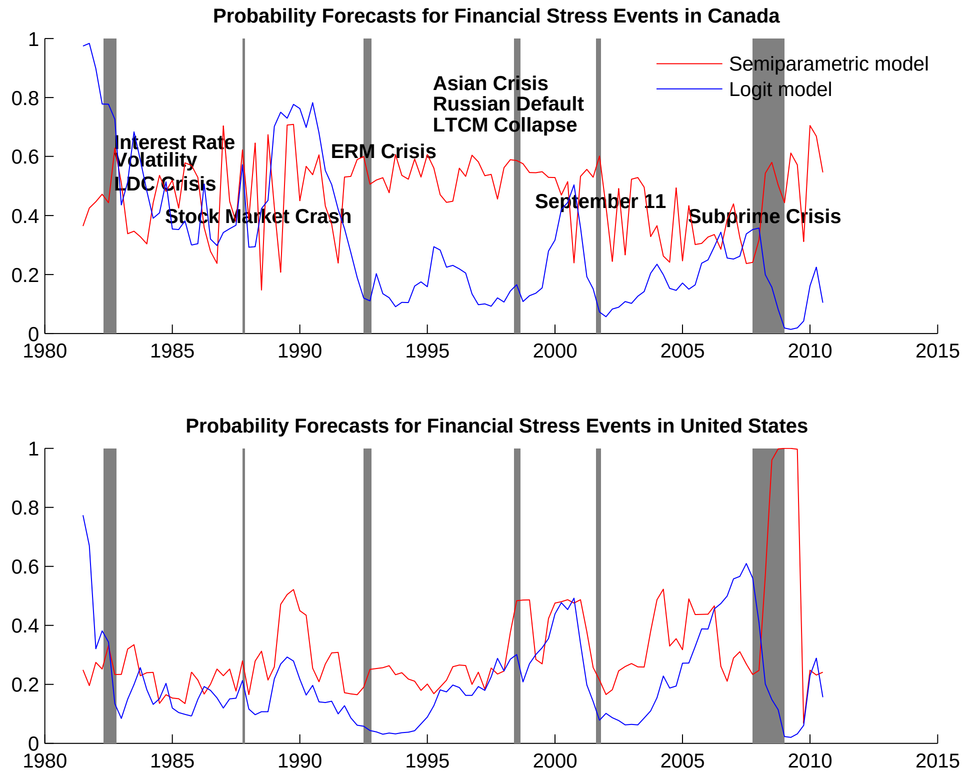
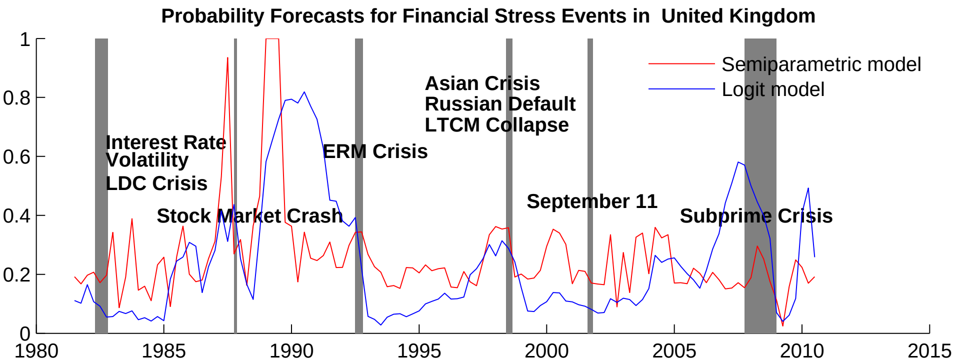


Figure 4 plots the probability forecasts for financial stress events for Canada and the United States for 1981Q2 to 2010Q2. In particular, the probabilities from 1981Q2 to 2007Q2 are the in-sample forecasts, and from 2007Q3 to 2010Q2 are the out-of-sample forecasts.

Figure 5: **Probability Forecasts for Financial Stress Events**



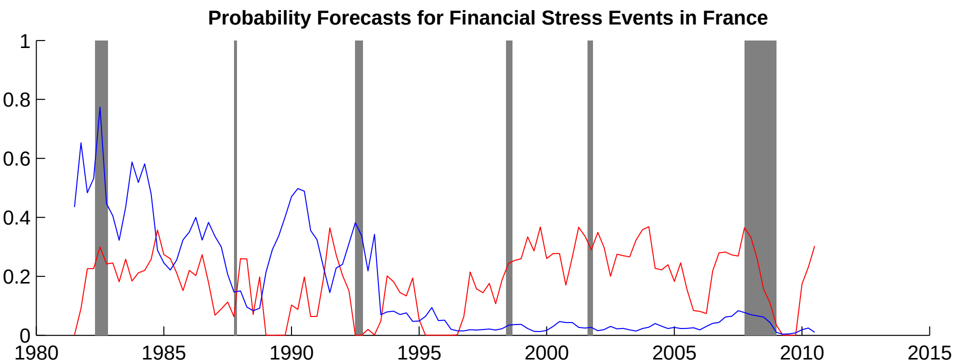


Figure 5 plots the probability forecasts for financial stress events for the United Kingdom and France for 1981Q2 to 2010Q2. In particular, the probabilities from 1981Q2 to 2007Q2 are the in-sample forecasts, and from 2007Q3 to 2010Q2 are the out-of-sample forecasts.

Figure 6: **Probability Forecasts for Financial Stress Events**

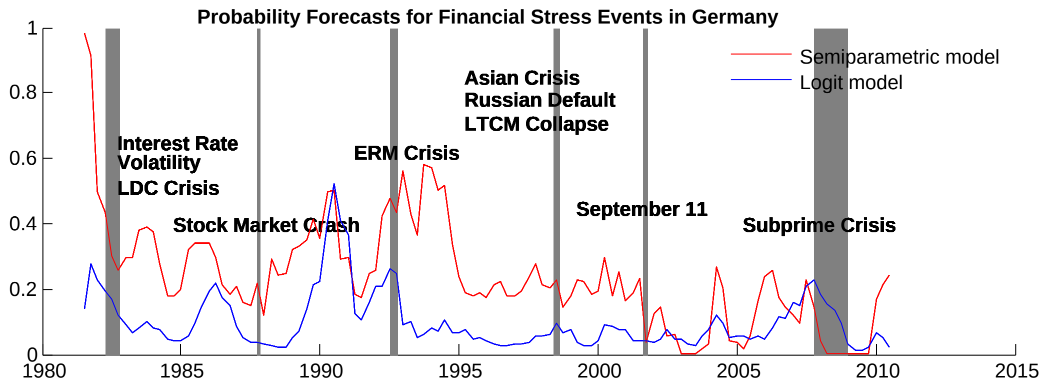


Figure 6 plots the probability forecasts for financial stress events for Germany for 1981Q2 to 2010Q2. In particular, the probabilities from the second quarter 1981Q2 to 2007Q2 are the in-sample forecasts, and from 2007Q3 to 2010Q2 are the out-of-sample forecasts.