Sudden Stops of Capital Flows to Emerging Markets: A New Prediction Approach*

Sangwon Suh†

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Abstract

In this paper, we propose a new prediction approach for forecasting sudden stop events of capital flows to emerging countries. The new approach is to combine conventional approaches (signal extraction and statistical regression approaches) in a way to maintain their advantages. We apply the new approach as well as conventional approaches into actual data and conduct prediction performance comparisons. The empirical results show that the new approach significantly improves prediction ability. The new approach proves to have some potential merits as an alternative approach to improve prediction ability and can also be applied into various types of financial crisis events.

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†School of Economics, Chung-Ang University; Email: ssuh@cau.ac.kr.

1 Introduction

An extreme financial turmoil, often referred to as financial crisis, typically entails significant costs to an economy. The financial crisis can happen in various sectors in an economy; e.g., crisis in banking sector (banking crisis) and crisis in external sector (foreign currency crisis). To effectively respond to financial crisis, it is an indispensable step to accurately predict a potential financial crisis. Correct predictions can help agents to make better economic decisions; however, incorrect predictions may distort their economic decisions in a wrong way and thereby cause economic inefficiencies.

Given that financial crises not only incur huge amounts of costs but also tend to recur, we have observed a large literature to improve the ability of predicting financial crises, and such effort is still going on. Even though many studies have been made for predicting financial crises, only two approaches have mainly been used for the prediction: the signal extraction (SE) approach and the statistical regression (SR) approach.

The SE approach individually monitors information variables and extracts signals in a nonparametric way from the perspective of predicting financial crises, and then constructs a composite index based on individual informativeness of the variables. This approach has an advantage of including many potential information variables. However, the SE approach has been typically used for predicting a financial crisis in an individual country but has not considered information variables which can capture cross-country variations. Such variables may include exchange rate regime, external openness, personal income level, capital control level, and so on. Since these variables usually change little for a considerable time, the time-series changes of these variables may not yield any informative signal for predicting financial crises. However, despite this time-series characteristics, the variables related with cross-country variations may convey useful predictive information in a multi-country framework. In addition, the SE approach cannot be applied into a country which has not experienced a financial crisis during the sample period. Since such country is not guaranteed to be free from a risk of financial crisis, this fact may restrict the applicability of the SE approach.

On the other hand, the SR approach takes an advantage of optimally fitting a statistical parametric model into crisis-event data and allowing us to rely on well-established statistical inferences. In addition, this approach is typically used in a multi-country analysis; therefore, we may include the variables related with cross-country variations under this approach. However, this approach has a disadvantage of including only a limited number of information variables for predicting financial crises. Including too many explanatory variables in a predictive regression model would incur estimation inefficiency and thus yield poor predictive performance. Moreover, including many explanatory variables would cost data losses in a usual situation where information variables may differ with data availability.

In this paper, for the purpose of predicting financial crises, we propose a new approach which combines both of the SE and the SR approaches. This new approach intends to maintain advantages of both approaches and also to alleviate their disadvantages; thereby, we hope the new approach to more accurately predict financial crises. In particular, we first categorize information variables into several sub-groups according to the information contents that the variables are expected to convey. We then construct sub-group indexes from the information variables belonging to the same sub-group. We utilize the SE approach to construct these sub-group indexes. Next, we include not only the sub-group indexes but also several relevant variables related with cross-country variations into the SR framework to predict financial crises. With this combination approach, we can consider many information variables without increasing the number of variables to be included by constructing sub-group indexes. Moreover, the SR framework in the second stage of the new approach allows for optimal fitting of a statistical parametric model as well as its associated statistical inferences and also for including variables related with cross-country variations.

The idea of constructing sub-group indexes has several advantages: First, it can limit the number of variables to be included in a regression analysis. Second, it may facilitate economic interpretation of estimational and predictive results by grouping variables according to their economic information contents. Third, it may potentially alleviate estimation inefficiencies arising from a strong co-movements among variables with similar economic characteristics by using a single variable representing them. Fourth, we are able to decompose the effects of a sub-group variable on the probability of a financial crisis into those of individual variables because, for constructing the sub-group variable, we use weights which are fixed and known. Lastly, assigning a variable for each sector would help to balance the analysis, because including too many variables belonging to a certain sub-group and considering them individually (without constructing a sub-group variable) would yield results tilted to the sub-group.

We apply the new approach for predicting sudden stops (SS) of capital flows to emerging markets (EMEs) and compare its predictive ability with those of the SE and the SR approaches. Indeed, it is of great interest to predict sudden stops of capital flows to EMEs at this present time of 2015/2016. Recent global financial crisis (GFC) which has begun in the U.S. 2007/2008 affected not only advanced countries but also EMEs. As policy responses to the GFC, the U.S. and other advanced countries policy makers actively utilized de facto zero policy interest rate as well as unconventional monetary policy (UMP) which is often referred to as "quantitative easing" (QE). After a long period of the UMP, the Fed hinted to "normalize" its UMP in 2013 and started its normalization from December 2015 by raising the policy interest rate. Many EMEs have received significant amounts of capital inflows during the UMP period, and the normalization of the UMP may cause capital outflows from EMEs. As of the end of 2015, many EMEs are concerned over the possibility that this capital flow reversal may happen in an abrupt and unexpected way. This SS of capital flows to EMEs may pose a significant risk to the EMEs because previous large scale capital inflows might contribute to economic imbalances of recipient countries as argued by Reinhart and Reinhart (2008).[1] Furthermore, this negative impact from the SS due to the normalization would more significantly affect the EMEs which are decoupled with the U.S. economy.[2]

We apply the new approach as well as the two conventional approaches for predicting the SS of capital flows to EMEs and find that the new approach significantly outperforms the conventional approaches. This relative outperformance of the new approach over the conventional ones should be confirmed with further financial-crisis predictions in the future; however, this new approach proves to have some potential merits to be considered as an alternative way to improve predictive ability.

[1] Reinhart and Reinhart (2008) argue that "Bonanzas are no blessing for advanced or emerging market economies. In the case of the latter, capital inflow bonanzas are associated with a higher likelihood of economic crises (debt defaults, banking, inflation and currency crashes)."

[2] Relatedly, there exists a large literature on the relationship between CFs and economic growth. Examples include Arteta, Eichengreen and Wyplosz (2001), Eichengreen (2001), Henry (2007), Reinhart and Reinhart (2008), BIS (2009), Kose, Prasad, Rogoff, and Wei (2009), Vo (2009), Choong, Baharumshah, Yusop, and Habibullah (2010), Aizenman, Jinjarak, and Park (2013), and Caballero (2014), among others.

The rest of this paper is organized as follows. In the next section, we present not only the new methodology but also the two conventional methods for expositional purposes. In Section 3, we explain the data and the variables to be used for our analysis. In Section 4, we present estimation results and compare the prediction performances. We conclude in Section 5.

2 Methodology

In this section, we explain the two conventional approaches for expositional purposes and then present the new methodology.

2.1 Signal Extraction Approach

The SE approach was proposed by Kaminsky, Lizondo and Reinhart (1998) and has been widely used for predicting financial crises. Examples include Edison (2003) and Christensen and Li (2014) among others.

Suppose we assume a certain operational definition of financial crisis (sudden stops of capital flows in this study), and introduce a dummy variable $S_{j,t}$ which takes value of one for the occurrence of the crisis and zero otherwise for country j $(j = 1, ..., J)$ and at time t; that is,

$$S_{j,t} \equiv \begin{cases} 1, & \text{crisis,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

With a pre-determined forecast horizon h, and a given n-th $(n = 1, ..., N)$ information variables $X^j_{n,t}$, we define an indicator variable $I^{j,h}_{n,t}$ as:

$$I^{j,h}_{n,t} \equiv \begin{cases} 1, & \text{if } X^j_{n,t} > \overline{X}^{j,h}_n, \\ 0, & \text{otherwise.} \end{cases}, \tag{2}$$

The indicator variable I takes value of one if an information variable X exceeds the associated threshold level $\overline{X}$, which intends to signal the crisis. To be consistent with this definition of the indicator variable, we first transform information variables by simply changing its sign in such a way that a higher value of an information variable will be associated with a higher probability of crisis occurrence. We will explain how to determine threshold level $\overline{X}$ later.

For country j and time t, a combination of a signal from an $X_{n,t}^{j}$ and the associated crisis indicator $S_{j,t+h}$ can be classified into one category among four categories which are demonstrated with the below table:

	Crisis $(S_{j,t+h}=1)$	No-crisis $(S_{j,t+h}=0)$
Signal $\left(I_{n,t}^{j,h}=1\right)$	$A_{n,t}^{j,h}$	$B_{n,t}^{j,h}$
No-signal $\left(I_{n,t}^{j,h}=0\right)$	$C_{n,t}^{j,h}$	$D_{n,t}^{j,h}$

In the above table, A indicates the case where the information variable issues a correct signal, B indicates a false signal, C indicates the case where the information variable fails to issue a signal, and D corresponds to the case where the information variable correctly issues no-signal. All variables from A to D take value of one if it is the case and zero otherwise. During an in-sample period of T_1 $(t=1,...T_1)$ for estimation, the total number of cases for each category is summed as:

$$A_{n}^{j,h} \equiv \sum_{t=1}^{T_1} A_{n,t}^{j,h}. \tag{3}$$

Other variables such as $B_{n}^{j,h}, C_{n}^{j,h}$ and $D_{n}^{j,h}$ are similarly defined.

With the above four classifications, the noise-to-signal ratio (NSR) is defined as follows:

$$\omega_{n}^{j,h} \equiv \frac{\frac{B_{n}^{j,h}}{B_{n}^{j,h}+D_{n}^{j,h}}}{\frac{A_{n}^{j,h}}{A_{n}^{j,h}+C_{n}^{j,h}}}. \tag{4}$$

The informativeness of a variable will be measured by its signal-to-noise ratio (SNR), the reciprocal of the NSR. Perfect predictions (i.e., $B=C=0$) would yield zero NSR while totally incorrect predictions (i.e., $A=D=0$) would yield positively infinite NSR. Therefore, the NSR varies from zero to infinity, and a smaller NSR corresponds to a better predictive ability. The individual threshold level $\overline{X}_{n}^{j,h}$ will be determined by minimizing the corresponding NSR, $\omega_{n}^{j,h}$.

To include N information variables, we construct a composite index. In this study, we consider two kinds of composite indexes, following Kaminsky, Lizondo and Reinhart (1998).[3] The first composite index (named SE1 henceforth) simply takes the number of cases of signal-issuances by individual variables at each time: that is,

$$K_{1,t}^{j,h} \equiv \sum_{n=1}^{N} I_{n,t}^{j,h}. \tag{5}$$

On the other hand, the second composite index (SE2) takes a weighted average of signal-issuances with its SNR as the weight: that is,

$$K_{2,t}^{j,h} \equiv \sum_{n=1}^{N} \frac{1}{\omega_n^{j,h}} \cdot I_{n,t}^{j,h}. \tag{6}$$

Given a threshold level, $\overline{K}_1^{j,h}$, the first composite index issues signal at time t if the index exceeds the threshold level, i.e., $K_{1,t}^{j,h} > \overline{K}_1^{j,h}$. We use the second composite index in a similar way. For the two composite indexes, we vary the threshold level $\overline{K}$, calculate the NSRs, and then determine the optimal threshold level as a level to minimize the corresponding NSR.

2.2 Statistical Regression Approach

The SR approach is a general approach to statistically model the probability of an event occurrence. This approach has also been used for predicting financial crises. The logistic regression (LR) approach (see, for example, Demirgüc-Kunt and Detragiache (1998), Wheelock and Wilson (2000), Bussiere and Fratzscher (2006), and Comelli (2014)) and probit models (see, for example, Agosin and Huaita (2012), Catão and Milesi-Ferretti (2014)) belong to the SR approach. Forbes and Warnock (2012) utilize an extreme value distribution as a parametric distribution assumption in a similar vein. Davis and Karim (2008a, 2008b) provide performance comparisons between the SE and the SR approaches. Literature on

[3] Among the three composite indexes suggested by Kaminsky, Lizondo and Reinhart (1998), we omit one index, following Christensen and Li (2014) who show that the omitted one does not relatevely perform well.

predicting financial crises are reviewed by Bell and Pain (2000), Demirguc-Kunt and Detragiache (2005), and Demyanyk and Hasan (2010). In this study, we choose the LR approach among several candidate models within the SR approach.

Given $(M \times 1)$ information variable vector $\widetilde{X}_t^j$ for country j at time t, the LR approach specifies the probability of financial crisis in h period ahead as follows:

$$\Pr\left[S_{j,t+h}=1\right] = F\left(\alpha_0^h + \alpha^{h\prime}\widetilde{X}_t^j\right) = \frac{e^{\alpha_0^h+\alpha^{h\prime}\widetilde{X}_t^j}}{1+e^{\alpha_0^h+\alpha^{h\prime}\widetilde{X}_t^j}}, \tag{7}$$

where $F(\cdot)$ is the cumulative logistic distribution. Note that the information variables may differ between the SE and the LR approaches.

The LR approach provides estimated probabilities of financial crisis which are informative per se. In addition, for the purpose of comparison between the two approaches, we set up a rule under which a signal for financial crisis will be issued when the estimated probability of financial crisis exceeds a certain threshold level. Like the SE approach, the threshold level is determined as a level to minimize the associated NSR.

2.3 New Approach

The new approach is to combine the SE and the LR approaches in order to maintain advantages of the both approaches. In the first stage, we classify information variables into sub-groups or into the variables related with cross-country variations. The sub-groups are classified according to their economic meaning. Given N_i information variables belonging to the i-th sub-group for country j at time t, we construct the sub-group variable according to the SE approach; that is, the i-th sub-group variable $Z_{i,t}^{j,h}$ with forecast horizon h is specified as:

$$Z_{i,t}^{j,h} \equiv \frac{\sum_{n\in\Omega_i}\frac{1}{\omega_n^{j,h}}\widetilde{\widetilde{X}}_{n,t}^{j}}{\sum_{n\in\Omega_i}\frac{1}{\omega_n^{j,h}}}, \tag{8}$$

where Ω_i indicates the set of information variable indexes belonging to the i-th sub-group with N_i elements. Unlike the SE approach, the sub-group variable is constructed as a weighted average of individual information variables belonging to the sub-group using the associated SNR as the weight. To account for scale difference among individual information variables, we normalize each variable by subtracting its mean and by dividing it by its standard deviation and denote it by $\widetilde{\widetilde{X}}$.

In the second stage, we collect k sub-group variables as well as l cross-country-variation-related variables and denote them by a vector $Y_t^{j,h}$; that is,

$$Y_t^{j,h} \equiv \left[Z_{1,t}^{j,h} \ \cdots Z_{k,t}^{j,h} \ X_{n_1,t}^{j} \cdots X_{n_l,t}^{j} \right]'. \tag{9}$$

We utilize the LR approach to estimate the probability of financial crisis in h period ahead; i.e.,

$$\Pr\left[S_{j,t+h} = 1\right] = F\left(\beta_0^h + \beta^{h\prime} Y_t^{j,h}\right) = \frac{e^{\beta_0^h + \beta^{h\prime} Y_t^{j,h}}}{1 + e^{\beta_0^h + \beta^{h\prime} Y_t^{j,h}}}. \tag{10}$$

For comparison purposes, we issue a signal for financial crisis if the estimated probability of financial crisis exceeds a certain threshold level. To be consistent with existing approaches, the threshold level is determined as a level to minimize the associated NSR.

3 Data and Variables

In this section, we provide operational definitions of the SS event of capital flows to EMEs and also explain the data and the variables to be used for our analysis.

3.1 Sudden Stop of Capital Flows

A sudden stop of capital flows usually refers to a significant contraction of capital flows. We use the ratio of capital flows to GDP to define the SS event. In particular, we consider the following three definitions:

$$S_{j,t}^1 \equiv \begin{cases} 1, & \text{if } \Delta CF_{j,t} < -5\%, \ \Delta CF_{j,t} < \overline{\Delta CF}_j - \sigma_{\Delta CF_j}, \\ 0, & \text{otherwise}, \end{cases} \tag{11}$$

$$S^2_{j,t} \equiv \begin{cases} 1, & \text{if } \Delta CF_{j,t} < -5\%, \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

$$S^3_{j,t} \equiv \begin{cases} 1, & \text{if } \Delta CF_{j,t} < \overline{\Delta CF}_j - \sigma_{\Delta CF_j}, \\ 0, & \text{otherwise,} \end{cases} \tag{13}$$

where $\Delta CF_{j,t}$ denotes the change in the capital-flow-to-GDP ratio from the previous period level, $\overline{\Delta CF}_j$ indicates its historical average, and $\sigma_{\Delta CF_j}$ is the corresponding standard deviation. The first definition of SS (named SS1 henceforth) event accounts for both an absolute threshold of -5% and a relative threshold of the historical average less one sigma. The second one (SS2) accounts only for the absolute threshold whereas the third one (SS3) accounts only for the relative threshold. We use the ratio of capital flows to GDP in order to account for economic significance and also for scale difference among countries. We exclude FDI-related capital flows, following Agosin and Huaita (2012).[4] Our definitions are largely consistent with Guidotti, Struzenegger, and Villar (2004), and Agosin and Huaita (2012).

With annual capital flow data, we identify the SS events for 48 EMEs from 1971 to 2014 for each of the three definitions. Figure 1 demonstrates the ratio of capital flows to GDP for each country and identifies SS events. Tables 1 and 2 show the summary of the SS events by year and by country. The first SS event (SS1) occurred 7.3% among the 1709 year-country observations, the second one (SS2) 9.9%, and the third one (SS3) 12.2%. The number of SS events hiked three times and well matched historical episodes of financial crises: Latin American currency crisis (1983), Asian currency crisis (1998), and the GFC (2008-2009). The SS1 occurred 51 times among Latin American countries, 29 times among Eastern Europe countries, and 25 times among Asian countries.

3.2 Variables

We include 22 information variables to predict the SS events and provide the list of variables in Table 3. These variables are commonly used in the literature (see, for example, Kaminsky,

[4] Agosin and Huaita (2012) argue that non-FDI capital flows have a shorter horizon than FDI and are susceptible to reversal while FDI capital flows have a longer horizon and are not so easily reversed.

Lizondo, and Reinhart (1998), Demirgüc-Kunt and Detragiache (1998), Edison (2003), Davis and Karim (2008a), Agosin and Huaita (2012), Forbes and Warnock (2012), Catão and Milesi-Ferretti (2014), and Christensen and Li (2014) among others).

We include real GDP growth, domestic real interest rate, central government debt to GDP ratio, and inflation as *macroeconomic* variables. A higher GDP growth would be associated with a lower probability of the SS event whereas a higher value of other variables would be associated with a higher probability. We consider M2 growth rate, depth of the financial system, return of stock market index and domestic-credit-to-GDP ratio as *financial* variables. Depth of the financial system and the return of stock market index would be negatively related with the SS event possibility while the other two variables would be positively related with the SS event. Depth of the financial system is proxied by the ratio of market capitalization in stock market to GDP, following Beck and Demirgüc-Kunt (2009) and Forbes and Warnock (2012). As *external* sector variables, we include current-account-to-GDP ratio, external-debt-to-exports ratio, terms of trade, real exchange rate, and M2-to-international-reserves ratio. Current-account-to-GDP ratio and terms of trade would negatively affect the SS event possibility while the other variables would positively affect. We also include several common variables such as GDP growth of G7 countries, foreign interest rate, the VIX, and M2 growth of world as *global* variables. The foreign interest rate is proxied by 3-month USD Libor rate. World M2 is measured by the sum of M2s of the U.S., the EU, Japan, and M4 of the U.K. in terms of USD. Both world GDP growth and world M2 growth would be negatively related with the SS event possibility while the other variables would be positively related.

In addition to these four sub-group variables, we also include five variables related with *cross-country* variations: Exchange rate regime is an index to indicate exchange rate rigidity with integer values from 1 to 6 where a fixed exchange rate regime is assigned by 1.[5] Levy-Yeyati and Sturzenegger (2005) use the exchange rate regime index in order to test the hypothesis that sudden stops are more likely in countries with fixed rather than flexible exchange rate regimes, and Agosin and Huaita (2012) also include the variable. Openness

[5] We retrieve exchange rate regime data from Carmen Reinhart's website (annual coarse classification) which covers until 2010. We assume that the same regime prevails during 2011-2014.

of an economy is measured as the ratio of the sum of exports and imports to GDP. GDP per capita is also included. Capital control is proxied by the KAOPEN measure of capital controls in Chinn and Ito (2008) which is also used in Forbes and Warnock (2012). Lastly, geographic proximity is an index to capture contagion effect which takes value one if a country in the same region has an SS event and zero otherwise. The geographic proximity is constructed by following Forbes and Warnock (2012).

4 Empirical Analysis

In this section, we apply the three prediction approaches into actual data and present empirical results of estimations and prediction performance comparisons.

4.1 Estimation Results

We present estimation results for each prediction approach in this subsection.

We first divide the sample period into two sub-periods: the first sub-period for in-sample estimation from 1971 to 2007 (i.e., pre-GFC) and the second sub-period for out-of-sample prediction from 2008 to 2014 (i.e., post-GFC). Since the SE approach cannot be applied into a country which has not experienced a financial crisis during the sample period, we exclude 13 countries which have no experience of an SS event during the in-sample period and use the remaining 35 EMEs for our analysis.[6]

Due to data limitation, some variables may have only few observations for certain countries, in which case it would be problematic to efficiently estimate NSR and the optimal threshold level. To overcome this problem faced by the SE approach, we first pool multi-country data for each information variable and then use the pooled data to determine the minimized NSR and the associated threshold level which are common across countries. For each of three SS definitions and forecast horizon of one year or two years, Table 4 shows the NSR for each information variable to indicate its informativeness from the perspective of SS

[6]Excluded are Bangladesh, Brazil, China, Colombia, Dominican Republic, India, Latvia, Lithuania, Malta, Mauritius, Russia, Slovenia, and Tunisia.

prediction. Following Christensen and Li (2014), the threshold level is found by grid-search from 70 to 90 percentile of empirical distribution of each variable.

For one-year forecast horizon, most information variables exhibit NSR less than one, proving their potential informativeness for prediction. Only VIX shows NSR more than one for both SS1 and SS3, and financial depth for SS3. Understandably, most variables lose their informativeness for a longer forecast horizon. With two-year forecast horizon, most variables show higher NSRs than those of one-year forecast horizon. Furthermore, three variables show NSR greater than one for both SS1 and SS2, and six variables for SS3. In particular, real GDP, M2, world GDP, and VIX fail to show their informativeness for two or three cases.

Next, we use the common NSR for each variable to construct two kinds of composite indexes, SE1 and SE2, for each country. For constructing the composite indexes, we exclude uninformative variables with NSR greater than one. To account for the difference in the number of available variables over time due to data limitation, the first kind composite index (SE1) is scaled by the total number of variables available at each time. The optimal threshold level is also found by grid-search from 70 to 90 percentile of empirical distribution of the composite index as a level to minimize the associated NSR. These in-sample individual NSR and the composite threshold level will be applied without updating during the post-GFC period for out-of-sample forecasts.

To implement the LR approach, we run the logistic regression with all variables to be considered whose results are provided in Table 5. We change the sign of variable so as to have positive expected sign for each variable. The threshold level to trigger a signal is found by grid-search over the estimated probability from 1 to 50 percent. As shown in Table 5, many variables unexpectedly exhibit negative sign. As a way to implement the LR approach, we choose only variables with expected sign from the estimation results in Table 5 (named LR1 henceforth). With forecast horizon of one year, LR1 includes 9 variables for SS1 and SS2 and 15 variables for SS3, among 22 variables. With forecast horizon of two years, LR1 includes 12 variables for SS1 and SS2 and 15 variables for SS3. As an alternative implementation way, we choose variables not only with expected sign but also with t-value greater than one in order to account for statistical significance which we name LR2. With forecast horizon of one year, LR2 includes 6 variables for SS1, 7 variables for SS2, and 9 variables for SS3.

With forecast horizon of two years, LR2 includes 5 variables for SS1 and 8 variables for SS2 and SS3.

We also run the logistic regression with four sub-group variables (instead of individual variables) along with variables representing cross-country variations to implement the new approach whose results are shown in Table 6. We consistently change the sign of variables so as to have expected positive sign for each variable. We employ grid-search to find the threshold level in the same way. Among 9 variables, two or three variables unexpectedly exhibit negative sign. Consistent with the LR approach, we choose only variables with expected sign from the estimation results in Table 6 when implementing the new approach. Among the variables to be considered, macroeconomic, exchange rate regime, capital control variables frequently show unexpected negative sign in the in-sample estimations.

4.2 Performance Comparisons

Using the in-sample estimation results from the previous subsection, we conduct prediction performance comparisons between the new approach versus conventional approaches for both in-sample and out-of-sample forecasts. As conventional approaches, we consider both the SE approach (SE1 and SE2) and the LR approach (LR1 and LR2). We utilize the NSR as a prediction performance measure. In addition, we employ Diebold-Mariano (1995) test to formally test the hypothesis that the new approach outperforms conventional approaches. The NSR will be calculated only for overall assessment by including all countries to be predicted because we have too few observations to effectively calculate the NSR for each country. On the other hand, Diebold-Mariano asymptotic test will be used for overall comparison while Diebold-Mariano exact finite-sample sign test will be used for individual country comparisons.

The performance comparison results are provided in Table 7. With one-year forecast horizon and the SS1 event, the new approach yields lower NSR than all of the contending conventional approaches for not only in-sample but also out-of-sample forecasts. With the SS2 event, the new approach outperforms in all cases except one (SE2 with out-of-sample forecast). Similarly, with the SS3 event, the new approach outperforms in all cases except two (LR1 and LR2 with in-sample forecast). Based on Diebold-Mariano test for overall assessment, the new approach outperforms the four conventional approaches in all cases which are also statistically significant except only one case (LR2 with in-sample forecast).[7] At an individual country level, the new approach also proves to outperform the conventional approaches, showing that the ratio of countries for which the new approach outperforms the contending conventional approach to all the countries to be predicted is fairly high and exceeds 80% in all cases. This result also holds with statistical significance in most cases. Roughly, similar results still hold with two-year forecast horizon. The new approach outperforms the conventional approaches in most cases, judged not only from the NSR measure (except only three cases for the SS2 event and two cases for the SS3 event) but also from Diebold-Mariano test results.[8]

The new approach differs from the SE approach in several aspects: It utilizes variables related with cross-country variations and employs a logistic regression model with a small number of sub-group variables. To investigate the sources of the outperformance by the new approach over the SE approach, we conduct again prediction performance comparisons while excluding variables representing cross-country variations so as to make the two approaches utilize the same set of variables. Table 8 (Panel A) provides the performance comparison results. With one-year forecast horizon, the new approach still yields lower NSR than the SE approach in most cases, implying that accounting for cross-country variations does not greatly contribute to forecasting ability, and the outperformance is more closely related with the way to utilize information variables. Interestingly, however, with a longer forecast horizon of two years, the new approach fails to yield lower NSR than the SE approach in most cases, implying that cross-country variations should be taken into account to improve forecasting ability. On the other hand, the results from Diebold-Mariano test are largely the same, suggesting that the way to utilize information variables may be the source of the

[7] Noteworthily, the NSR measure penalizes both incorrect forecasts (i.e., type I error (event C) and type II error (event B)) in a nonlinear way whereas Diebold-Mariano test equally penalize them. It would be better to penalize both types of error in an optimal way, which is beyond the scope of this paper.

[8] Noticeably, the LR approach utilizes only a limited number of observations for the in-sample estimations due to data limitations. In contrast, the new approach can advantageously overcome this problem by constructing the sub-group variables.

prediction outperformance.

The new approach differs from the LR approach by using a small number of sub-group variables instead of many individual variables. By excluding variables representing cross-country variations which are commonly used in both approaches, we can focus on the relative advantage of using the sub-group variables. Table 8 (Panel B) provides the performance comparison results. Interestingly, we obtain results similar to the case of comparison with the SE approach. Judged from the NSR measure, the new approach outperforms the LR approach for one-year forecast horizon but fails to do so for two-year forecast horizon. This fact may suggest that the relative advantage of using the sub-group variables prevails only for a short horizon. On the other hand, the results from Diebold-Mariano test differently suggests that the relative advantage may prevail regardless of horizon.

5 Conclusion

In this paper, we propose a new prediction approach for forecasting sudden stop events of capital flows to emerging market countries. We apply the new approach as well as conventional approaches into actual data and conduct prediction performance comparisons. The empirical results show that the new approach significantly improves prediction ability and that this outperformance may come from a novel way to utilize information for prediction.

The new approach can be applied not only into sudden stop events of capital flows but also into various types of financial crisis events. The relative outperformance of the new approach over the conventional ones should be confirmed with further financial-crisis predictions in the future; however, the new approach proves to have some potential merits to be considered as an alternative approach to improve prediction ability.

In the present context that the U.S. policy makers started to normalize the unconventional monetary policy from December 2015, it would be of great interest to predict the sudden stop events of capital flows to emerging countries. To effectively predict the sudden stop events, the prediction should be conditional on a possible scenario for a future normalization path. In addition, not only direct but also potential indirect effects of the normalization on capital flows to emerging markets should also be taken into account.[9] Equipped with these conditioning information, the new approach may be utilized to predict the sudden stop events of capital flows to emerging markets conditional on the normalization.

[9] Relatedly, there exists a large literature on the unconventional monetary policy. Examples include Fratzscher, Duca, and Straub (2013), IMF (2013a, 2013b), Rey (2013), Avdjiev and Takáts (2014), Bauer and Neely (2014), Bruno and Shin (2015), Chen, Filardo, He, and Zhu (2015), Eichengreen and Gupta (2015), Koepke (2013, 2015), McCauley, McGuire, and Sushko (2015), and Neely (2015), among others.

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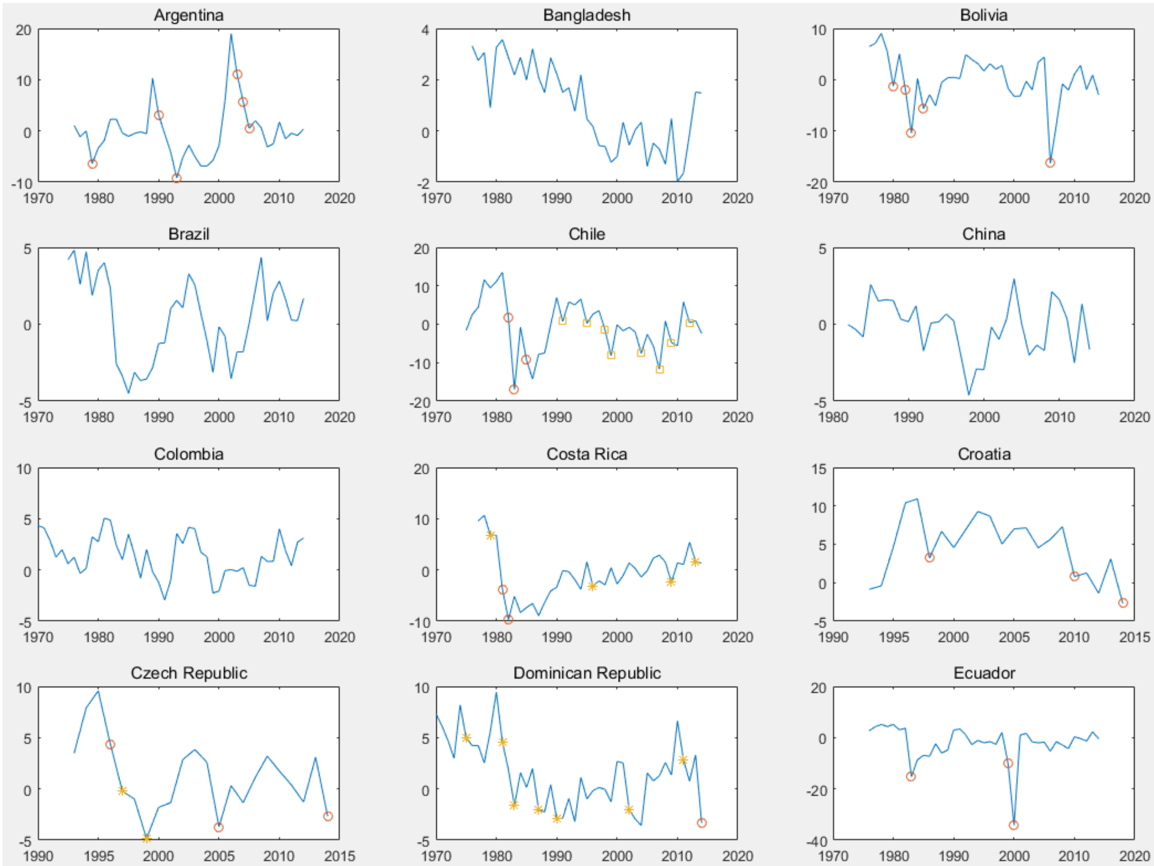

Figure 1-a. Ratio of capital flows to GDP by country.

This figure demonstrates the ratio (%) of capital flows to GDP by country from 1970 to 2014. The SS event is marketed by '○' for SS1, '□' for SS2 (but not SS1), and '*' for SS3 (but not SS1).

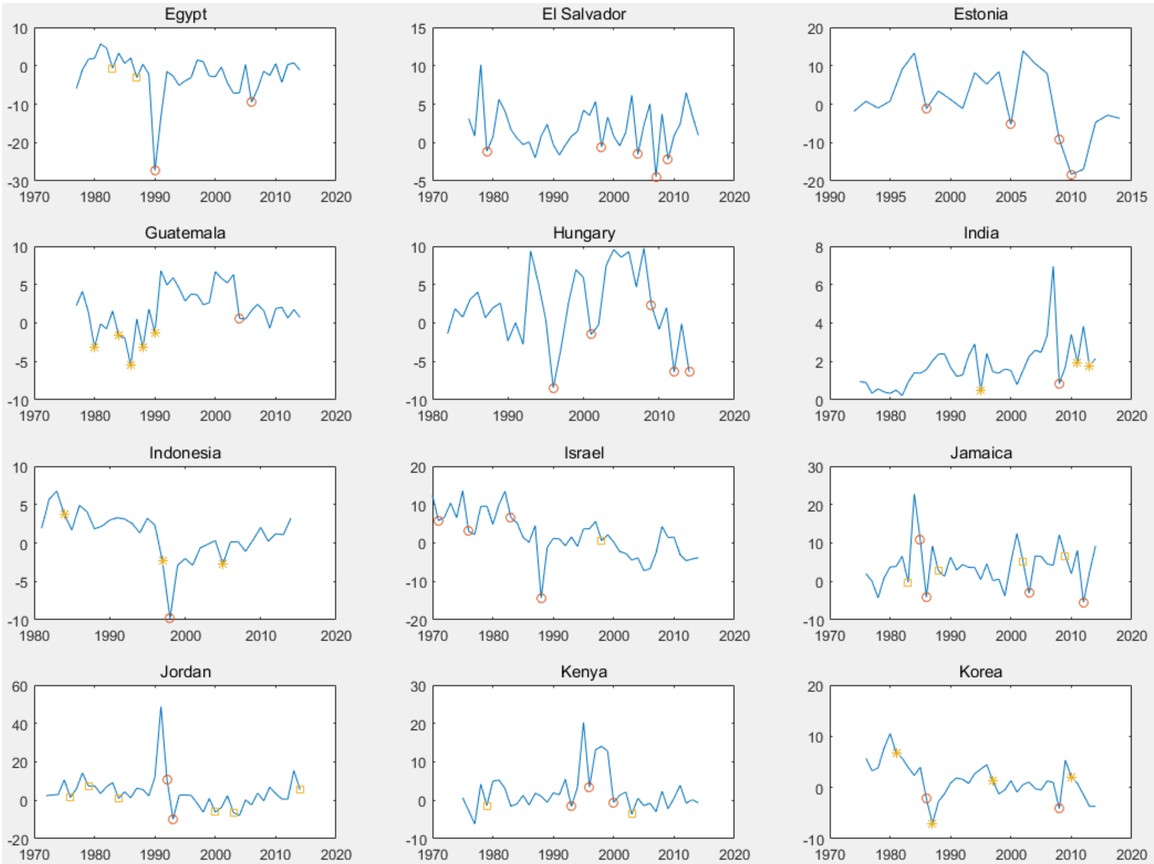

Figure 1-b. Ratio of capital flows to GDP by country.

Refer to the explanation in Figure 1-a.

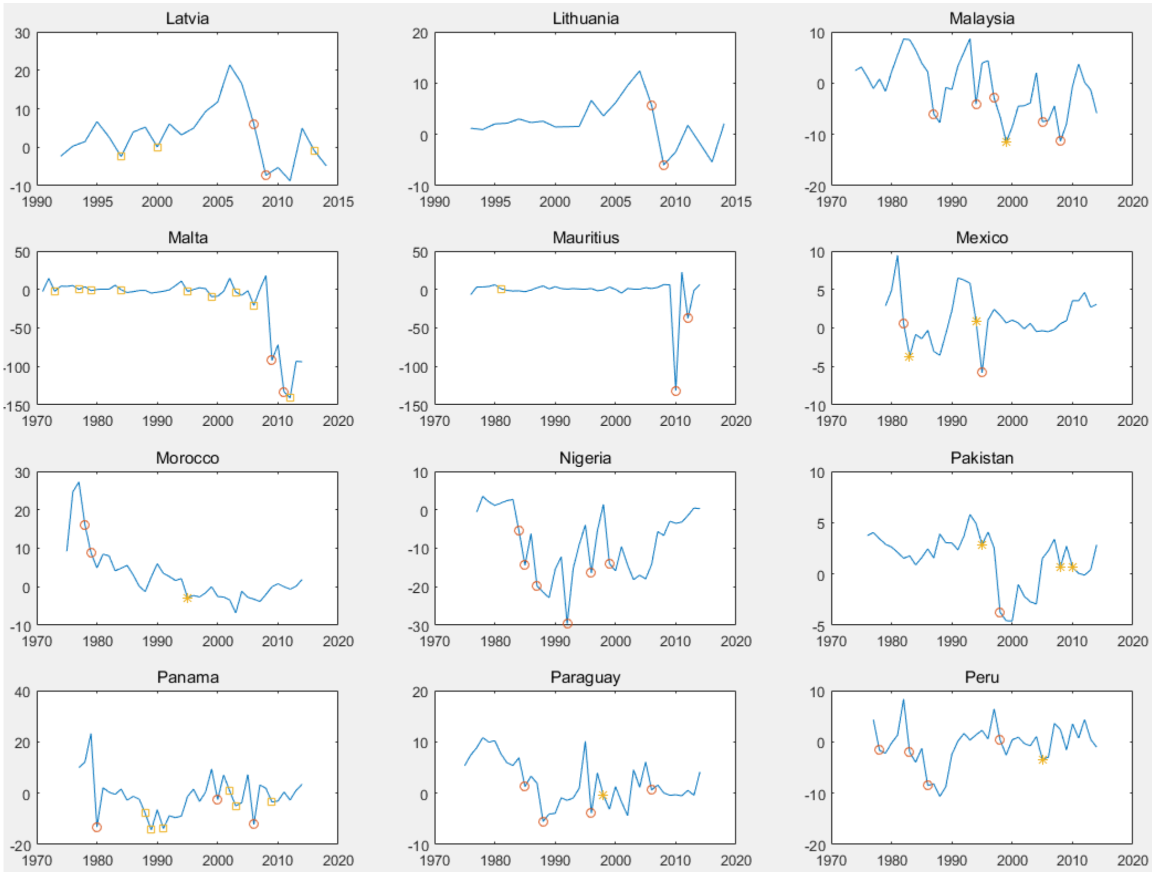

Figure 1-c. Ratio of capital flows to GDP by country.

Refer to the explanation in Figure 1-a.

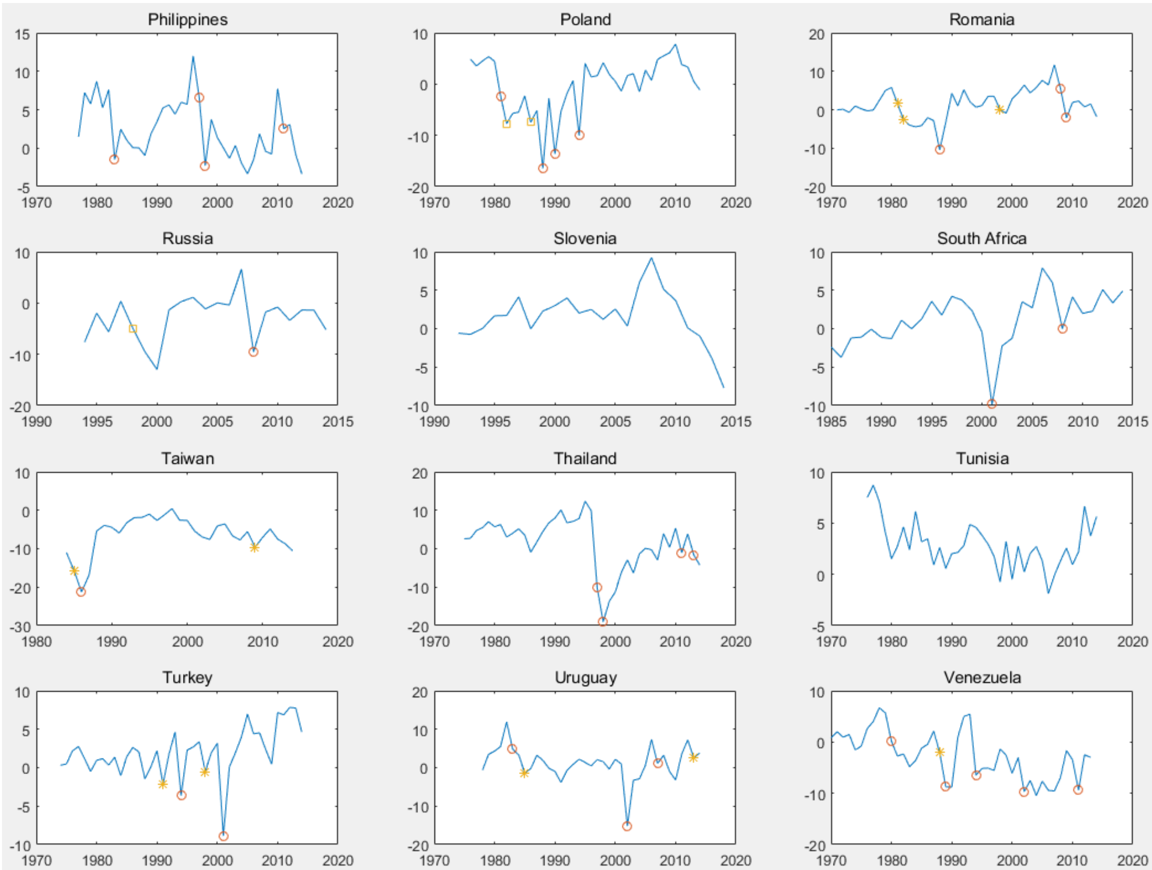

Figure 1-d. Ratio of capital flows to GDP by country.

Refer to the explanation in Figure 1-a.

Table 1. Sudden stop events by year.

This table shows the number of sudden stop events according to three definitions: SS1 for (11), SS2 for (12), and SS3 for (13).

Year	No. Countries	No. SS			SS1 by region			
		SS1	SS2	SS3	Asia	Eastern Europe	Latin America	Other
1971	4	1	1	1	1	0	0	0
1972	6	0	0	0	0	0	0	0
1973	7	0	1	0	0	0	0	0
1974	7	0	0	0	0	0	0	0
1975	9	0	0	1	0	0	0	0
1976	16	1	2	1	1	0	0	0
1977	27	0	1	1	0	0	0	0
1978	34	2	2	2	0	0	1	1
1979	35	3	6	7	0	0	2	1
1980	36	3	3	5	0	0	3	0
1981	36	2	3	5	0	1	1	0
1982	37	4	5	5	0	0	4	0
1983	39	7	9	11	2	0	5	0
1984	39	1	3	3	0	0	0	1
1985	40	5	5	8	0	0	4	1
1986	41	4	5	6	2	0	2	0
1987	41	2	3	6	1	0	0	1
1988	41	4	6	6	1	2	1	0
1989	41	1	2	2	0	0	1	0
1990	41	3	3	5	0	1	1	1
1991	41	0	2	1	0	0	0	0
1992	41	2	2	3	1	0	0	1
1993	44	3	3	3	1	0	1	1
1994	47	4	4	5	1	1	1	1
1995	48	1	3	5	0	0	1	0
1996	48	5	5	6	0	2	1	2
1997	48	3	4	8	3	0	0	0
1998	48	8	11	14	4	2	2	0
1999	48	2	4	6	0	0	1	1
2000	48	3	5	4	0	0	2	1
2001	48	3	3	3	0	1	0	2
2002	48	2	4	5	0	0	2	0
2003	48	2	6	2	0	0	2	0
2004	48	3	4	3	0	0	3	0
2005	48	4	4	8	1	2	1	0
2006	48	4	5	6	0	0	3	1
2007	48	2	3	2	0	0	2	0
2008	48	8	8	10	3	4	0	1
2009	48	7	10	10	0	6	1	0
2010	48	3	3	6	0	2	0	1
2011	48	4	4	8	2	1	1	0
2012	48	3	5	4	0	1	1	1
2013	48	1	2	5	1	0	0	0
2014	47	4	5	6	0	3	1	0

Table 2. Sudden stop events by country.

This table shows the number of sudden stop events according to three definitions: SS1 for (11), SS2 for (12), and SS3 for (13).

Country	SS1	SS2	SS3
Argentina	6	6	6
Bangladesh	0	0	4
Bolivia	5	5	5
Brazil	0	0	6
Chile	3	11	3
China	0	0	7
Colombia	0	0	7
Costa Rica	2	2	6
Croatia	3	3	3
Czech Republic	3	3	5
Dominican Republic	1	1	8
Ecuador	3	3	3
Egypt	2	4	2
El Salvador	5	5	5
Estonia	4	4	4
Guatemala	1	1	6
Hungary	5	5	5
India	1	1	4
Indonesia	1	1	4
Israel	4	5	4
Jamaica	4	8	4
Jordan	2	8	2
Kenya	3	5	3
Korea	2	2	6
Latvia	2	5	2
Lithuania	2	2	2
Malaysia	5	5	6
Malta	2	11	2
Mauritius	2	3	2
Mexico	2	2	4
Morocco	2	2	3
Nigeria	6	6	6
Pakistan	1	1	4
Panama	3	9	3
Paraguay	4	4	5
Peru	4	4	5
Philippines	4	4	4
Poland	4	6	4
Romania	3	3	6
Russia	1	2	1
Slovenia	0	0	4
South Africa	2	2	2
Taiwan	1	1	3
Thailand	4	4	4
Tunisia	0	0	9
Turkey	2	2	4
Uruguay	3	3	5
Venezuela	5	5	6

Table 3. List of variables.

This table shows the variables to be used for this analysis. The variables are classified according to their attributes. 'Sign' indicates the expected sign of the effects of a variable on the SS event possiblilty.

Attribute	Variable	Abbreviation	Sign
Macroeconomic	Real GDP growth	RGDP	-
	Domestic real interest rate	DRINT	+
	Central government debt to GDP	GDEBT	+
	Inflatioin	INFLA	+
Financial	M2 growth	M2	+
	Depth of the financial system	FDEPTH	-
	Return of stock market index	STOCK	-
	Domestic credit to GDP	CREDIT	+
External	Current account to GDP	CA	-
	External debt to exports ratio	EXDEBT	+
	Terms of trade	TOT	-
	Real exchange rate	RER	+
	M2-International Reserves Ratio	FRES	+
Global	GDP growth of G7 countries	WGDP	-
	Foreign interest rate	FINT	+
	VIX	VIX	+
	M2 growth of world	WM2	-
Cross-country	Exchange rate regime	EXREG	-
	Openness	OPEN	+
	GDP per capita	GDPCAP	-
	Capital control	CAPCON	-
	Geographic proximity	GEOPROX	+

Table 4. Informativeness of variables in the signal extraction approach.

This table shows informativeness of variables in the signal extraction approach by providing the noise-to-signal ratio (NRS) for each of three SS definitions and forecast horizon of one year or two years. The threshold level is provided in terms of percentile of empirical distribution of each variable.

	A. Forecast horizon = 1 year					
	SS1		SS2		SS3	
Variable	Threshold	NSR	Threshold	NSR	Threshold	NSR
RGDP	90	0.665	90	0.624	90	0.685
DRINT	90	0.597	86	0.597	90	0.659
GDEBT	77	0.565	82	0.672	89	0.817
INFLA	71	0.785	71	0.958	71	0.780
M2	89	0.762	90	0.669	83	0.895
FDEPTH	71	0.887	71	0.959	71	1.058
STOCK	88	0.880	89	0.672	85	0.917
CREDIT	90	0.324	90	0.370	90	0.406
CA	90	0.256	90	0.304	90	0.343
EXDEBT	70	0.744	70	0.702	70	0.699
TOT	75	0.869	75	0.854	89	0.888
RER	88	0.733	88	0.950	78	0.977
FRES	90	0.534	90	0.507	90	0.628
WGDP	90	0.668	85	0.759	90	0.831
FINT	85	0.586	90	0.664	85	0.601
VIX	70	1.269	90	0.786	77	1.171
WM2	87	0.483	87	0.518	87	0.448
	B. Forecast horizon = 2 years					
	SS1		SS2		SS3	
Variable	Threshold	NSR	Threshold	NSR	Threshold	NSR
RGDP	90	1.284	90	1.265	90	0.990
DRINT	84	0.622	84	0.826	85	0.624
GDEBT	80	0.763	80	0.698	80	1.069
INFLA	71	0.736	70	0.847	71	0.902
M2	75	0.984	76	1.039	71	1.120
FDEPTH	88	0.591	88	0.670	88	0.805
STOCK	71	0.948	73	0.832	73	1.079
CREDIT	84	0.463	84	0.540	88	0.524
CA	90	0.370	90	0.453	85	0.504
EXDEBT	89	0.811	89	0.778	87	0.834
TOT	87	0.913	87	0.938	87	1.018
RER	90	0.830	71	0.870	90	0.855
FRES	81	0.638	90	0.671	81	0.732
WGDP	70	1.077	70	1.004	70	1.174
FINT	90	0.641	90	0.637	90	0.658
VIX	77	1.159	90	0.809	70	1.581
WM2	90	0.542	89	0.517	90	0.457

Table 5. Estimation results of the logistic regression approach.

This table shows the coefficient estimates and t-values from the logistic regression for each of three SS definitions and forecast horizon of one year (Panel A) or two years (Panel B). Constants are omitted.

	A. Forecast horizon = 1 year					
	SS1		SS2		SS3	
variable	coef.	t-value	coef.	t-value	coef.	t-value
RGDP	-0.0686	-0.9727	-0.0363	-0.5403	0.0017	0.0290
DRINT	0.0693	1.0936	0.0416	0.6946	0.1036	2.4198
GDEBT	0.0197	1.6652	0.0309	2.7568	-0.0005	-0.0538
INFLA	-0.0041	-0.1008	-0.0336	-0.8053	0.0456	1.4211
M2	-0.0086	-0.3930	0.0205	0.9939	-0.0154	-0.7562
FDEPTH	-0.0112	-1.7106	-0.0142	-2.1676	0.0025	0.5106
STOCK	-0.0130	-1.2193	-0.0072	-0.6954	-0.0082	-1.1711
CREDIT	-0.0234	-1.4749	-0.0291	-1.8764	0.0143	1.6854
CA	-0.0023	-0.0417	-0.0108	-0.2042	0.0513	1.1915
EXDEBT	0.0043	1.2038	0.0046	1.3476	0.0040	1.6467
TOT	-0.0090	-0.3202	-0.0141	-0.5271	-0.0044	-0.2402
RER	-0.0001	-0.5222	-0.0001	-0.6628	0.0001	0.7056
FRES	0.0048	2.1837	0.0057	2.4695	0.0006	0.6924
WGDP	-0.7910	-1.3669	-0.8921	-1.5655	-0.8430	-2.0756
FINT	-0.5519	-1.5718	-0.5437	-1.7637	-0.6767	-2.6644
VIX	0.0373	0.5009	0.0826	1.1575	-0.0925	-2.0110
WM2	0.2406	2.1427	0.2095	2.1356	0.2199	2.9516
EXREG	-0.3970	-0.8482	-0.2769	-0.5983	0.2874	1.0555
OPEN	0.0163	1.3826	0.0157	1.3637	0.0072	1.1051
GDPCAP	0.0001	1.0374	0.0001	1.3774	0.0001	1.7004
CAPCON	-0.0391	-0.1300	-0.0884	-0.3123	0.1050	0.5603
GEOPROX	0.0076	0.0124	-1.1120	-1.8946	0.0367	0.0877

Table 5. continued.

	Forecast horizon = 2 year					
	SS1		SS2		SS3	
variable	coef.	t-value	coef.	t-value	coef.	t-value
RGDP	0.0335	0.4103	-0.0069	-0.0979	0.0089	0.1459
DRINT	0.0317	0.5015	0.0321	0.5481	0.0568	1.3487
GDEBT	0.0094	0.7378	0.0180	1.7177	-0.0062	-0.6375
INFLA	-0.0309	-0.6574	-0.0149	-0.3373	0.0053	0.1542
M2	0.0424	2.1957	0.0231	1.4229	0.0311	2.1799
FDEPTH	-0.0084	-1.0786	-0.0081	-1.2055	0.0050	0.8576
STOCK	0.0190	1.6673	0.0144	1.3177	0.0124	1.6066
CREDIT	-0.0111	-0.6771	-0.0091	-0.6827	0.0168	1.8978
CA	-0.0152	-0.2630	-0.0356	-0.7067	0.0776	1.7117
EXDEBT	0.0080	2.1052	0.0050	1.6341	0.0049	1.8726
TOT	-0.0024	-0.0887	0.0005	0.0223	-0.0034	-0.1683
RER	0.0000	-0.4273	-0.0001	-0.6774	0.0000	0.6323
FRES	0.0018	1.1517	0.0019	1.3576	-0.0006	-0.6173
WGDP	0.5689	1.0351	0.6233	1.2290	0.2084	0.5505
FINT	0.1456	0.5753	0.2766	1.2069	-0.0040	-0.0221
VIX	-0.0823	-1.1182	-0.0122	-0.1980	-0.0898	-1.9331
WM2	-0.0638	-0.8223	-0.0306	-0.4444	-0.0610	-1.1804
EXREG	-0.0974	-0.2129	0.0271	0.0671	0.4836	1.6641
OPEN	0.0090	0.7232	0.0035	0.3156	0.0056	0.7615
GDPCAP	0.0001	0.8692	0.0001	1.2339	0.0002	1.6421
CAPCON	-0.2092	-0.7104	-0.3580	-1.3504	0.1454	0.7093
GEOPROX	-1.5603	-2.1441	-0.6666	-1.2147	-0.4494	-0.9992

Table 6. Estimation results of the new approach.

This table shows the coefficient estimates and t-values from the logistic regression under the new approach for each of three SS definitions and forecast horizon of one year (Panel A) or two years (Panel B). Constants are omitted.

	SS1		SS2		SS3	
variable	coef.	t-value	coef.	t-value	coef.	t-value
A. Forecast horizon = 1 year						
Macro	0.1698	0.7162	0.3705	1.9524	-0.0009	-0.0049
Financial	0.3718	1.8595	0.3459	1.9146	0.2873	2.0071
External	0.9324	4.7665	0.7313	4.3646	0.7248	4.7388
Global	0.1777	0.9128	0.0995	0.5765	0.2302	1.5647
EXREG	-0.2046	-2.1197	-0.0855	-1.0010	-0.1275	-1.6854
OPEN	0.0052	1.5441	0.0065	2.4147	0.0030	1.0758
GDPCAP	0.0000	0.5390	0.0000	0.0739	0.0000	0.8613
CAPCON	-0.1433	-1.4776	-0.1059	-1.3288	-0.0214	-0.2800
GEOPROX	0.1801	0.7393	-0.0606	-0.2886	0.2615	1.3582
B. Forecast horizon = 2 year						
Macro	-0.3316	-1.2624	-0.2098	-0.9523	-0.0761	-0.4002
Financial	0.3385	1.5534	0.3191	2.1114	0.2128	1.7442
External	0.4695	2.3111	0.3494	1.9387	0.4274	2.9837
Global	0.2972	1.7943	0.2903	1.9431	0.2108	1.6767
EXREG	-0.0443	-0.4487	0.0498	0.5487	0.0465	0.6093
OPEN	0.0007	0.1928	0.0041	1.5351	-0.0010	-0.3590
GDPCAP	0.0000	0.5430	0.0000	-0.0660	0.0000	0.5979
CAPCON	-0.1471	-1.5440	-0.0635	-0.7983	-0.0283	-0.3742
GEOPROX	0.0548	0.2245	0.0511	0.2391	0.2333	1.2136

Table 7. Prediction performance comparison: New vs. conventional approach.

This table shows in-sample ('In') and out-of-sample ('Out') prediction performance with NSR ('NSR0' for the new approach and the 'NSR1' for the conventional approach to be compared) and Diebold-Mariano (1995) test (with test statistic 'DM' and its p-value). Diebold-Mariano (1995) test is also conducted for each country, and 'Country' indicates the ratio of countries where the new approach outperforms the contending conventional approach to all the countries to be predicted, and 'Sig. Country' is similar to the 'Country' but with statistical significance. The new approach is compared with each of SE1, SE2, LR1, or LR2 for each of three SS definitions and forecast horizon of one year (Panel A) or two years (Panel B).

Forecast horizon = 1 year									
SS	Approach	Period	Nobs	NSR0	NSR1	DM	p-value	Country	Sig. Country
SS1	SE1	In	958	0.283	0.421	-9.271	0.000	1.000	0.971
		Out	244	0.507	0.573	-7.451	0.000	0.971	0.686
	SE2	In	884	0.272	0.388	-7.928	0.000	1.000	0.943
		Out	237	0.523	0.581	-7.944	0.000	0.971	0.714
	LR1	In	362	0.362	0.612	-9.032	0.000	0.914	0.743
		Out	230	0.637	1.008	-8.246	0.000	0.914	0.629
	LR2	In	362	0.362	0.630	-9.614	0.000	0.914	0.743
		Out	230	0.637	0.892	-8.994	0.000	0.914	0.657
SS2	SE1	In	1033	0.329	0.509	-7.617	0.000	0.974	0.872
		Out	272	0.629	0.640	-5.121	0.000	0.949	0.615
	SE2	In	954	0.327	0.476	-6.022	0.000	0.974	0.872
		Out	266	0.645	0.608	-4.981	0.000	0.949	0.615
	LR1	In	394	0.455	0.639	-7.949	0.000	0.923	0.641
		Out	258	0.609	1.174	-7.215	0.000	0.821	0.615
	LR2	In	410	0.420	0.657	-7.924	0.000	0.949	0.718
		Out	265	0.604	1.098	-6.677	0.000	0.872	0.590
SS3	SE1	In	1195	0.413	0.488	-6.105	0.000	0.953	0.953
		Out	300	0.431	0.651	-6.889	0.000	1.000	0.628
	SE2	In	1115	0.403	0.490	-5.523	0.000	0.953	0.953
		Out	291	0.446	0.621	-6.831	0.000	1.000	0.628
	LR1	In	559	0.492	0.475	-2.424	0.008	0.860	0.744
		Out	265	0.419	0.678	-4.077	0.000	0.814	0.581
	LR2	In	872	0.436	0.425	-0.996	0.160	0.907	0.860
		Out	279	0.420	0.526	-3.125	0.001	0.884	0.605

Table 7. continued.

Forecast horizon = 2 year									
SS	Approach	Period	Nobs	NSR0	NSR1	DM	p-value	Country	Sig. Country
SS1	SE1	In	943	0.420	0.497	-7.360	0.000	1.000	0.971
		Out	244	0.422	0.583	-5.653	0.000	0.971	0.771
	SE2	In	882	0.384	0.482	-6.624	0.000	1.000	0.943
		Out	240	0.430	0.502	-5.388	0.000	0.971	0.743
	LR1	In	220	0.490	0.636	-6.472	0.000	0.686	0.571
		Out	174	n.a.	0.717	-9.162	0.000	0.686	0.486
	LR2	In	321	0.420	0.583	-5.760	0.000	0.743	0.686
		Out	181	0.104	0.677	-8.799	0.000	0.714	0.486
SS2	SE1	In	998	0.551	0.515	-2.801	0.003	0.923	0.872
		Out	265	0.830	1.050	-2.471	0.007	0.897	0.436
	SE2	In	939	0.528	0.523	-2.412	0.008	0.923	0.821
		Out	258	0.843	1.090	-3.317	0.000	0.923	0.487
	LR1	In	231	0.872	0.827	-3.263	0.001	0.641	0.462
		Out	188	0.878	0.702	-3.594	0.000	0.615	0.333
	LR2	In	253	0.656	0.770	-3.765	0.000	0.692	0.513
		Out	195	0.866	0.882	-4.149	0.000	0.692	0.333
SS3	SE1	In	1157	0.424	0.507	-4.853	0.000	0.930	0.837
		Out	293	0.522	0.548	-3.040	0.001	0.884	0.674
	SE2	In	1098	0.438	0.506	-4.278	0.000	0.884	0.837
		Out	289	0.515	0.651	-3.764	0.000	0.884	0.698
	LR1	In	366	0.635	0.497	-2.461	0.007	0.721	0.581
		Out	216	0.670	0.656	-4.982	0.000	0.674	0.372
	LR2	In	437	0.478	0.549	-3.919	0.000	0.744	0.581
		Out	216	0.670	0.689	-4.642	0.000	0.698	0.488

Table 8. Prediction performance comparisons with a subset of variables.

This table shows the results of prediction performance comparisons between the new and conventional approaches. Variables representing cross-country variatons are excluded in these predictions Refer to Table 7 for other explanations.

Panel A. The new versus the SE approach

SS	Approach	Period	nobs	NSR0	NSR1	DM	p-value	Country	Sig. Country
				Forecast horizon = 1 year					
SS1	SE1	In	1008	0.275	0.433	-10.365	0.000	1.000	0.943
		Out	244	0.591	0.573	-7.177	0.000	0.971	0.714
	SE2	In	928	0.273	0.398	-8.928	0.000	1.000	0.943
		Out	237	0.610	0.581	-7.769	0.000	0.971	0.743
SS2	SE1	In	1084	0.359	0.522	-8.289	0.000	1.000	0.949
		Out	272	0.568	0.640	-5.730	0.000	0.974	0.641
	SE2	In	1001	0.341	0.479	-6.920	0.000	1.000	0.949
		Out	266	0.582	0.608	-5.648	0.000	0.974	0.641
SS3	SE1	In	1248	0.412	0.500	-6.244	0.000	0.930	0.884
		Out	300	0.559	0.651	-5.696	0.000	0.977	0.605
	SE2	In	1163	0.406	0.500	-5.562	0.000	0.953	0.930
		Out	291	0.580	0.621	-5.833	0.000	1.000	0.605
				Forecast horizon = 2 year					
SS1	SE1	In	1002	0.521	0.490	-5.795	0.000	1.000	0.971
		Out	244	0.718	0.583	-5.227	0.000	0.971	0.800
	SE2	In	934	0.476	0.479	-5.218	0.000	1.000	0.971
		Out	240	0.731	0.502	-4.850	0.000	0.971	0.771
SS2	SE1	In	1045	0.555	0.519	-3.082	0.001	0.974	0.821
		Out	272	1.174	1.062	-4.311	0.000	0.974	0.667
	SE2	In	983	0.533	0.528	-2.733	0.003	0.949	0.846
		Out	265	1.209	1.097	-5.331	0.000	1.000	0.692
SS3	SE1	In	1197	0.499	0.511	-3.126	0.001	0.953	0.837
		Out	300	0.533	0.549	-2.100	0.018	0.907	0.651
	SE2	In	1138	0.529	0.512	-2.534	0.006	0.930	0.837
		Out	296	0.525	0.653	-2.970	0.001	0.930	0.674

Table 8. continued.

Panel B. The new versus the LR approach

SS	Approach	Period	nobs	NSR0	NSR1	DM	p-value	Country	Sig. Country
				Forecast horizon = 1 year					
SS1	LR1	In	362	0.304	0.522	-9.117	0.000	0.857	0.800
		Out	230	0.764	1.125	-8.887	0.000	0.886	0.657
	LR2	In	398	0.274	0.571	-10.341	0.000	0.943	0.857
		Out	244	0.591	1.229	-10.502	0.000	0.943	0.686
SS2	LR1	In	391	0.470	0.635	-7.901	0.000	0.872	0.692
		Out	251	0.497	1.013	-8.736	0.000	0.872	0.641
	LR2	In	409	0.408	0.593	-7.841	0.000	0.949	0.692
		Out	265	0.545	1.005	-8.327	0.000	0.897	0.641
SS3	LR1	In	421	0.619	0.551	-4.042	0.000	0.837	0.651
		Out	272	0.598	0.820	-6.725	0.000	0.860	0.488
	LR2	In	668	0.519	0.503	-3.268	0.001	0.930	0.814
		Out	286	0.600	0.789	-4.842	0.000	0.907	0.581
				Forecast horizon = 2 year					
SS1	LR1	In	217	0.392	0.776	-6.574	0.000	0.686	0.571
		Out	174	0.911	0.774	-9.302	0.000	0.686	0.457
	LR2	In	239	0.337	0.706	-6.562	0.000	0.714	0.600
		Out	181	0.570	0.760	-9.841	0.000	0.714	0.486
SS2	LR1	In	237	1.228	0.793	-5.799	0.000	0.692	0.564
		Out	195	1.193	0.828	-7.429	0.000	0.692	0.436
	LR2	In	262	0.645	0.760	-5.988	0.000	0.718	0.590
		Out	202	1.102	0.869	-7.069	0.000	0.718	0.410
SS3	LR1	In	359	0.808	0.536	-2.383	0.009	0.744	0.558
		Out	223	0.577	0.791	-6.530	0.000	0.698	0.395
	SE2	In	505	0.512	0.460	-3.018	0.001	0.767	0.651
		Out	230	0.570	0.700	-6.189	0.000	0.744	0.419