Finding a needle in a haystack: Do Early Warning Systems for Sudden Stops work?

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Keywords: EarlyWarning System; Sudden Stops; EmergingMarkets; External Crisis.

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Finding a needle in a haystack:

Do Early Warning Systems for Sudden Stops work?*

Umberto Collodel†

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Abstract

The paper develops an Early Warning System (EWS) to identify the build up of vulnerabilities in the external sector of 31 Emerging Markets (EMs) across the period 1995-2017 and avoid the painful sudden reversal of capital flows associated to them. It contributes to the literature on the prediction of financial discontinuities in three ways. First, it uses a discrete choice model to calculate and compare the marginal effect of different domestic and global factors on the probability of a sudden stop materializing. Second, it analyzes the performance of the model with a recursive framework that reflects accurately the information set available to policymakers at the time of the prediction. Third, it investigates the relationship between ex-ante probability of a sudden stop and the ensuing output loss. We find that domestic and global factors contribute to the reversal of capital flows in a comparable way. Our model calls half of the pre-crisis periods, exhibiting a high specificity and a proper timing. Moreover, we find a positive link between the ex-ante probability of a sudden stop and the associated ex-post loss. These results call for an active use of Early Warnings in the policy-making sphere.

Keywords: Early Warning System; Sudden Stops; Emerging Markets; External Crisis

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Introduction

The global retrenchment of capital flows during the Great Recession and the upheavals concomitant with the raise of US target rate at the end of 2015 have once again raised the issue of inflows-fueled booms and following busts in Emerging Markets (EMs). Fickle capital markets put under severe strain these countries: plummeting currencies, external adjustment and in some cases, defaults, resulted in dramatic output losses and rising poverty. The recent Covid-19 crisis, although differs markedly from the usual boom-bust cycle, is exacerbating existing domestic vulnerabilities in the aforementioned countries: while capital flows appear rather stable, investors could soon decide to withdraw from their most risky positions, hence jeopardising financial stability (Kalemli-Ozcan [2020]). A timely identification of the vulnerabilities giving rise to sudden stops can prevent the painful consequences associated to them.

For this reason, interest toward Early Warning System (EWSs) has re-kindled in policy institutions such as the IMF and national central banks (e.g. Basu et al. [2019], Suss and Treitel [2019], Beutel et al. [2018], Duca and Peltonen [2013]). Nevertheless, many scholars remain doubtful about the predictive power of EWSs: while in-sample they generally work well, out-of-sample they "consistently fail to predict the upcoming wave of external crises" [Rose and Spiegel, 2011, 2010].

In this paper, we exploit a discrete choice model to predict the materialization of sudden stops within six quarters of advance and understand its determinants. We expand the literature in different directions. First, we test a large pool of both domestic and global indicators of macro-financial vulnerabilities and relative transformations. We uncover a near equivalence between the marginal effect of domestic and global factors on the probability of a sudden stop: this result stands in stark contrast with the proposition that EMs are solely at the mercy of a Global Financial Cycle [Rey, 2015]. Since domestic factors play a more substantial role than previously maintained, the usefulness of Early Warnings for financial stability purposes increases significantly: indeed, the reception of a signal by policymakers can trigger a pronounced correction of the fundamentals responsible for the rise in probability. Policy options are, instead, far more constrained in the case of a Global Cycle dominance.

Second, we offer a framework to analyze the performance of the model recursively, mirroring accurately the information set available to forecasters at the time of the prediction and appraise our model based on it. The model exhibits good sensitivity i.e. number of crises correctly called (47%) and very high specificity i.e. tranquil times correctly called (85%), largely improving over the chosen alternative, a naive-decision benchmark. Moreover, we show that the sensitivity of a classifier can be a misleading evaluation metric when dealing with problems such as financial crises prediction. We find that the estimated ex-ante probabilities of a sudden stop are highly correlated with the output impact of the ensuing event: episodes with a catastrophic impact on real activity are predicted with virtual certainty by the model, while those that entail only mild slowdowns are either missed or called with low probability. This result is robust to the choice of different measures of output impact.

The paper is structured as follows. Section 1 summarizes the relevant literature. Section 2 explains our identification of sudden stops and introduces the indicators tested. Section 3 delves into our methodology. Section 4 presents all our main results. Lastly, section 5 concludes.

1 Related Literature

This paper relates to different strands of the international finance literature. First, it links to the growing literature on the determinants of capital flows cyclical behaviour in emerging markets and the disruptive events associated to their reversal. In particular, the recent debate revolves around the relative importance of global ("push") and domestic ("pull") factors. While initially these works focused on net capital flows (Calvo et al. [2004], Levchenko and Mauro [2007]), after the pioneering work of Forbes and Warnock [2012] the attention has gradually shifted to monitoring gross flows. For a large sample of emerging and advanced economies alike spanning the period 1980-2009, Forbes and Warnock [2012] find that sudden stops in gross inflows are mainly caused by global factors: surge in risk aversion, proxied by the VIX, and slowdown in global economic activity. Local factors, including different capital controls measures, are, instead, not relevant. Fratzscher [2012] studies the high-frequency dynamics of portfolio flows for 50 emerging and advanced economies in the period around the 2007-2008 crisis. He finds that common shocks, spike in risk aversion and liquidity risk, drove the reallocation of capital flows from emerging markets to advanced economies amidst the GFC. Nevertheless, sensitivity to these common factors is largely explained by country-specific characteristics. Moreover, in the immediate recovery period, there seems to have been a re-balancing between push and pull factors. Eichengreen and Gupta [2016] analyze sudden stops in gross inflows for a sample of 34 emerging markets. The authors compare the magnitude and significance of different correlates between the years 1980-2003 and 2003-2013. They find that risk aversion played a key role in the more recent waves of sudden stops, while the impact of local factors have been mostly insignificant. The opposite holds for the earlier period. Cerutti et al. [2017] claim that the importance of global factors has been overstated by the literature. Working on a panel of 63 advanced and emerging economies, they show that the goodness-of-fit of push regressions is always extremely low. Eichengreen et al. [2018] employ data on capital flows disaggregated by type and instrument for the same sample as in Eichengreen and Gupta [2016]. They ask whether different flows react to the same set of covariates. Their result suggest that FDI inflows react more to pull factors, while portfolio debt and equity inflows to push factors. Other inflows, that represent the greatest share of total inflows to emerging markets and are mainly composed by banking flows, respond to both similarly.

Second, it clearly relates to the EWS literature on financial crises. This strand aims at the construction of a model able to forecast in advance the occurrence of different types of rare and disruptive events. Timely and reliable signals, in turn, can allow the intervention of policymakers and avoid the devastating macroeconomic consequences usually ensuing. EWSs have been developed and tailored specifically for different type of crises: mainly currency crises (Frankel and Rose [1996], Reinhart et al. [1998], Berg and Patillo [1999], Kaminsky [2003], Bussière and Fratzscher [2006], Bussière [2007], Bussière [2013]) and banking crises (Alessi and Detken [2009], Babecký et al. [2012], Duca and Peltonen [2013], Alessi and Detken [2018], Aldasoro et al. [2018], Beutel et al. [2018]), but also sovereign debt crises (Manasse et al. [2003], Manasse and Roubini [2009]), external crises [Catão and Milesi-Ferretti, 2014], IMF interventions [Frankel and Saravelos, 2012] and more recently, also sudden stops [Basu et al., 2019]. The techniques used range from the discrete-dependent variable approach (logit and probit models) to the leading indicators approach, in which single indicators send a signal when crossing a critical threshold and those signals are then aggregated and weighed and more modern machine learning (ML) techniques.

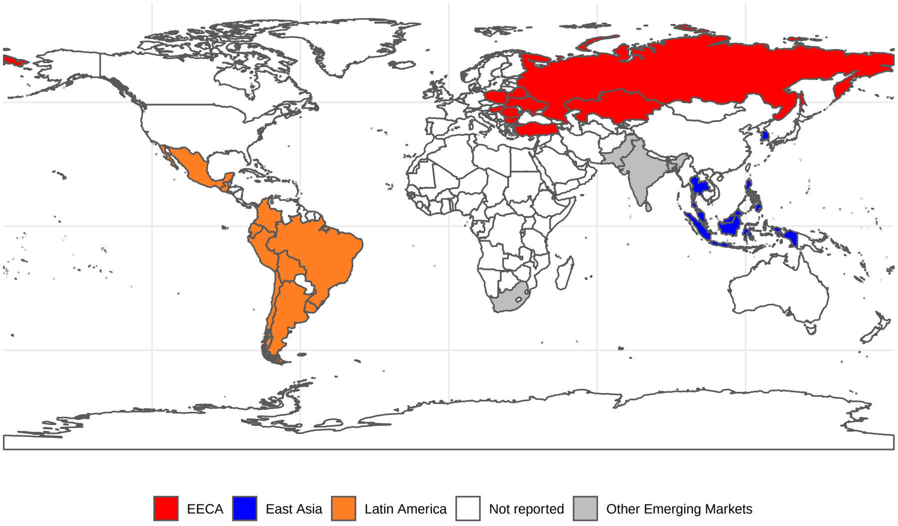
Third, it is connected to the literature on the 2007-2008 financial crisis and the heterogeneous cross-country incidence it had on real activity. Gourinchas and Obstfeld [2012] analyze the behaviour of different indicators around crisis events for advanced and emerging economies during the second part of the 20th century and compare it to the pre-GFC period. They conclude that countries that avoided large appreciations of their currencies, credit booms and hoarded international liquidity during the 2000s also were most likely to avoid the worst effects of the twenty-first century first global crisis. Frankel and Saravelos [2012] review the most consistent early warnings indicators found in the literature and ask whether these were able to predict the incidence of the GFC across countries. Their results comply with the findings of Gourinchas and Obstfeld [2012]. On the other hand, earlier papers such as Blanchard et al. [2010] and Rose and Spiegel [2010] do not find any relationship between the causes of the crisis and its severity.

Compared to previous literature, in this paper we test a large pool of global and local factors and explicitly quantify their marginal effect on the probability of sudden stops. In addition, from the methodology standpoint, we introduce a recursive framework to appraise realistically the past performance of an Early Warning and debate the use of sensitivity as a correct evaluation metric.

2 Data

We collect quarterly frequency data for 31 emerging markets over the period 1995Q4- 2017Q1. In Figure 1 we display the regional composition of our sample.[1]

Figure 1: Countries Sample



2.1 Sudden stops

Our definition of sudden stop follows step-by-step the algorithm developed by Forbes and Warnock [2012] and matches our theoretical understanding of sudden stops: a large drop in foreign capital inflows that persists over a prolonged period of time. For all the countries in our sample, we obtain total gross inflows in a quarter by summing up the total liabilities flows in the Financial Account i.e. Foreign Direct Investments (FDIs), portfolio investments and other investments liabilities. Data on inflows are retrieved from the International Financial Statistics (IFS) database of the IMF.

In practice, let us define $C_{i,t}$ as the total inflows for a country i in a quarter t. We calculate the cumulative sum of yearly inflows for each country as $C^{sum}_{i,t} = \sum_{s=0}^{3} C_{i,t-s}$ and calculate the yearly growth rate $\Delta C^{sum}_{i,t} = C^{sum}_{i,t} - C^{sum}_{i,t-4}$ to remove seasonality issues. We then compute the rolling mean and standard deviation for ΔC^{sum}_{it} over a period of 5 years. We identify a sudden stop when $\Delta C^{sum}_{i,t}$ drops by more than 2 standard deviations below its rolling mean. The episode, however, begins when the drop is greater than one standard deviation from the mean.[2][3] Figure 2 shows a graphical example of the algorithm.

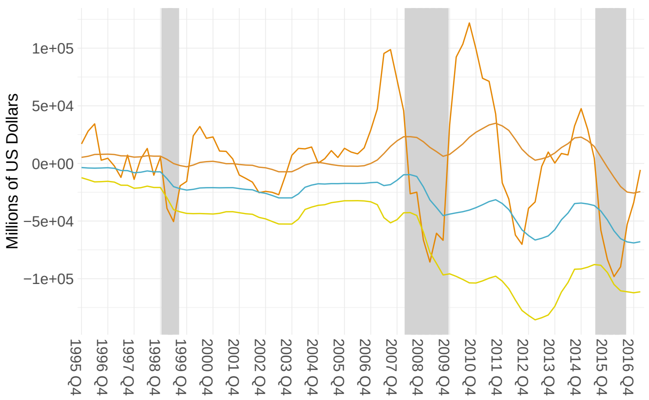
[1] For a full list, see Table 8 in the appendix.

[2] We exclude episodes that last only one quarter and collapse adjacent sudden stops into the same episode if the gap among the end of the former and the start of the latter is equal or lower than two quarters.

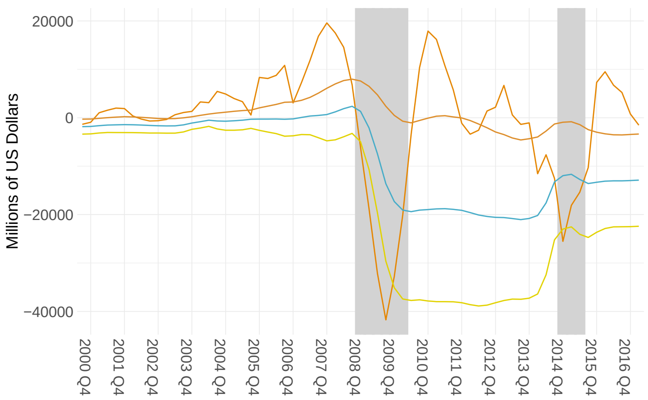
[3] We also create an alternative longer definition of ending: in this case inflows have to come back to their rolling mean in order to mark the end of an

Figure 2: Examples of Sudden Stops Identification

(a) Brazil



(b) Ukraine

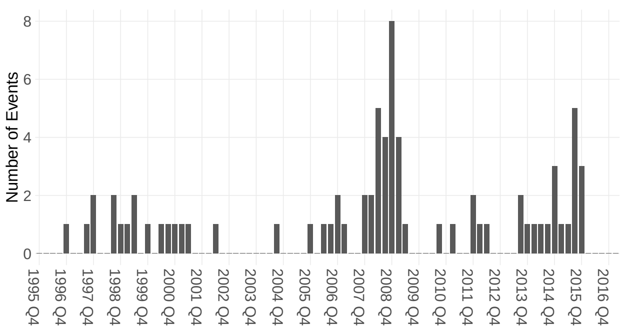


Note: The figure shows the algorithm proposed by Forbes and Warnock [2012] for the identification of sudden stops applied to our sample. A sudden stop begins when the y-o-y gross capital inflows (dark orange line) go below their rolling mean minus one standard deviation (light blue line) conditional on crossing the rolling mean minus two standard deviations (yellow line). The episode ends when y-o-y gross inflows come back above their rolling mean minus one standard deviation. The duration is highlighted by the grey shaded area.

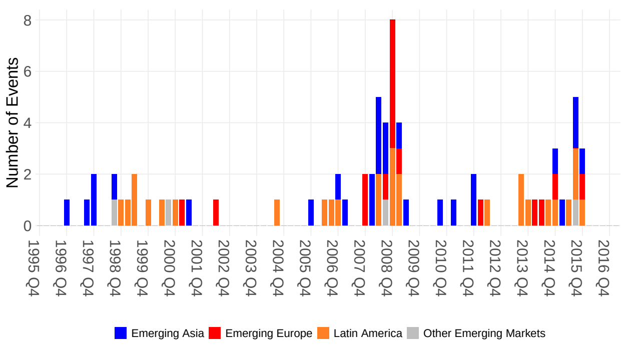
We identify a total of 75 sudden stops ($SS_{i,t}$).[4] Figure 3a shows the number of countries experiencing a sudden stop throughout the sample period. Clusters of sudden stops generally correspond to very well known macroeconomic and financial events e.g. the East Asian crisis, the Global Financial Crisis (GFC) and the turbulence following the normalization of US monetary policy in the post-GFC period. Panel 3b, instead, highlights the characteristic of regional contagion in sudden stops: episodes tend to occur temporally closely in the same EM region.

Figure 3: Number of Sudden Stops over time

(a) Aggregate



(b) By Region



episode. We use this longer definition of duration in the robustness part.

[4] For 10 episodes,the two thresholds criterion is missed by a whisker. Nevertheless, after consulting the IMF Article IV, they are included.

2.2 Explanatory Variables

We test an extensive set of indicators that includes both domestic and global factors, drawing from the literature on financial crises.[5] Starting from domestic factors, we evaluate the significance of real economic developments through growth and inflation. A low growth pre-crisis can spark some doubts on the willingness of the monetary authority to raise the policy rate in response to capital outflows and fuel a self-fulfilling speculative attack [Obstfeld, 1986]. Similarly, low growth may undermine fiscal solvency and spread fear of repayment across external creditors. On the other hand, high growth can create problems in the financial sector of the economy through higher risk appetite, credit growth and the formation of asset bubbles (Gourinchas and Obstfeld [2012]). Likewise, periods of high inflation often signal excesses on the monetary and fiscal side, but low inflation may be dangerous as well, especially for small open economies, warning of a surge in inflows and a rapidly appreciating currency. The pre-2008 EWSs literature has also highlighted the importance of external sector variables, in particular real exchange rate, international reserves and current account [Bussière and Fratzscher, 2006]. Other variables belonging to this category are the trade balance, as an alternative to the current account, and short-term liabilities, that expose countries to roll-over risk and have been cited as a key factor in the Asian meltdown of 1997-98 [Rodrik et al., 1999]. We also test the significance of bilateral trade contagion: crisis countries "infect" their main trading partners through import compression and higher competitiveness of their products, given the real devaluation that often follows a sudden stop.[6] The interplay between domestic banking problems and capital flows [Kaminsky and Reinhart, 1999] is captured through measures of credit developments. Lastly, we include both trade and capital openness measures for which we do not have a clear prior on the direction of the impact.

Moving to global factors, after the influential paper by Rey [2015], the VIX has become the standard proxy for the Global Financial Cycle.[7] Another measure that we use to capture global risk is the TED spread.[8] Inter alia, Fratzscher [2012] finds an important negative relationship between liquidity risk and flows to EMEs in the pre-2008 period. We also try different rates: the 10-years global and US bonds yield and the 3-months T-bills rate. Historically, there has been a strong negative correlation between gross capital inflows to EME and interest rates

[5] See for example Frankel and Saravelos [2012].

[6] For a detailed review of contagion variables and their transmission mechanism, see Caramazza et al. [2000]. In theory, trade contagion can also occur through competition in third markets, but capturing this channel properly is extremely difficult as it would require bilateral trade data dis-aggregated at the product level: two countries may have a common trading partner, but sell two entirely different and unrelated products.

[7] While many papers confirm the central role this variable plays in outflows from EME (Forbes and Warnock [2012], Comelli [2015], Eichengreen and Gupta [2016]), its importance has been recently challenged (Cerutti et al. [2017] and Avdjiev et al. [2017]).

[8] The spread rises when either the inter-bank market is fragmented and banks prefer to sit idle on their excess liquidity or when the demand for safe assets increases, driving down their return

in the financial centres [Reinhart, 2018]. High money growth in centre countries can flag rising vulnerabilities in the banking and financial sector and be positively correlated with sudden stops. That said, it can also portray the monetary and debt management stance in AE and thus, be negatively correlated. Other interesting variables are measures of global economic activity. Broner et al. [2013] find that capital flows both in EME and AE are procyclical: they flow out in good times and flow in during bad times. We test both global growth and inflation as proxies.

2.3 Data Transformation

Different variables previously listed are non stationary. To avoid cases of spurious relationship, we need to remove their deterministic and/or stochastic trend. This process is carried out in two distinct manners: by way of a one-sided HP filter or through the calculation of growth rates. When dealing with EWSs, one must also be careful to not include future information in the out-of-sample forecasting exercise: the one-sided filter ensures the fulfillment of this criterion. We compute absolute deviations from the HP trend (gaps) using two different values for λ, the smoothing parameter. In one case we set $\lambda = 1600$ while in the other $\lambda = 400000$, allowing for a more slowly updating trend and more ample fluctuations.[9] Equivalently, growth rates are also calculated on two frequencies: year-on-year and the four-years horizon. Without imposing any *a priori* constraint on the model, we keep the best performers in the final specification of the EWS. We report all variables with the respective transformations tested in Table 1.[10]

[9] Some financial variables like banking credit to the private sector might exhibit a lower frequency cycle [Drehmann et al., 2012]. In the same way, real exchange rates deviations might be quite persistent, especially for countries adopting a fixed exchange rate regime [Beutel et al., 2018].

[10] To further verify that there is a true relationship between the underlying variables and the probability of a sudden stop, in other words that our results do not hinge on the de-trending approach chosen, we substitute the variable of interest with its alternative transformation in the robustness part of the paper.

Table 1: List of variables tested

Variable	Level	Year-on-year growth rate	Four-years growth rate	HP Filter ($\lambda = 1600$)	HP Filter ($\lambda = 400000$)
Global Factors:					
VIX	x				
TED Spread	x				
Global 10-years nominal rate	x				
US 10-years nominal rate	x				
US Federal Funds Rate	x				
Global Real GDP		x	x		
Global CPI		x	x		
Global Liquidity (M2)		x	x		
Domestic Factors:					
Real GDP		x	x	x	x
Current Account over GDP (%)	x				
Private Credit over GDP (%)		x	x	x	x
Real Exchange Rate		x	x	x	x
International Reserves over GDP (%)	x				
International Reserves		x	x		
Short-term Liabilities to BIS Banks over GDP (%)	x				
Reserves (% of ST Liabilities)	x				
CPI		x	x		
Trade Balance over GDP (%)	x				
Trade Openess (% GDP)	x				
Trade Contagion	x				
Capital Controls Measures	x				
Macroprudential Measures (Loan-to-Value) - IMaPP	x				

Note: The table reports the main indicators tested in the construction of the Early Warning. The first column shows the description of the variable; the ”Level” column indicates whether the level of the variable has been tested; the ”Year-on-year growth rate” and ”Four-years growth rate’ columns indicate whether, respectively, yearly and four years growth rates of the variable have been tested; the ”HP Filter ($\lambda = 1600$)” and ”HP Filter ($\lambda = 400000$)” indicate whether percentage deviations from Hodrick–Prescott trends of the variable have been tested: “short” (“long”) Hodrick–Prescott trend is computed with the smoothing parameter λ set to 1600 (400000).

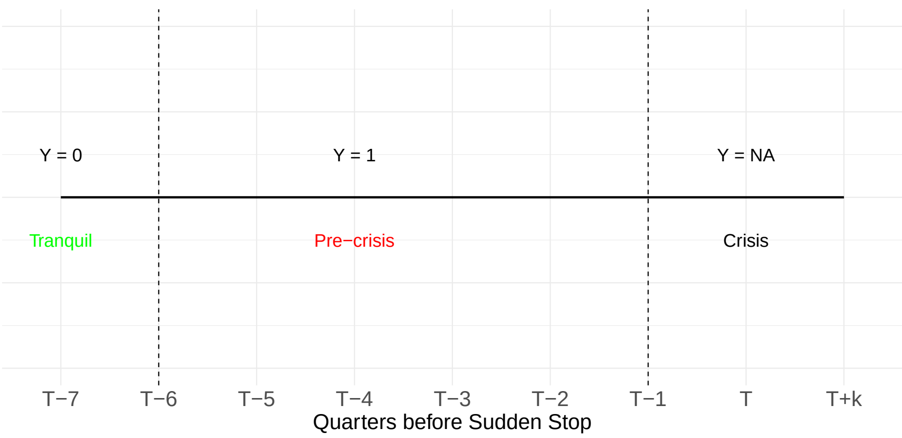
Finally, to normalise the scale of the regressors and address the problem of large outliers, we convert all variables in country specific percentiles [Berg et al., 2005]: the fundamental assumption behind this normalisation is that it is not the value of the indicators *per se* that matters, but rather their position with respect to their historical distribution.

3 Methodology

3.1 Dependent Variable

We focus on forecasting a sudden stop in gross inflows within a time window before the happening of the event. This kind of flexibility is usually allowed in EWSs given the intrinsic difficulty in predicting with precision the timing of a crisis.[11] We set this time interval to 6 quarters before the realization of the sudden stop: nevertheless, we leave out a gap of one quarter between the window and the start of the crisis so that the dependent variable is equal to 1 between 2 and 6 quarters before the actual sudden stop ("pre-crisis period)". The reasons for this last choice are two. First, we want to mitigate endogeneity concerns. Endogeneity could arise because the behaviour of our indicators in the quarter preceding the sudden stop is driven by expectations of an upcoming crisis. In the same way, the actual time of start of the sudden stop may precede our definition because of measurement errors. This would lead us to include a crisis period in our dependent variable, thus introducing a bias in our estimates. Second, a useful Early Warning must leave enough time for policy action after a signal is issued and a single quarter may not be sufficient. We drop the start of the sudden stop and the quarters of its duration before the estimation. If not removed, these observations would generate a post-crisis bias for variables that during the crisis magnify the movement pre-crisis.[12] Figure 4 shows in a stylized way the definition of our dependent variable.

Figure 4: Dependent Variable Definition



Note: T and K indicate, respectively, the start of the sudden stop and the duration of each individual episode.

[11] While the buid-up of domestic vulnerabilities and the worsening of global macroeconomic conditions is observable (the "causa remota"), the "causa proxima" that drives foreign investors away is random and not foreseeable.

[12] See Bussière and Fratzscher [2006].

3.2 Estimation Strategy

We employ a standard Logit model to estimate the model and compute in and out-of-sample probabilities. The non-linear properties of this kind of models is ideal for our classification problem. Most probably, indeed, the effect of the relevant indicators is not linear, but follows an S-shape.

While scholars have recently applied new techniques that exploit Machine Learning (ML) algorithms to solve these classification problems, clear-cut evidence on the best performing method does not exist.[13] Interpretability is also a concern. Logit models provide a clear ranking of the predictors, enhancing the understanding of crises by policymakers. This is particularly important in the context of our study since we include both domestic and global variables and has deep implications. If local factors are found to matter, the usefulness of predicting a crisis rises: policymakers receiving the signal, indeed, have the possibility to target the fundamentals responsible for the rise in probability and lower the overall risk, possibily avoiding the materiliazation of the event. On the other hand, if capital outflows are only determined by policy decisions in the centre countries, even if a crisis is predicted well in advance, the scope for reaction is heavily limited. Compared to parametric methods, causal inference in ML is not clear.[14]

For the estimation, we pool observations across time and countries.[15] The final specification is:

$$P(Y_{i,t}=1)=F(X_{i,t}\beta)=\frac{e^{X_{i,t}\beta}}{1+e^{X_{i,t}\beta}} \tag{1}$$

3.3 Evaluation

To classify predicted probabilities into binary signals, we need to impose a threshold: if the predicted probability crosses this value, a signal is sent, otherwise not. The signals are then compared to the actual value and the performance of the model is evaluated. This choice implies a trade-off between Type 1 error i.e. missing a crisis and Type 2 error i.e. issuing a fake alarm. The lower the threshold, the more fake alarms are issued and the other way around. The four possible outcomes of a classification problem are shown in table 2.

[13] Beutel et al. [2018] and Comelli [2014], for banking and currency crises respectively, find that standard Logit models outperform different ML algorithms in the out-of-sample forecasting, while Holopainen and Sarlin [2016] find exactly the opposite for banking crises.

[14] Although some steps have been recently taken in this direction, see for example Suss and Treitel [2019].

[15] In the robustness part, we also control for the sensitivity of our results to the introduction of country fixed effects.

Table 2: Example of Confusion Matrix

		Predicted	
		$Signal_{i,t} = 0$	$Signal_{i,t} = 1$
Actual	$Y_{i,t} = 0$	True Negative (TN)	Fake Positive (FP)
	$Y_{i,t} = 1$	Fake Negative (FN)	True Positive (TP)

It follows that for any fixed threshold τ the loss function of a policy-maker can be written as:

$$L(\theta, \tau) = \theta \frac{FN(\tau)}{FN(\tau) + TP} + (1 - \theta) \frac{FP(\tau)}{FP(\tau) + TN} \tag{2}$$

where θ indicates the preference for Type 2 errors as compared to Type 1 errors. A θ higher than 0.5 indicates that missed crises weigh more than fake alarms on the policy-maker loss function. It has become standard to set the optimal threshold τ^* to maximize the relative usefulness of a model:

$$U_r(\theta, \tau) = 1 - \frac{L(\theta, \tau)}{min(\theta, 1 - \theta)} \tag{3}$$

This function compares the usefulness of an EWS with a naive rule. The rationale is that policy-makers can always realize a loss of $min(\theta, 1-\theta)$ disregarding any model by always or never signalling an alarm . If θ is smaller than 0.5, policy-makers give more weight to Type 2 errors: the benchmark is obtained by ignoring the EWS, which amounts to never having any signals issued so that TP = FP = 0. The resulting loss according to equation 2 is θ. If θ exceeds 0.5, they give more weight to Type 1 errors. The benchmark is to assume there is always a sudden stop: in this case a signal is always issued so that FN = TN = 0. The resulting loss is $1 - \theta$. When $\theta = 0.5$, indipendently from the naive rule chosen, the loss is the same and equal to 0.5. From equation 3, an EWS is the more useful, the lower the loss it generates with respect to a completely uninformed decision. In this context, not only this function is appropriate to find an optimal threshold, but also furnishes a natural and simple way to evaluate and compare the overall performance of different models.[16]

[16] The parameter θ is unobservable and must be set exogenously. For our benchmark forecasts, we choose a standard value of $\theta = 0.5$ that indicates a policymaker weighing equally Type 1 and Type 2 errors.

3.4 Forecasting Procedure

We must spend some words on the out-of-sample forecasting procedure. Our analysis is conducted in a quasi real-time manner and the evaluation period goes from 2006Q1 to 2017Q1, a time span that corresponds to half of our original sample. Hereafter we list all the steps of the exercise:

(i) At each quarter t of the evaluation period, we divide between a training sample that goes from 1995Q4 (the beginning of the original sample) to quarter $t-1$ and a test sample composed exclusively by quarter t. The indicators are transformed into country-specific percentiles for the training sample.

(ii) We estimate the model on the training sample and save the optimal threshold i.e. the one that maximizes the in-sample relative usefulness function.

(iii) Re-calculating the percentiles, we compute the pre-crisis probability for quarter t. We store it together with the respective optimal threshold and recursively repeat these three steps for every quarter t until 2017Q1.[17]

(iv) *Ex post*, we compare the collected probabilities with the respective threshold, count the number of missed signals and fake alarms and evaluate the model.

The whole procedure is designed so as to mimic as closely as possible the information available to policy-makers in each quarter and at the same time, we are careful to not introduce future information in the forecasts produced and bias the results in favor of our model.[18][19]

4 Results

4.1 Determinants of Sudden Stops

Table 3 shows the result for our preferred specification considering the whole sample period (1995-2017): we include in our benchmark model only indicators that are significant at the 5% level and have the expected sign. For variables that are highly collinear e.g. alternative transformations or overlapping definitions, we include the

[17] This passage is needed to have the position of the new observation with respect to the historical distribution.

[18] A pitfall of this exercise is the forward-looking nature of the dependent variable $Y_{i,t}$. This tricky point can be better explained with an example. Imagine we are in 2005Q4 and want to estimate the pre-crisis probability for the first quarter of the out-of-sample exercise, 2006Q1. The training model will be estimated with data from 1995Q4 to 2005Q4. If between 2006Q1 and 2007Q2 a sudden stop occurs, the dependent variable in the training sample will identify some pre-crisis observations with value 1, hence incorporating future knowledge in the model. To correct, at each recursive update of the training sample, we set the last 6 quarters observations equal to 0 before estimating the model. This correction is consistent with the noise in the information set of the policy-maker: they do not know whether the build-up observed in other countries will materialize in a sudden stop.

[19] Step (ii) and (iii) entail that the out-of-sample optimal threshold is time-varying and step (iii) that the estimation sample is an expanding-window.

one that maximizes the goodness of fit as measured by the relative usefulness function. Robustness checks and alternative variables are reported in appendix C.1.1.

Table 3: Full Sample Logit

	Dependent variable:
	Pre-crisis
TED Spread	1.504***
	(0.236)
Global Liquidity Growth	−1.258***
	(0.264)
Credit-Gap	1.059***
	(0.245)
RER-Gap	−1.912***
	(0.251)
ST Liabilities to BIS Banks/GDP	0.725***
	(0.237)
CA/GDP	−1.108***
	(0.240)
Trade Contagion	0.700***
	(0.170)
Controls on Capital Inflow	−0.432**
	(0.198)
Constant	−1.281***
	(0.291)
Observations	1,753
Log Likelihood	−716.762
Akaike Inf. Crit.	1,451.524

Note: The sample consists of 31 Emerging Markets over the period 1995Q1-2017Q1. Robust standard errors in parentheses. Global liquidity growth is calculated on the four-years horizon. RER-Gap and Credit-Gap are deviations from Hodrick-Prescott trends with $\lambda = 1600$. Controls on capital inflows are from Fernández et al. [2015]. * Statistical significance at 10% level. ** Statistical significance at 5% level. *** Statistical significance at 1% level.

Table 4 reports the relative goodness-of-fit statistics. The model calls correctly 62.6 % of the pre-crisis quarters with only 20% of fake alarms. The conditional probability of a crisis given a signal from the model is 40%, double the unconditional probability of experiencing a crisis (23%). Similarly, compared to a completely uninformed decision (see section 3.3), the model generates a relative usefulness for a policymaker of roughly 40%.

Table 4: In-sample Performance

	$S_{i,t}=0$	$S_{i,t}=1$
$Y_{i,t}=0$	1108	311
$Y_{i,t}=1$	125	209

True Positives rate: 62.6%

True Negatives rate: 78.1%

Prob. pre-crisis given a signal: 40.2%

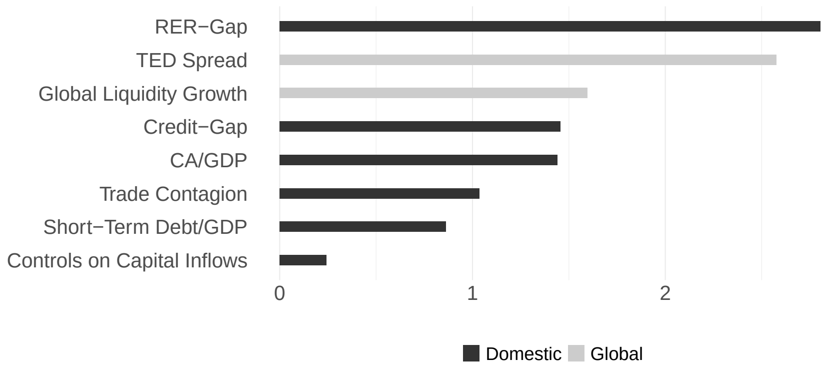
Prob. pre-crisis given no signal: 10.1%

Relative Usefulness: 40.7%

Note: The table reports the results for the in-sample performance of the benchmark logit. The forecast horizon is 1-6 quarters ahead and the preference parameter θ is equal to 0.5. The evaluation is carried out through the above measures: True Positives rate = TP/(TP+FN), True Negatives rate = TN/(TN+FP), Prob. sudden stop given a signal = TP/(TP+FP), Prob. sudden stop given no signal = FN/(FN+TN) and Relative Usefulness U_r (see formula 3-4). Threshold optimized in-sample to maximize the relative usefulness and equal to 23.4%.

Are crises the byproduct of domestic shortcomings or are emerging markets solely at the mercy of policy decisions and economic conditions in the global financial centres? Since our model is non-linear, we cannot directly interpret its coefficients. To calculate marginal effects and understand the relative importance of each indicator, we have, instead, to set precise values for all variables. Figure 5 shows marginal effects under a specific scenario i.e. moving the variable of interest from its tranquil time to its pre-crisis average, while other indicators are kept equal to their tranquil time average.

Figure 5: Marginal Effects Covariates



Note: Marginal effects calculated increasing the value of each variable individually from its tranquil time average to its pre-crisis average and keeping other covariates at their tranquil time average. Coefficients retrieved from the benchmark specification. X-axis in percentage points.

Exchange rate overvaluation and rise in the TED spread have the strongest impact, increasing the probability of a sudden stop by more than 2.5 percentage points (pp). Global liquidity tightening, credit booms and current account deficits compose a second group and have a smaller impact (1.5 pp). At the end of the spectrum follow trade contagion and short-term debt (1 pp) and last, controls on capital inflows (less than 0.5 pp). Even though these effects may appear relatively small, one must bear in mind different points: first, the pre-crisis period is long, starting a year and a half prior to the crisis, thus influencing the value of the pre-crisis average. Second, the reference point matters: while to isolate the effects we have kept all other indicators to their tranquil average, in practice a rise in the TED spread might have a much larger effect, for example, when also the current account deficit is large. All in all, we do not find strong evidence of predominance by neither of the two group of factors: this is suggestive that policymakers have at least some leeway to act targeting weak fundamentals when confronted with a newly issued signal.

4.2 Out-of-Sample Performance and Forecast Horizon

The paper by Berg and Patillo [1999] pointed to a large divergence between the in and out-of-sample performance for EWSs. Since then it has become standard to evaluate the predictive power of these models on the base of their out-of-sample performance. The framework developed in section 3.4 allows us to do so in a quasi-real time manner i.e. having the same information set of the policymaker at the time of the prediction and without introducing future knowledge in the model.[20] The results of the out-of-sample estimation are reported in Table 5.

Table 5: Out-of-sample Performance

	$S_{i,t} = 0$	$S_{i,t} = 1$
$Y_{i,t} = 0$	648	117
$Y_{i,t} = 1$	129	116

True Positives rate: 47.4%

True Negatives rate: 84.7%

Prob. sudden stop given a signal: 50%

Prob. sudden stop given no signal: 16%

Relative Usefulness: 32%

Note: The table reports the results for the quasi real-time out-of-sample performance of the benchmark logit. The forecast horizon is defined in section **??** and the preference parameter θ is equal to 0.5. The evaluation is carried out through the above measures: True Positives rate = TP/(TP+FN), True Negatives rate = TN/(TN+FP), Prob. sudden stop given a signal = TP/(TP+FP), Prob. sudden stop given no signal = FN/(FN+TN) and Relative Usefulness U_r (see formula 3-4).

The EWS predicts almost 50% of the pre-crisis episodes while sending relatively few alarms, about 15% of the total tranquil quarters. This means every time a signal is sent, there is a 50% probability of a correct call, a percentage higher than its in-sample counterpart. Thus, the uncertainty involved by our model in the out-of-sample predictions is limited. Overall, the EWS would result in a 32% gain compared to a completely uninformed decision for a policy-maker with balanced preferences between Type 1 and Type 2 errors.

[20] Choosing an appropriate de-trending approach and correcting for the forward-looking nature of the dependent variable.

The result is robust to the choice of a different time horizon as shown in Table 6. The relative usefulness statistics always remains around 30% and reaches its maximum for our 6 quarters benchmark, validating *ex post* our choice. Moving to the 8 quarters specification, the number of correctly identified pre-crisis periods increases (TP Rate), but also does the amount of fake alarms (1-TN Rate). This is suggestive that for policymakers with a greater value for θ the choice of a longer horizon span would be preferable.

Table 6: Different forecast horizons out-of-sample performance

Forecast Horizon	**TP**	**TN**	**FP**	**FN**	**TP Rate**	**TN Rate**	**P(Pre-crisis|Signal)**	**P(Pre-crisis|No Signal)**	$U_r(\theta)$
4 Quarters	73	719	137	81	47.4%	84%	34.8%	10.1%	31.4%
6 Quarters	116	648	117	129	47.4%	84.7%	50%	16%	32%
8 Quarters	163	538	142	163	49.4%	79.1%	53%	23.7%	28%

Note: The table reports the results for the quasi real-time out-of-sample performance of the benchmark logit changing the forecast horizon. The preference parameter θ is equal to 0.5. The evaluation is carried out through the above measures: True Positives rate = TP/(TP+FN), True Negatives rate = TN/(TN+FP), Prob. sudden stop given a signal = TP/(TP+FP), Prob. sudden stop given no signal = FN/(FN+TN) and Relative Usefulness U_r (see formula 3-4).

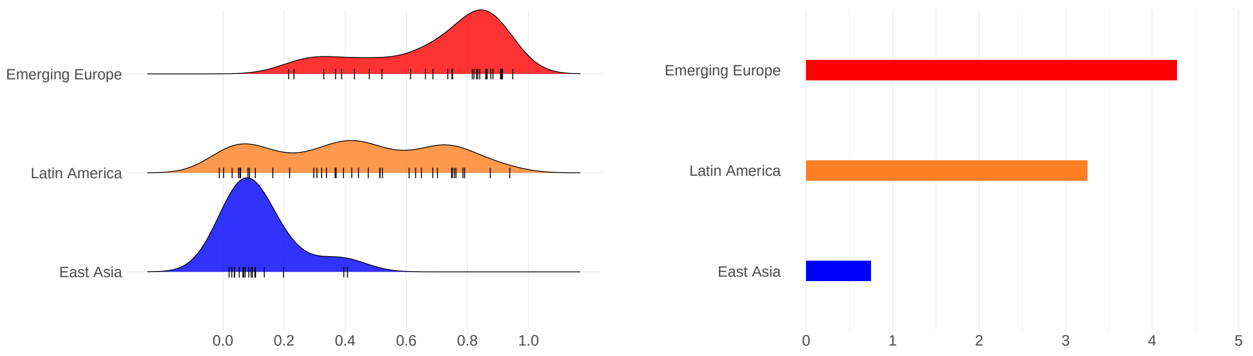
4.3 Timing

How did our model work with particular reference to the 2008 crisis? With how much certainty were the signal sent? And were they timely? In panel 6a we show the distribution of the out-of-sample predicted probabilities for the GFC episodes during the individual pre-crisis periods and we condition on the EM regional group. While for Emerging Europe the bulk of the distribution i.e. the probability of being in a pre-crisis quarter, is around 80%, for East Asia most of the individual probabilities reach only 20%. For Latin American the distribution is, instead, more uniform. For the first group of countries, the first signal was sent, on average, more than one year before the sudden stop (Figure 6b). For the second, instead, episodes were not signalled at all or just with a small advance. Latin America, as before, lies in between.

Figure 6: GFC Sudden Stops

(a) Out-of-sample probabilities

(b) First Signal



Note: Panel (a) shows the distribution of the predicted probabilities for the out-of-sample recursive exercise in the pre-crisis period of each country-specific Global Financial Crisis sudden stop. We consider Global Financial Crisis sudden stops those episodes occurring in the time window 2006Q4 - 2008Q4. Panel (b) shows for the aforementioned episodes the advance, on average, of the model in issuing a signal. X-axis indicates quarters before the sudden stop.

Domestic factors largely explain this heterogeneity of results between regional groups. East Asian countries enforced counter cyclical fiscal and monetary policy in the years that followed the regional crisis of 1997-98, approaching 2008 with large current account surpluses, a competitive and flexible exchange rate and a solid financial sector.[21][22] EECA countries, instead, neared the GFC with extremely flawed fundamentals. Pre-2008 capital inflows financed exceptionally large current account deficits with a considerable part of this foreign capital that was channeled into short-term maturities: real exchange rates appreciated steeply and there was a lending boom operated by the banking sector [Gourinchas and Obstfeld, 2012]: this surge was allowed by a simultaneous liberalization of capital markets.

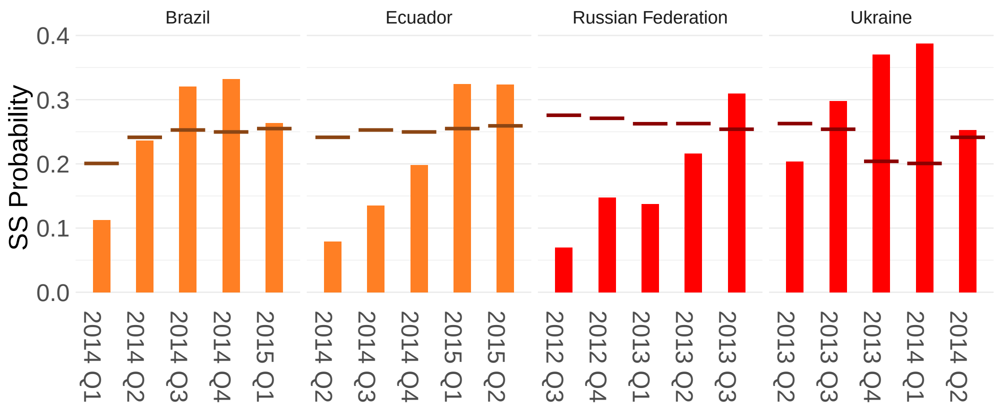
We then move to the post-GFC period and ask the same question. While sudden stops in the GFC are more or less synchronized, afterwards they are more distributed across the test period: instead of a regional aggregation, we proceed on a case-by-case basis. In particular, we study the behavior of fitted probabilities before four interesting crises: Russia 2014 Q1, Ukraine 2014 Q3, Brazil 2015 Q3 and Ecuador in 2015 Q4 (Figure 7). [23]

[21] See for example Park et al. [2013].

[22] South Korea and Indonesia are the countries in the group with the highest predicted probabilities. The first had sound macroeconomic fundamentals, but a large level of short-term dollar denominated liabilities in the banking sector. The second was the last country in the region to experience a reversal of gross inflows and as such probabilities are greatly influenced by shattered global factors and regional contagion.

[23] We focus on these occurrences because they are associated with at least a quarter of recession throughout the sudden stop duration, while other episodes are not.

Figure 7: Post GFC Sudden Stops



Note: Out-of-sample fitted probabilities in the pre-crisis period for four different sudden stops episodes: Brazil 2015Q3, Ecuador 2015 Q4, Russian Federation 2014 Q1 and Ukraine 2014 Q4. The thick line corresponds to the time-varying optimal threshold.

Our EWS sends a signal half a year before for Russia, the minimum allowed. For the other crises, the advance widens: Ukraine is called more than one year in advance, Brazil one year and Ecuador three quarters. Even though probabilities are much lower compared to the GFC, owing mostly to improved global conditions, is extremely encouraging that all the four episodes would have been signalled with advance.[24] Moreover, this result is achieved without considering important factors that analyst have linked to these crises: worsening political landscape (Ukraine and Brazil) and the occurrence of natural disasters (Ecuador). This means that even if the last two may have contributed to the drop in inflows, multiple factors exerted pressure on these countries.

4.4 Sudden Stop Impact and Fitted Probabilities

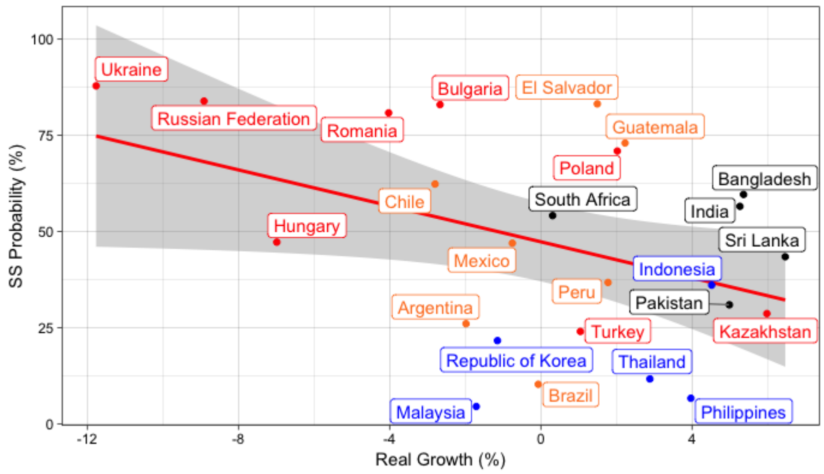
Hitherto we based the evaluation of our EWS solely on missed crises (Type 1 errors) and fake alarms (Type 2 errors), in line with the literature. The underlying assumption of such an evaluation framework is that external crises are alike episodes and produce the same effects on the economies hit. Nevertheless, it is a well-known fact that some crises are more painful than others. This owes to different factors: the magnitude of the external shock, the conditions of the domestic economy at the time and of course, the policy response that follows as well as the behaviour of domestic investors. These elements are not mutually exclusive, but rather complementary.

Therefore, when evaluating an EWS, policymakers should also be concerned about which specific events are predicted and which not. In doing so, the novelty of this paper is that we link two parts of the literature that have so far been kept separated: one is the classic EWS literature that tries to predict in advance the occurrence

[24] Another interesting feature is that fitted probabilities rise next to monotonically in the pre-crisis period.

of a crisis, while the second, instead, tries to predict its incidence. Figure 8 shows the relationship between the estimated pre-crisis median probability and the median growth experienced during the episode for every country-specific sudden stop in the GFC.

Figure 8: Fitted Probabilities and Ex-Post Growth



Note: The figure shows the relationship between the median out-of-sample probability in the pre-crisis period for GFC related sudden stops and the median growth during the associated sudden stop. Red line is the regression line with 95% confidence intervals.

At a first glance, EECA countries monopolize the north-western quadrant. This means these are the countries that suffered more during the GFC sudden stops and contemporaneously those that exhibit the highest median probabilities. Further, from Figure 6b, they are also the sudden stops for which a signal was sent with large advance by our model. On the other hand, East Asian countries occupy mostly the south eastern quadrant i.e. countries that suffered less and with the lowest median probabilities. Latin American countries are, once again, highly heterogeneous. We consider two countries during the GFC, one from the EECA and the other from the East-Asian group e.g. Romania and Thailand. The first suffered from a full-fledged recession with a median quarterly contraction of 4% of GDP, while the second continued to grow at a moderate pace, around 2.5%. For the first a signal would have been sent early and with extreme certainty, while the second belongs to the group of missed crises.[25]

We further proceed investigating formally the issue: we pool all the out-of-sample observations together and estimate the cross-sectional relationship. Table 7 shows the regression results. We find that an increase in median

[25]While median growth rate during the sudden stop is a simple proxy of output impact, this measure, however, ignores that countries might have different trend growth rates before the event: therefore, we test robustness of the relationship using a different metric. We construct this new measure as the median growth rate during the sudden stop minus the median growth rate in the preceding tranquil period: the resulting scatter plot displays a similar pattern (See Figure 11 in the appendix).

pre-crisis probability by a percentage point decreases significantly growth during the sudden stop by 0.07%. Sudden stops predicted with more certainty by our EWS are also the most destructive ones in terms of output losses, while those that are not identified (Type 1 error) or identified with relatively low probabilities are those with mild consequences for the real economy. Against this new evidence, reporting standard evaluation metrics without investigating for which sudden stops a signal would have been sent and for which not, would highly underestimate the true value of an Early Warning for policymakers.

Table 7: Predicted Probability and Sudden Stop Incidence

	Dependent variable: Median Growth			
	Coeff.	Std. error	t-statistic	P> $\|t\|$
Pre-crisis probability	−0.070	0.027	−2.54	0.02
Observations	41			

Note: The sample comprises the 41 sudden stops episodes occured after 2006 Q1, the beginning of the out-of-sample period. Dependent variable is the median growth calculated over the duration of each episode. Indipendent variable is the median out-of-sample probability estimated over the whole pre-crisis period. Intercept omitted and robust standard error reported.

5 Conclusion

This paper contributes to the financial crisis literature investigating the predictability of sudden stops in emerging markets. We extend the existing literature in different ways. First, we test a large variety of domestic and global indicators and evaluate their relative importance in the materialization of sudden stops: if emerging markets are only at the mercy of policy decisions in the global financial centres, the scope for intervention by domestic policymakers results highly limited even when a signal is issued. Second, we propose a framework to evaluate the performance of the model in quasi-real time, taking heed not to include future information in the recursive exercise. Third, we study the relationship between the probabilities estimated by our model and the output loss associated with the ensuing sudden stop.

We find a near equivalence between the marginal impact of domestic and global factors on the probability of a crisis: this result highlights the role EWSs can play not only as a surveillance, but also as a stability tool available to policymakers. We then proceeded evaluating the out-of-sample performance of the model. The recursive exercise yields encouraging results with a parsimonious specification: the pre-crisis periods correctly called are close to 50% of the total with fake alarms corresponding to less than 15%. This means that the uncertainty involved with the predictions is low: compared to the unconditional probability of being in a pre-crisis quarter (roughly 20%), the conditional probability given a signal rises to 50%. Finally, we brought forward a new argument in "defense" of EWSs. We show that there is a negative, statistically and economically significant relationship between the median probability predicted for the whole pre-crisis period and median economic growth experienced during the associated sudden stop: in other words, the model works well in predicting catastrophic events and less so for rather innocuous ones.

All in all, even if the prediction of rare events like sudden stops remains a humbling task, our model would have sent reliable, timely and relevant signals. This is especially promising in view of the lengthy out-of-sample horizon chosen and the different non-economic factors that exerted pressure on emerging markets in the recent decade.

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Appendices

A Data

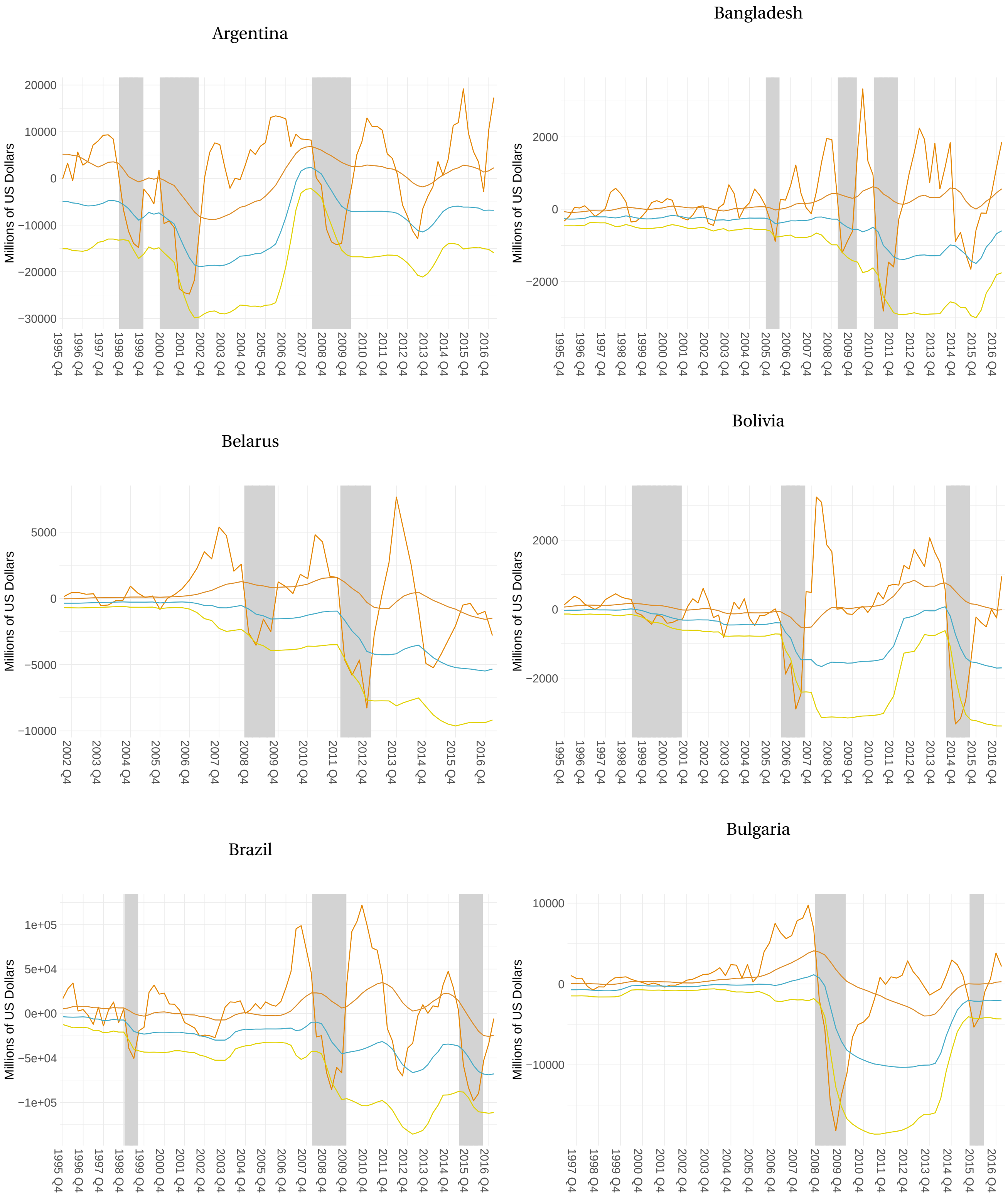
Table 8: Countries List

Country	Region
Argentina	Latin America
Bangladesh	Other Emerging Markets
Belarus	EECA
Bolivia (Plurinational State of)	Latin America
Brazil	Latin America
Bulgaria	EECA
Chile	Latin America
Colombia	Latin America
Ecuador	Latin America
El Salvador	Latin America
Guatemala	Latin America
Hungary	EECA
India	Other Emerging Markets
Indonesia	East Asia
Kazakhstan	EECA
Malaysia	East Asia
Mexico	Latin America
Pakistan	Other Emerging Markets
Peru	Latin America
Philippines	East Asia
Poland	EECA
Republic of Korea	East Asia

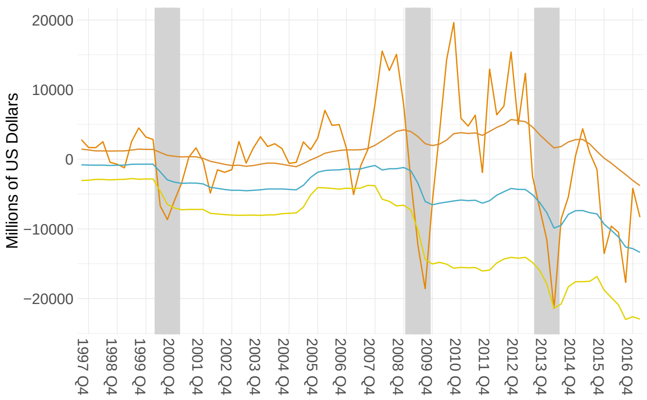
Country	Region
Romania	EECA
Russian Federation	EECA
South Africa	Other Emerging Markets
Sri Lanka	Other Emerging Markets
Thailand	East Asia
Turkey	EECA
Ukraine	EECA
Uruguay	Latin America
Venezuela, Bolivarian Republic of	Latin America

A.1 Sudden Stops

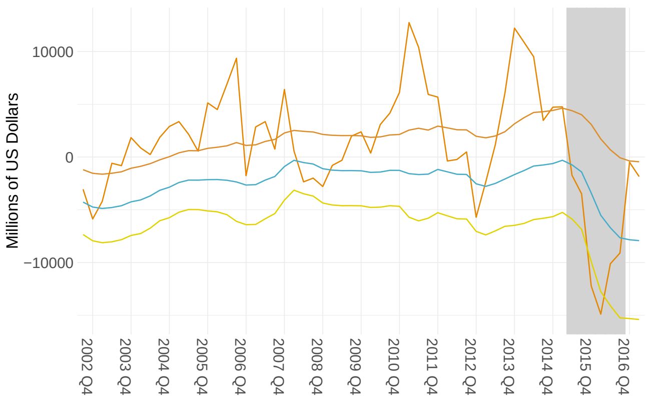
Figure 9: Sudden Stops Identification



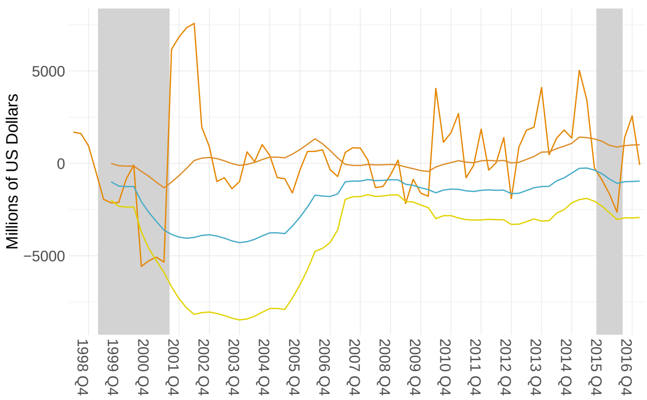
Chile



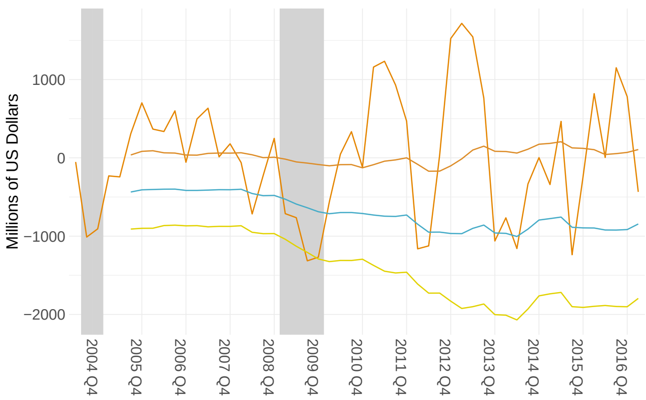
Colombia



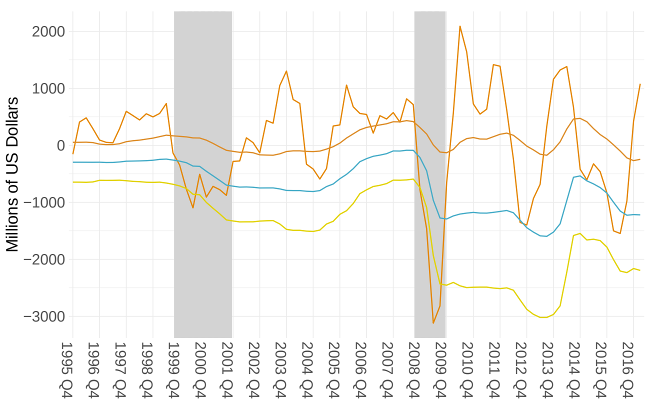
Ecuador



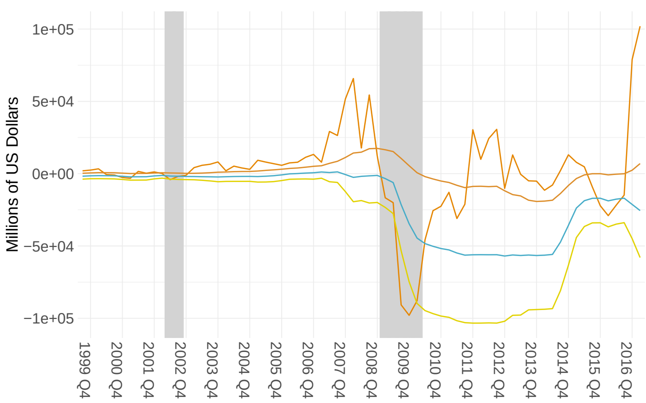
El Salvador



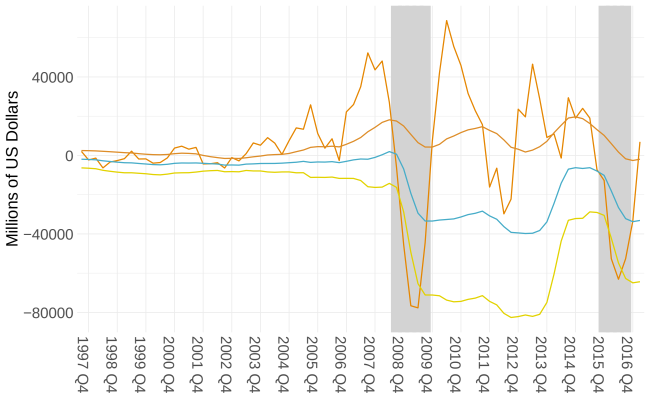
Guatemala



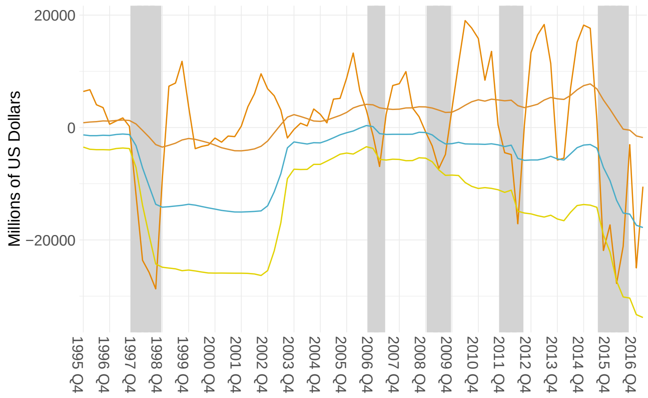
Hungary



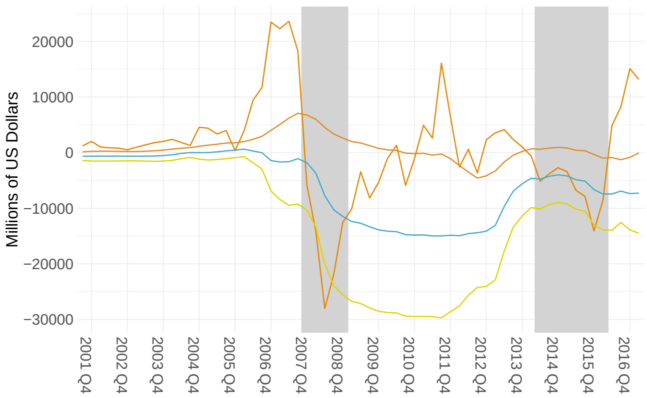
India



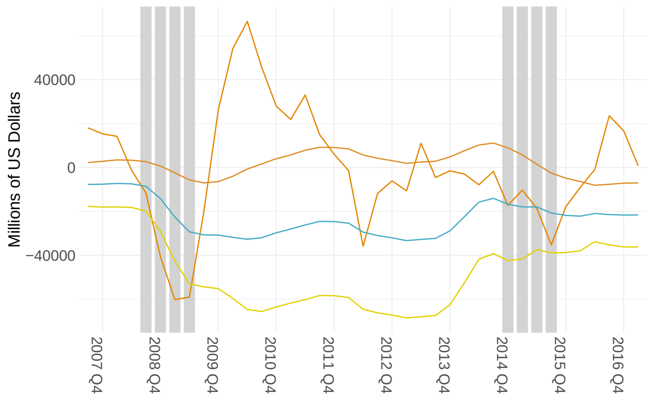
Indonesia



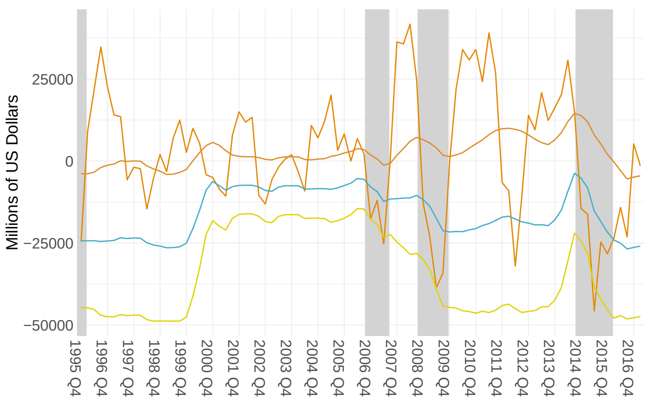
Kazakhstan



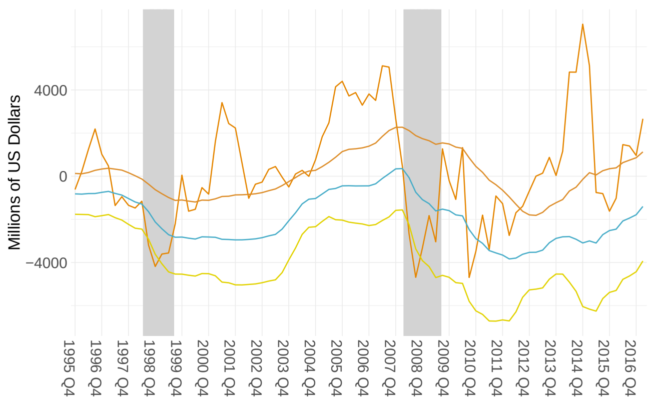
Malaysia

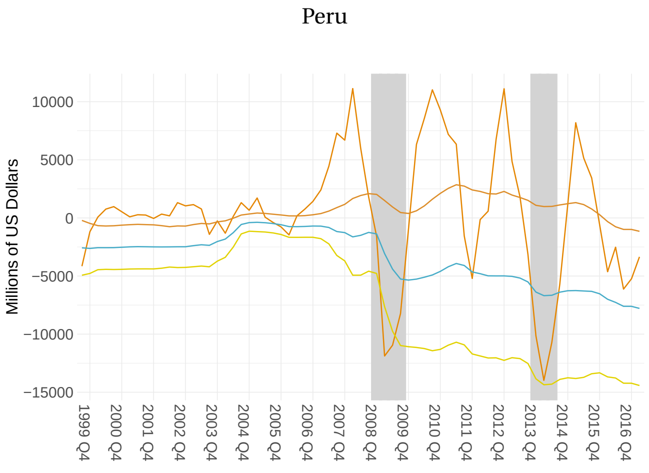


Mexico



Pakistan




Peru
Millions of US Dollars
10000
5000
0
−5000
−10000
−15000
1999 Q4
2000 Q4
2001 Q4
2002 Q4
2003 Q4
2004 Q4
2005 Q4
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2007 Q4
2008 Q4
2009 Q4
2010 Q4
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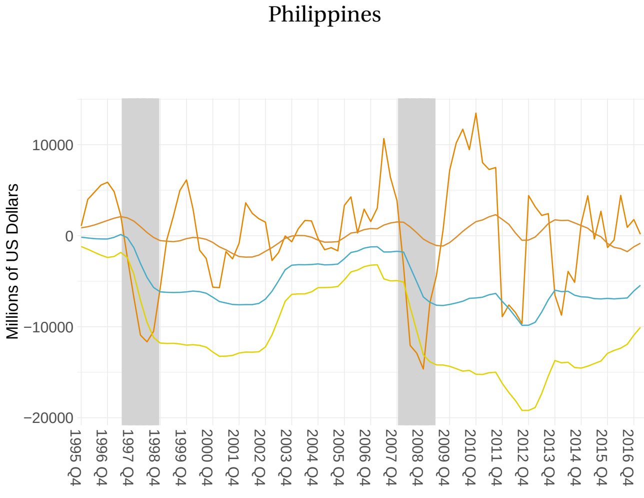
2012 Q4
2013 Q4
2014 Q4
2015 Q4
2016 Q4


Philippines
Millions of US Dollars
10000
0
−10000
−20000
1995 Q4
1996 Q4
1997 Q4
1998 Q4
1999 Q4
2000 Q4
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2002 Q4
2003 Q4
2004 Q4
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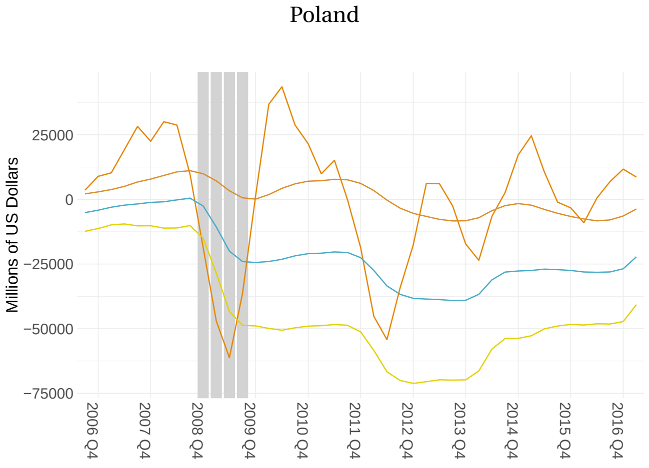
2014 Q4
2015 Q4
2016 Q4


Poland
Millions of US Dollars
25000
0
−25000
−50000
−75000
2006 Q4
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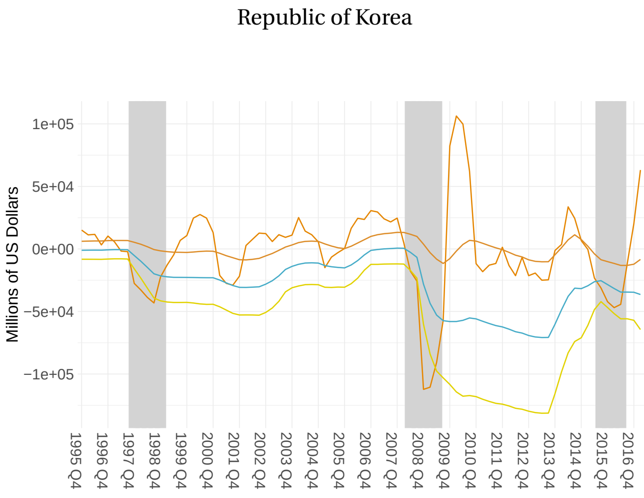
2014 Q4
2015 Q4
2016 Q4


Republic of Korea
Millions of US Dollars
1e+05
5e+04
0e+00
−5e+04
−1e+05
1995 Q4
1996 Q4
1997 Q4
1998 Q4
1999 Q4
2000 Q4
2001 Q4
2002 Q4
2003 Q4
2004 Q4
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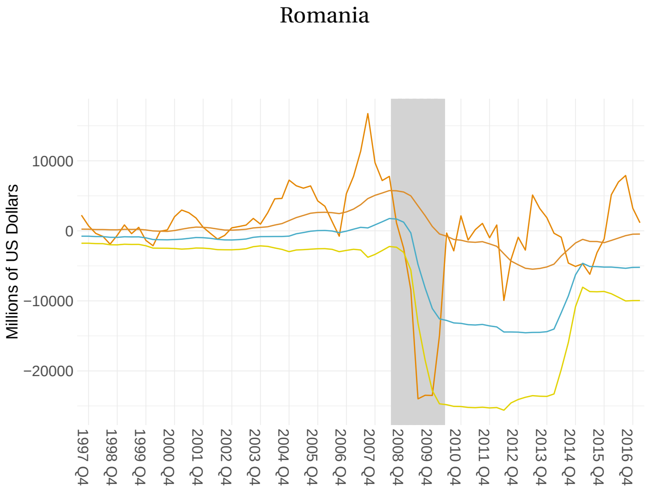
2014 Q4
2015 Q4
2016 Q4


Romania
Millions of US Dollars
10000
0
−10000
−20000
1997 Q4
1998 Q4
1999 Q4
2000 Q4
2001 Q4
2002 Q4
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2004 Q4
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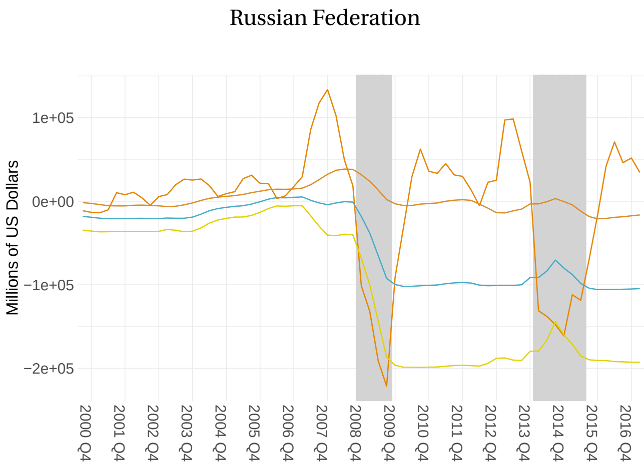
2014 Q4
2015 Q4
2016 Q4


Russian Federation
Millions of US Dollars
1e+05
0e+00
−1e+05
−2e+05
2000 Q4
2001 Q4
2002 Q4
2003 Q4
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2005 Q4
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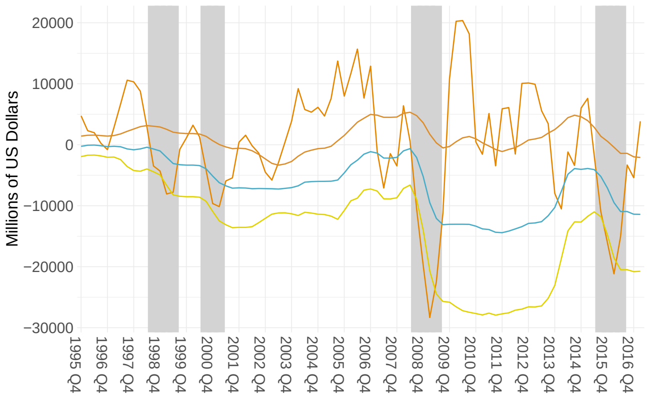
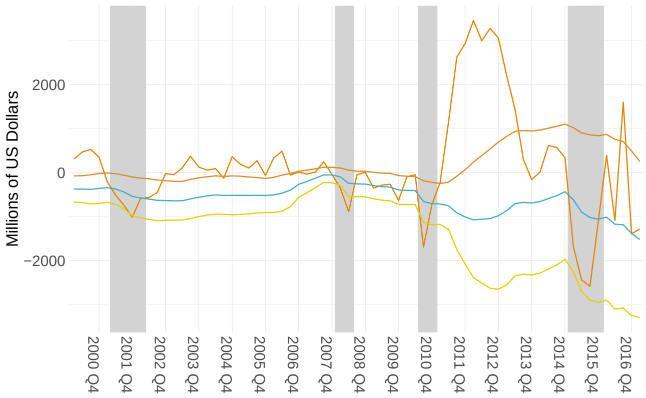
2013 Q4
2014 Q4
2015 Q4
2016 Q4

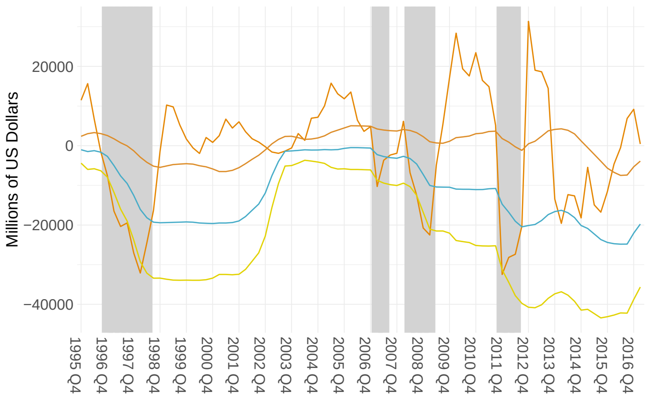
South Africa



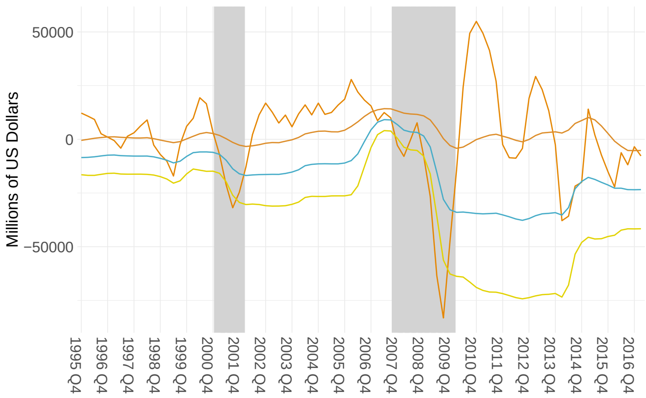
Sri Lanka



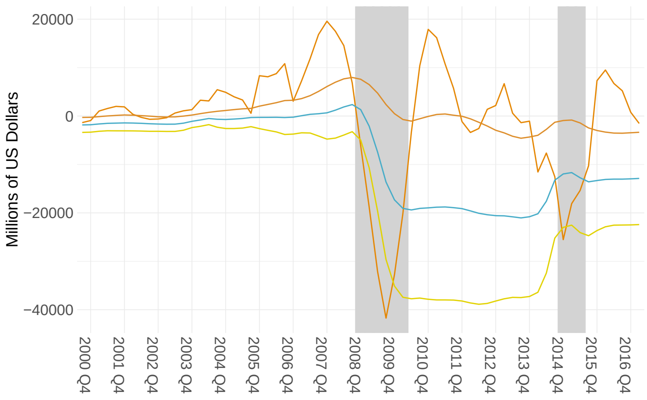
Thailand



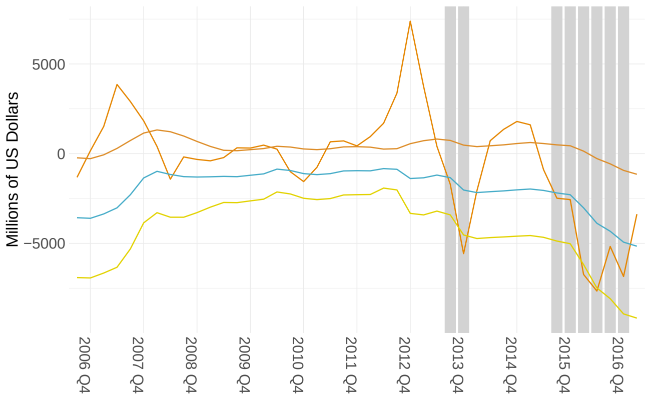
Turkey



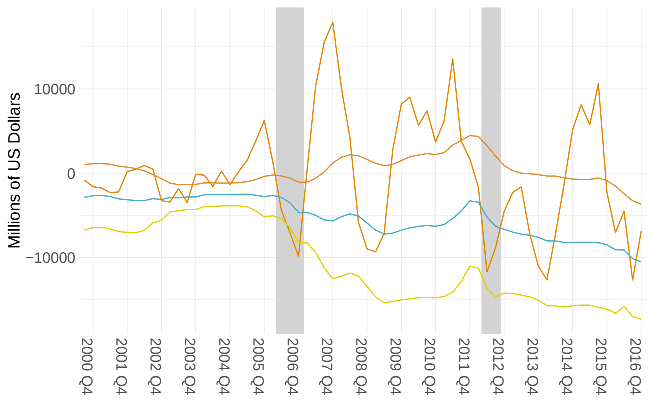
Ukraine



Uruguay



Venezuela



Note: The figure shows the algorithm proposed by Forbes and Warnock [2012] for the identification of sudden stops applied to our sample. A sudden stop begins when the y-o-y gross capital inflows (dark orange line) go below their rolling mean minus one standard deviation (light blue line) conditional on crossing the rolling mean minus two standard deviations (yellow line). The episode ends when y-o-y gross inflows come back above their rolling mean minus one standard deviation. The duration is highlighted by the grey shaded area.

Table 9: List of Sudden Stops

Country	Quarter	Duration (in quarters)
Argentina	1998 Q4	4
Argentina	2000 Q4	7
Argentina	2008 Q2	7
Bangladesh	2005 Q4	2
Bangladesh	2009 Q2	3
Bangladesh	2011 Q1	4
Belarus	2008 Q4	4
Belarus	2012 Q1	4
Bolivia (Plurinational State of)	1999 Q2	9
Bolivia (Plurinational State of)	2006 Q3	4
Bolivia (Plurinational State of)	2014 Q3	4
Brazil	1999 Q1	2
Brazil	2008 Q2	6
Brazil	2015 Q3	4
Bulgaria	2008 Q4	5
Bulgaria	2015 Q4	2
Chile	2000 Q2	3
Chile	2009 Q1	3
Chile	2013 Q3	3
Colombia	2015 Q2	6
Ecuador	1999 Q2	9
Ecuador	2015 Q4	3
El Salvador	2004 Q3	2
El Salvador	2009 Q1	4
Guatemala	1999 Q4	8
Guatemala	2008 Q4	4

Country	Quarter	Duration (in quarters)
Hungary	2002 Q2	2
Hungary	2009 Q1	5
India	2008 Q3	5
India	2015 Q4	4
Indonesia	1997 Q4	4
Indonesia	2006 Q4	2
Indonesia	2009 Q1	3
Indonesia	2011 Q4	3
Indonesia	2015 Q3	4
Kazakhstan	2007 Q4	5
Kazakhstan	2014 Q2	8
Malaysia	2008 Q3	4
Malaysia	2014 Q4	4
Mexico	2006 Q4	3
Mexico	2008 Q4	4
Mexico	2014 Q4	5
Pakistan	1998 Q3	4
Pakistan	2008 Q2	5
Peru	2008 Q4	4
Peru	2013 Q4	3
Philippines	1997 Q3	5
Philippines	2008 Q1	5
Poland	2008 Q4	4
Republic of Korea	1997 Q4	5
Republic of Korea	2008 Q2	5
Republic of Korea	2015 Q3	4
Romania	2008 Q3	7
Russian Federation	2008 Q4	4

Country	Quarter	Duration (in quarters)
Russian Federation	2014 Q1	6
South Africa	1998 Q3	4
South Africa	2000 Q3	3
South Africa	2008 Q3	4
South Africa	2015 Q3	4
Sri Lanka	2001 Q2	4
Sri Lanka	2008 Q1	2
Sri Lanka	2010 Q3	2
Sri Lanka	2015 Q1	4
Thailand	1996 Q4	7
Thailand	2007 Q1	2
Thailand	2008 Q2	4
Thailand	2011 Q4	3
Turkey	2001 Q1	4
Turkey	2007 Q4	9
Ukraine	2008 Q4	6
Ukraine	2014 Q4	3
Uruguay	2013 Q3	2
Uruguay	2015 Q3	6
Venezuela, Bolivarian Republic of	2006 Q2	3
Venezuela, Bolivarian Republic of	2012 Q2	2

A.2 Explanatory Variables and Data Transformation

Table 10: Raw data description and sources

Serie	Description	Source
TED Spread	Difference between 3-months USD LIBOR and 3-months T-Bills rate	FRED
VIX	CBOE Volatility Index	FRED
Global Liquidity Growth	Year-on-year and fours-years growth rate of global money supply - sum of M2 in United States, euro area and Japan	IFS Statistics
Global Real GDP Growth	Median year-on-year growth rate in the United States, euro area, Japan and UK	IFS Statistics
Global 10-years interest rate	Median yield 10-years government bonds United Stated, euro area, Japan and UK	IFS Statistics
10-years US interest rate		IFS Statistics
T-bills rate	3-months US Treasury bills rate	FRED
Global Inflation	Median year-on-year CPI inflation in the United States, euro area, Japan and UK	IFS Statistics
Nominal GDP		IFS Statistics and national sources. When not available, interpolated annual from WEO
Real GDP growth	Year-on-year growth rate real GDP	IFS Statistics and national sources. When not available, interpolated annual from WEO
CPI Inflation	Year-on-year growth rate CPI	IFS Statistics
International Reserves	Gold excluded	IFS Statistics
Real Exchange Rate	The bilateral US dollar real exchange rate calculated as the nominal exchange rate against the US dollar times the US CPI and divided by the domestic CPI	
Private Credit	Deposit money banks and other financial institutions claims on private sector	IFS Statistics. To have full sample availability we extend we the non-standardized presentation (line 22d) using the growth rate of the standardized one
ST Liabilities to BIS reporting banks		Joint External Debt Hub (JEDH)
Current Account		IFS Statistics
Capital Controls	Overall restrictions on capital mobility, inflows and outflows specific measures	Different versions: Chinn and Ito [2008], Fernández et al. [2015]
Macroprudential Indicators	Loan-to-Value threshold	iMaPP Database
Trade Contagion	$\sum_{n=1}^{j} \frac{Exports_{i,j,t}+Imports_{i,j,t}}{Exports_{i,t}+Imports_{i,t}} * SS_{j,t}$	Aggregate and bilateral trade data from Direction of Trade (DOT) Statistics

B Methodology

C Results

C.1 Determinants of Sudden Stops

C.1.1 Robustness

De-trending: We replace the HP-filtered RER and private credit over GDP ($\lambda = 1600$) by their year-on-year growth rate. We want to make sure the significance is not only a by-product of the de-trending approach chosen, but that there exists a true relationship between these indicators and dependent variable. The coefficients remain significant and similar in magnitude. The two fit measures, however, are lower than in the benchmarkk suggesting that the use of an HP filter is better than simple growth rates for forecasting purposes.

Short-term indicators: We remove observations up to 1 year before the sudden stop. If some external crises start before our dating or there are some expectation mechanisms at play, the indicators could be affected by endogeneity issues. Results are similar to the benchmar, but with one main difference: trade contagion loses significance. This means contagion variables act as really short-term indicators and may be less useful from a policy-maker perspective.

Post-crisis bias: Employing the alternative definition of sudden stop duration we can check for the presence of a post-crisis bias. Since few variables would be affected by the latter in our benchmark specification, we include two other domestic factors, real growth and inflation. The latter have not been found significant with the normal definition, but often appear in EWSs: these two variables, in turn, can be heavily affected by the aforementioned bias. We find, however, no relationship between the two and the dependent variable.

Fixed effects: We introduce country fixed effects. This sensitivity check is particularly important for the result on capital controls: if some countries have established a better relationship with markets and this allows them to maintain an high level of capital controls on inflows, and the other way around, the associated coefficient would be downward biased. Nevertheless, the introduction of country dummies does not change the capital controls coefficient and there is no other important coefficient variation. Notice that the fixed effect model shows a better fit than its pooled counterpart. This means country dummies are actually capturing some characteristics correlated with our dependent variable, but the latter are orthogonal to our indicators. This result is the opposite out-of-sample: the fixed effect model exhibits a typical problem of overfitting.

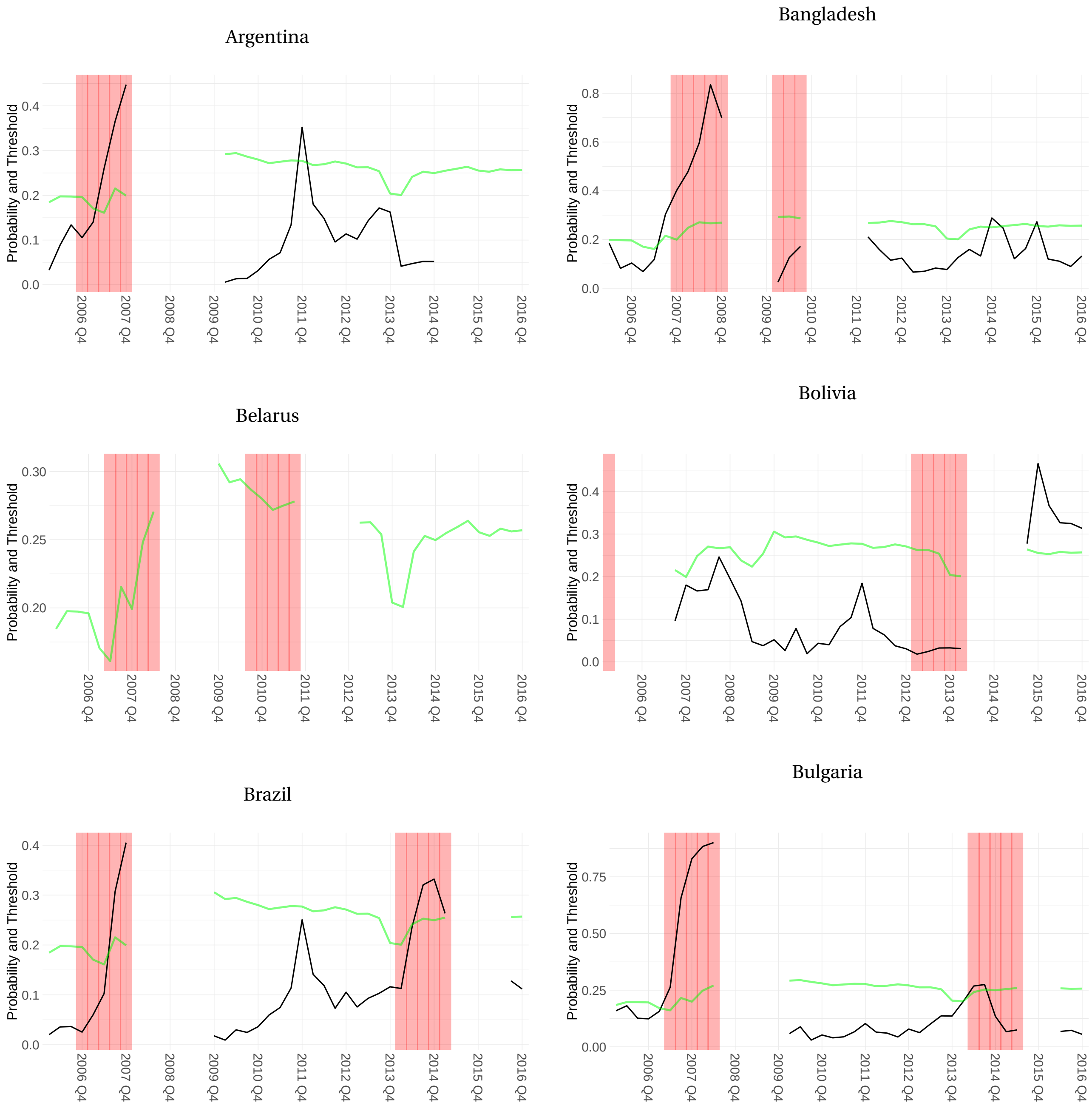
Table 11: Robustness Analysis

	De-trending	Pre-crisis Period 4-6	Post-Crisis Bias	Country FE
	(1)	(2)	(3)	(4)
TED Spread	1.495***	1.540***	1.348***	1.579***
	(0.238)	(0.294)	(0.253)	(0.245)
Global Liquidity Growth	−1.780***	−1.477***	−1.400***	−1.549***
	(0.276)	(0.320)	(0.274)	(0.280)
Real GDP Growth (y-o-y)			0.324	
			(0.259)	
Inflation (y-o-y)			−0.075	
			(0.267)	
Private Credit-Gap	1.018***	0.865***	1.069***	1.111***
	(0.241	(0.297)	(0.252)	(0.259)
RER-Gap	−1.249***	−1.517***	−1.717***	−2.095***
	(0.256)	(0.312)	(0.259)	(0.268)
ST Liab. to BIS Banks/GDP	0.817***	0.770***	0.748***	0.977***
	(0.237)	(0.294)	(0.249)	(0.260)
CA/GDP	−1.145***	−1.177***	−1.027***	−1.152***
	(0.237)	(0.294)	(0.248)	(0.260)
Trade Contagion	0.804***	0.341	0.640***	0.807***
	(0.167)	(0.209)	(0.174)	(0.177)
Capital Controls on Inflows	−0.511***	−0.507**	−0.362*	−0.662***
	(0.196)	(0.241)	(0.206)	(0.228)
Observations	1,748	1,560	1,618	1,753
Relative Usefulness	38%	38%	38.5%	45.8%

Note: Robust standard errors in parentheses. The ”De-trending” column substitutes from the benchmark specification the HP-Filtered RER and Credit-Gap with the year-on-year growth rate. The ”Pre-crisis Period 4-6” column is equivalent to the benchmark specification with a pre-crisis period that goes from 4 quarters to 6 quarters before the sudden stop. The ”Post-crisis bias” column employs an alternative definition of sudden stop duration (see section 2.1 for details) and includes in the benchmark specification the yearly growth rate of GDP and yearly inflation. The ” Country FE” column is equivalent to the benchmark specification with the addition of country fixed effects. * Statistical significance at 10% level. ** Statistical significance at 5% level. *** Statistical significance at 1% level.

C.2 Out-of-sample Performance and Forecast Horizon

Figure 10: Out-of-sample Estimated Probabilities



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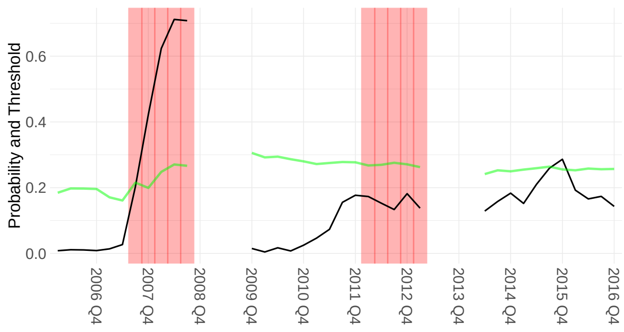
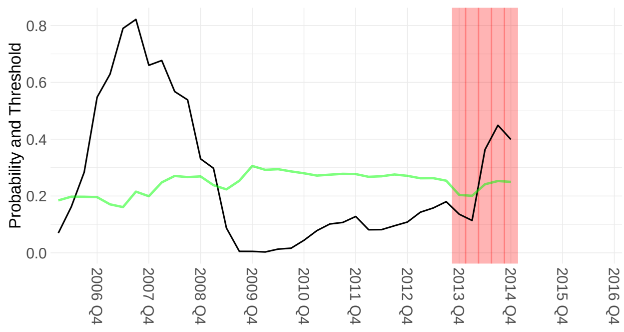
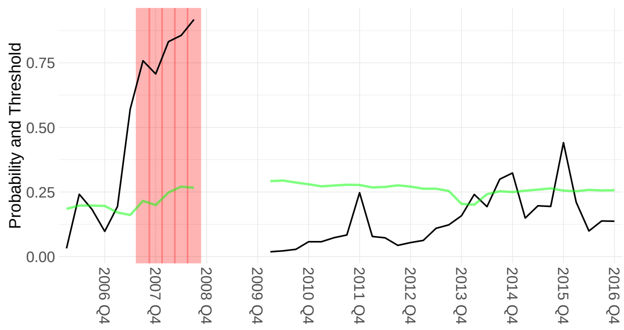


Colombia

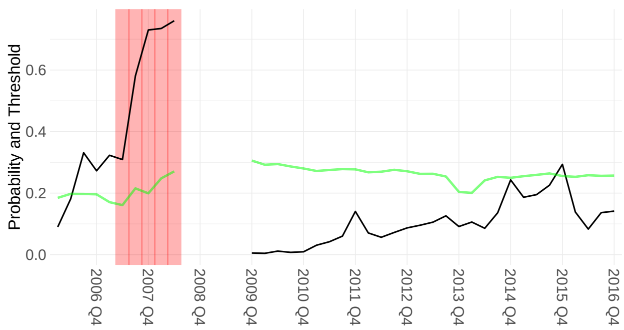


Ecuador

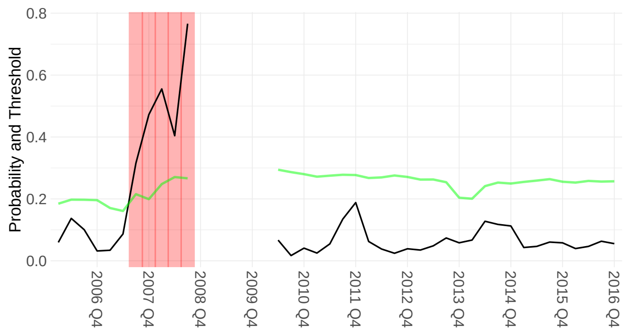
El Salvador



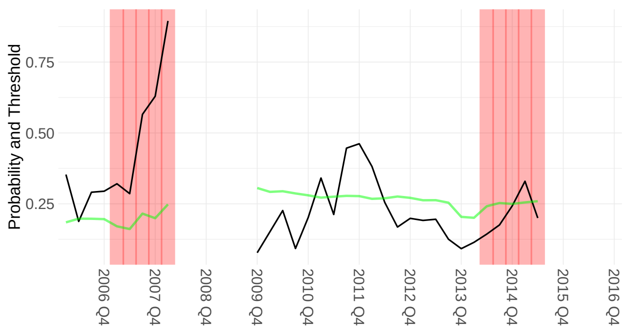
Guatemala



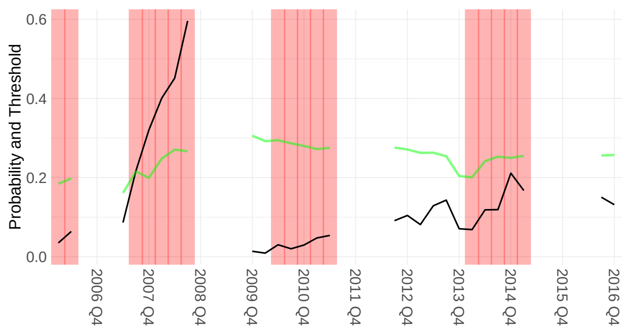
Hungary

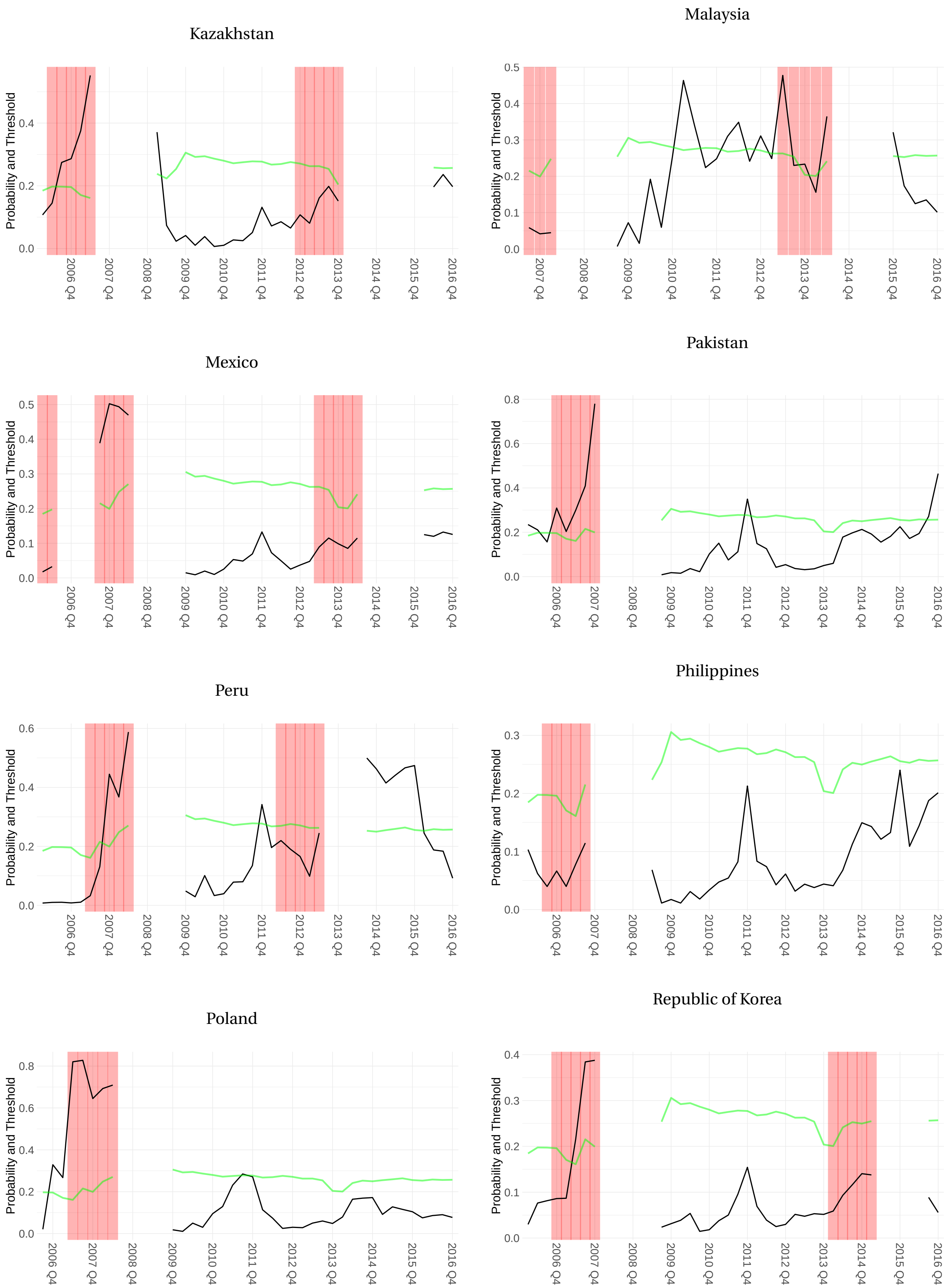


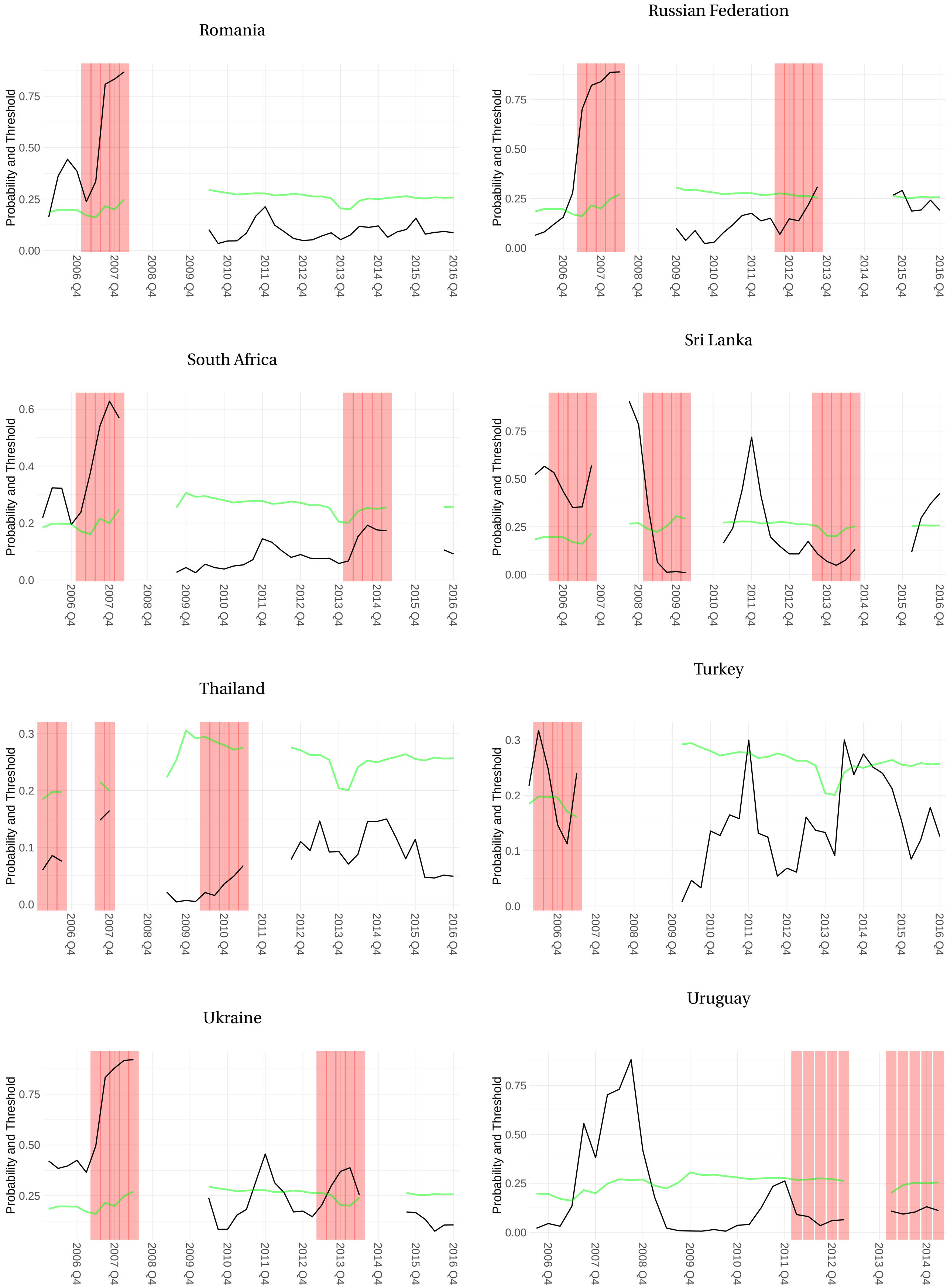
India



Indonesia




Kazakhstan
Malaysia
Mexico
Pakistan
Peru
Philippines
Poland
Republic of Korea
Probability and Threshold


Romania
Russian Federation
South Africa
Sri Lanka
Thailand
Turkey
Ukraine
Uruguay
Probability and Threshold
2006 Q4
2007 Q4
2008 Q4
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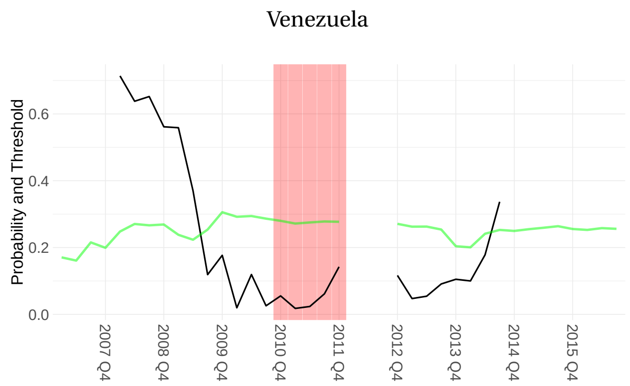
2014 Q4
2015 Q4
2016 Q4

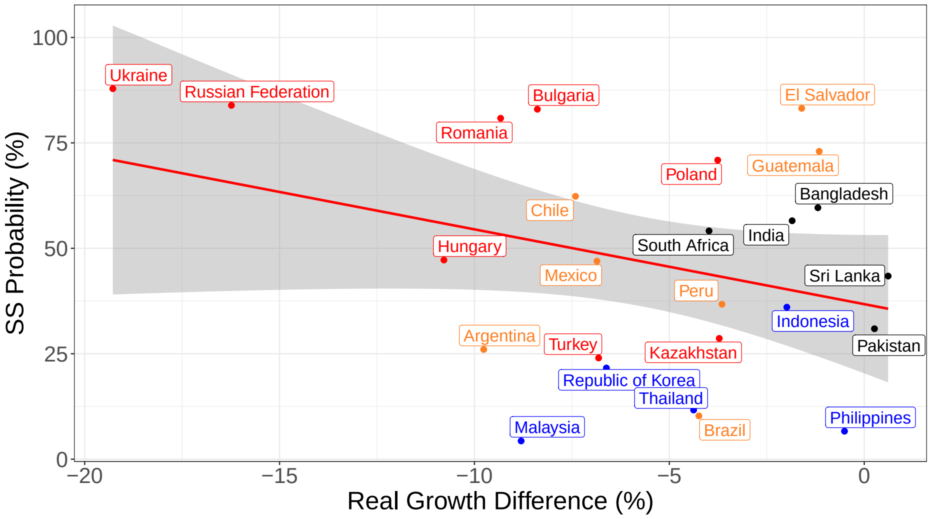


Note: The figure shows the estimated probabilities from the out-of-sample recursive exercise (black line), the time-varying optimal threshold above which a signal is sent by the model (green line) and the pre-crisis period (red area). Blank areas correspond to the quarter before and the duration of the sudden stop.

C.3 Timing

C.4 Sudden Stops Impact and Fitted Probabilities

Figure 11: Fitted Probabilities and Ex-Post Growth - Robustness



Note: The figure shows the relationship between the median out-of-sample probability in the pre-crisis period for GFC related sudden stops and a measure of output impact constructed as the difference between median growth during the sudden stop and median growth in the preceding tranquil period. Red line is regression line with 95% confidence intervals.