Emerging Market Sovereign Credit Spreads: In-Sample and Out-of-Sample Predictability*

Alena Audzeyeva[†]
Keele Management School, Keele University

Ana-Maria Fuertes[‡]
Cass Business School, City University of London

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Abstract

This paper investigates the quarter-ahead predictability of Brazil, Mexico, Philippines and Turkey credit spreads for short and long maturity bonds during two separate periods preceding and following the Lehman Brothers' default. A model based on the current country-specific credit spread curve predicts no better than the random walk and slope regression benchmarks. Extensions with the global yield curve factors and short-term interest rate volatility notably outperform the benchmark models post-Lehman. Our findings suggest that uncertainty indicators, both global and domestic, contain information about future credit spreads and that bond prices did better align with fundamentals post-crisis.

Keywords: Sovereign credit spreads; Emerging Markets; Out-of-sample predictability; Term structure; Macroeconomic uncertainty.

JEL Classifications: F34; F15; F17.

*Correspondence to: A.-M. Fuertes, Faculty of Finance, Cass Business School, City University of London, 106 Bunhill Row, London EC1Y 8TZ.

[†]Email: a.audzeyeva@keele.ac.uk

[‡]Email: a.fuertes@city.ac.uk

"*Developing economies are on course to raise a record sum in global debt markets this year, as ultra-low rates in the developed world cheapen borrowing costs*" (CNBC, September 4 2016)

"[...] *investors are now more cautious and discriminating, and market access is more uncertain*" (Moody's, April 20 2016)

1 Introduction

Little is known about the predictability of sovereign credit spreads in markets where investors are non-trivially exposed to default risk. Beyond academia, filling this vacuum is important for several reasons. Being able to generate accurate out-of-sample (or real-time) predictions of *emerging* sovereign credit spreads at various maturities is essential for pricing emerging market assets and derivatives, and for international portfolio management. Furthermore, understanding how domestic and global factors affect future international borrowing costs should enable emerging market borrowers to develop better informed economic policies. The systemic importance of the emerging sovereign debt market makes the construction of predictive models of emerging market credit spreads a very relevant task for financial market regulators. The defaults of several Latin American and Asian governments (besides Russia) during the 1990s and 2000s triggered global market turmoil. The stock of tradable emerging market debt grew by 17% per annum since 2002 reaching 11.7 trillion U.S. dollars in 2011 (Bank of America Merrill Lynch, 2012). Furthermore, emerging market bonds have recently attracted large portfolio capital flows due to their remarkable resilience during the 2008-2009 global financial crisis and post-crisis relatively favorable risk-return characteristics; see, for instance, IMF (2010) and JP Morgan (2012).

This paper contributes to the nascent literature on sovereign bond yield predictability with a comprehensive in- and out-of-sample forecasting analysis for four relatively mature emerging markets: Brazil, Mexico, Philippines and Turkey. The goal is to test three novel hypotheses that stem from extant financial economic theory and evidence. The first hypothesis states that the current emerging-market credit spread curve alone is a sufficient statistic to predict future credit spreads (*Hypothesis* 1). This hypothesis is motivated by the rational expectations theory of interest rates that has been widely scrutinized in the riskless debt context. The main idea is that, since the credit spread curve embeds forward credit spreads, it contains market expectations about future credit spreads.[1] Likewise, popular affine term-structure models of riskless debt imply that all the necessary information to predict credit spreads is impounded in the current credit spread curve. In order to test *Hypothesis* 1, we specify a parsimonious (baseline) predictive model for future credit spreads that exploits the information content of the *credit spread curve* alone; that is, the only predictors are the current spread level, slope and curvature factors.

The second hypothesis is that indicators of *uncertainty* about global business conditions and about the emerging borrower's future ability to repay debt convey additional information about the future credit spread over and above the current credit spread curve (*Hypothesis* 2). To formally test this hypothesis, we deploy a hierarchical predictive regression approach by which the baseline emerging-market credit spread curve model is gradually extended with various predictors. Aligned with the first part of the hypothesis, we consider as key *global macroeconomic* indicators the U.S. interest rate curve factors that reflect expectations about future global riskless rates and, more pertinently, the volatility of the U.S. short-term interest rate that reflects uncertainty therein. The established wisdom is that, on the one hand, global interest rates influence the country-specific default component of the credit spread. Specifically, the U.S. interest rate influences domestic business conditions – it explains about

[1] Akin to the one-to-one relationship that exists between yields on pure discount bonds and current forward interest rates for riskless bonds, credit spreads on defaultable bonds are linked to current forward spreads.

20% of output variability in emerging markets (Uribe and Yue, 2006) – by determining the borrowing costs faced by the sovereign. Through its signaling role about the global financial market conditions, on the other hand, the U.S. interest rate impacts on common factors such as global market liquidity and investors' risk appetite and hence, it influences also the non-default-related risk premium component of the credit spread (Hartelius et al., 2008; Longstaff et al., 2011). The volatility of the U.S. interest rate is therefore a natural candidate predictor of uncertainty about both components of the emerging-market sovereign credit spread.

Next, as predictors to test *Hypothesis* 2 are two emerging economy's external sector indicators: *trade balance* and *terms of trade growth*. Noting that our conjecture concerns specifically the uncertainty about the emerging economy's ability to generate funds in hard currencies for debt repayment, we assess the signaling ability of the *volatility* of trade balance and terms of trade growth while controlling for the information content in their levels. The motivation for this aspect of *Hypothesis* 2 stems from open-economy theory. The savings-under-uncertainty neoclassical model of Mendoza (1997) states that the variability of the terms of trade growth affects output growth (positively or negatively depending on the level of risk aversion) and reduces social welfare. The real business cycle model of Aguiar and Gopinath (2007) establishes that the variability of net exports is associated with productivity trend growth shocks. In particular, trend growth shocks have been empirically linked to the frequency of defaults in emerging markets (Aguiar and Gopinath, 2006).

Third, we conjecture that emerging market sovereign bond spreads became more aligned with global/domestic fundamentals post-Lehman (*Hypothesis* 3). This conjecture is inspired by the notion of "wake-up calls" or learning effects in financial markets as originally put forward by Goldstein et al. (2000) and Bekaert et al. (2011). A theoretical framework for "wake-up calls" is recently offered by Ahnert and Bertsch (2015) using global coordination games. Their model predicts that in calm market conditions investors may not have sufficient incentives to acquire costly information about a market; consequently, this may induce some divergence of the market prices from fundamentals. However, a crisis event in another market induces investors to acquire information about the first market and re-assess its fundamentals even if investors learn that the two markets are unrelated to each other. Inspired by this theory, we conjecture that the collapse of Lehman Brothers served as a wake-up call for emerging-market sovereign bond investors, urging them to pay closer attention to the global and domestic fundamentals that influence the sovereign's ability to repay debt.

Using cross-sections of individual bond prices per sovereign borrower sampled at the weekly frequency from July 1, 2003 to December 31, 2013, we begin our analysis by estimating the latent factors of the spread curve *à la* Nelson and Siegel (1987). Given the limited cross-section of bonds available, the relative parsimony of this approach is important to preserve degrees of freedom in estimation and achieve as much accuracy as possible in the factor extraction. For the same reason, we focus on four sovereigns with relatively large and liquid markets for U.S. dollar denominated bonds spanning the typical maturity spectrum: Brazil, Mexico, Philippines and Turkey.[2] We make formal inferences using both in-sample and out-of-sample (OOS) predictive ability tests. The horizon for the OOS forecasts is one quarter ahead (in the context of our weekly data, $h = 13$ weeks).

We find pervasive evidence that the emerging-market credit spread curve is not a sufficient statistic for predicting the quarter-ahead spread, against *Hypothesis* 1, as the baseline model forecasts are no better than those from the random walk and credit-slope benchmarks. Adding the global riskless yield curve information reduces significantly the model's in- and out-of-sample predictive errors. The spread curve factors and the global riskless yield curve

[2] The cross-sections of bond prices available for other emerging markets that we could have included in the analysis are notably smaller, particularly, in the early years of the sample period.

factors together constitute a superior predictive model that is able to beat the benchmarks.

Both in- and out-of-sample tests indicate that the volatility of the U.S. short-term interest rate, the *volatility* of the emerging-market sovereign trade balance and terms-of-trade growth are useful predictors of the quarter-ahead emerging market spread, in line with *Hypothesis* 2. These results provide insights that may help in refining extant structural and reduced-form models of emerging-market sovereign debt (Gibson and Sundaresan, 2005; Duffie et al., 2003; Pan and Singleton, 2008). Finally, consistent with *Hypothesis* 3 about the "wake-up call" effect of the Lehman Brothers' collapse on emerging-market debt markets, we find superior in- and out-of-sample predictive ability of most global and domestic macroeconomic indicators after this negative event. We interpret this finding as evidence that credit spreads became closer aligned with fundamentals post-Lehman.

Related Literature. Our paper relates to a very sparse literature on the OOS predictability of emerging-market sovereign credit spreads. To our knowledge, there are only two studies in this spirit broadly speaking. Sueppel (2005) predicts the cointegration path of the spread on the Merril Lynch Emerging Market Bond index. Hilscher and Nosbusch (2010) construct a hazard model for forecasting the sovereign's default probability using the J.P. Morgan Emerging Markets Bond Index Global index;[3] they utilize the default probability forecasts to construct hazard-model-implied spreads. Our paper distinguishes itself from these two studies in various aspects. First, the target variable is different. We seek to predict an observable variable, the sovereign credit spread, at a relatively short (quarter ahead) horizon whereas Sueppel (2005) is interested instead in the latent long-run equilibrium path of the spread. Unlike Hilscher and Nosbusch (2010) that focus on the default component of the

[3]Focusing on the J.P. Morgan Emerging Market Bond Index as debt portfolio, Comelli (2012) estimates a model of emerging-market sovereign credit spreads based on credit risk ratings and global factors such as the VIX volatility index, and U.S. interest rates, but they do not assess the OOS predictability of spreads.

spread, we aim to predict the entire spread that comprises a default risk related component and a non-default related risk premium; the latter is sizeable and non-negligible (see, e.g., Longstaff et al., 2011). Second, our predictability analysis is based on disaggregated data for bonds of short and long maturities instead of relying on an index (that pools bonds of different maturities) as proxy for a country's debt portfolio. Finally, these two predictive studies are not concerned with the term structure; namely, they do not analyze the OOS predictive content of the sovereign credit spread curve or the global riskless yield curve.

Our paper builds on contributions in the riskless bond yield predictability literature. Diebold and Li (2006), Diebold et al. (2008) and Christensen et al. (2011) show that the interest rate curve conveys information about future interest rates. Ang and Piazzesi (2003), Moench (2008), and Ludvigson and Ng (2009) show that U.S. macroeconomic indicators carry additional information content for future U.S. Treasury bond yields. There is a vacuum of knowledge on these issues, however, in the context of risky debt. The one extant contribution is Khrishnan et al. (2010) but their focus is instead the corporate bond market. They provide evidence that the credit spread curve is not a sufficient statistic to predict future corporate credit spreads since the riskless yield curve adds significant predictive accuracy.

Our paper is evidently related to the literature that investigates the drivers of emerging-market sovereign credit spreads. The established wisdom is that both global factors (e.g., Uribe and Yue, 2006; Hartelius et al., 2008; Longstaff et al., 2011) and domestic macroeconomic indicators (e.g., Edwards, 1986; Min, 1998; Ferrucci, 2003; Baldacci et al., 2008) play a role. However, a common feature of these papers is that they do not analyze the OOS predictive ability of the drivers. This is an important extension of our paper because good in-sample model fit and significance from standard tests is not tantamount to useful OOS predictive ability. The intuition is that typical model estimation approaches using all available sample data are, by construction, avoiding large in-sample prediction errors and thus susceptible to over-fitting (mistaking noise for signal in the data). An OOS forecasting analysis of this nature is not only relevant for investors but it can also inform the development of theoretical models of emerging-market sovereign debt.

Finally, our paper speaks to a still sparse literature that has adduced evidence of "wake-up calls" in bond markets. In the context of Eurozone sovereign debt markets, Caceres et al. (2010), Mink and Haan (2013) and Saka et al. (2015) show that, while early in the crisis the spreads largely reflected changes in global risk aversion, at a later stage domestic macroeconomic fundamentals began to matter more; the stronger role played by the fundamentals is observed not only for Eurozone countries severely affected by the crisis but also for other countries in the region. Our paper distinguishes itself from these studies not only in its focus on emerging-market sovereign bond markets but also in that we shed light on the "wake-up call" notion from the different lens of OOS predictability.

The paper proceeds as follows. Section 2 outlines the predictive models while Section 3 describes the data. Section 4 discusses the empirical findings. Section 5 concludes the paper.

2 Methodology

2.1 Emerging market zero-coupon credit spreads

The time t price of a zero-coupon bond that pays \$1 at $t + \tau$ obeys the relation

$$p_{i,t}(\tau) = e^{-y_{i,t}(\tau)\tau} \tag{1}$$

where i denotes the sovereign bond issuer, and $y_{i,t}(\tau)$ is the yield to maturity τ. The target variable in our predictability analysis is the emerging market zero-coupon bond yield spread

$$s_{i,t}(\tau) \equiv y_{i,t}(\tau) - y_{f,t}(\tau) \tag{2}$$

where $y_{f,t}(\tau)$ is the time t yield on a U.S. Treasury zero-coupon bond. We extract at the weekly frequency the unsmoothed yields on zero-coupon riskless bonds by applying the Fama and Bliss (1987) methodology to cross-sections of market prices of U.S. Treasuries.[4] The unsmoothed Fama-Bliss yields price U.S. Treasuries exactly (see Diebold and Li, 2006). Next we fit the Nelson-Siegel-Svensson decomposition to those unsmoothed Fama-Bliss yields by Nonlinear Least Squares (NLS) to obtain the smoothed yields on zero-coupon riskless bonds which are denoted $y_{f,t}(\tau)$ in (2). The Nelson-Siegel-Svensson equation enables superior riskless bond yield estimation accuracy relative to simpler representations (see Svensson, 1994). With these zero-coupon riskless bond yields in hand, we can construct the corresponding emerging-market credit spreads on zero-coupon bonds, denoted $s_{i,t}(\tau)$, as follows.

We adopt the parsimonious Nelson and Siegel (1987) decomposition for the spread on the (zero-coupon) maturity τ bond of the emerging-market sovereign i

$$s_{i,t}(\tau) = \beta_{i0,t} + \beta_{i1,t}\left(\frac{1-e^{-\lambda_{i,t}\tau}}{\lambda_{i,t}\tau}\right) + \beta_{i2,t}\left(\frac{1-e^{-\lambda_{i,t}\tau}}{\lambda_{i,t}\tau} - e^{-\lambda_{i,t}\tau}\right) \tag{3}$$

where $t = 1, 2, ..., T$ are sample weeks, $\beta_{i0,t}$, $\beta_{i1,t}$ and $\beta_{i2,t}$ are the *level*, *slope* and *curvature* factors, respectively. We extract these latent factors at the weekly frequency by NLS minimization of the distance between the cross-section of observed coupon-paying emerging market bond prices and the corresponding fitted bond prices from eqs. (1)-(3) with exponen-

[4] We thank Robert Bliss for sharing his software and data files.

tial decay parameter fixed at $\lambda_{i,t} = 0.7308$ (annualized yields), as in Diebold and Li (2006). Then with the weekly spread factors in hand, $\hat{\beta}_{i0,t}, \hat{\beta}_{i1,t}, \hat{\beta}_{i2,t}, t = 1, ..., T$, we can construct weekly zero-coupon emerging market bond spreads for any maturity, $s_{i,t}(\tau)$, using eq. (3).

2.2 Hierarchical predictive regressions

Following Diebold and Li (2006) and Khrishnan et al. (2010) in the riskless debt and risky corporate debt contexts, respectively, we construct *baseline* forecasts for the h-week-ahead spread as forward projections of the current spread curve using the predictive equation

$$s_{i,t+h}(\tau) = \alpha_i + \gamma_{i0}\hat{\beta}_{i0,t} + \gamma_{i1}\hat{\beta}_{i1,t} + \gamma_{i2}\hat{\beta}_{i2,t} + \varepsilon_{i,t+h},\ t = 1, 2, .., T. \tag{4}$$

The parameters α_i and $\gamma_{ij}, j = 0, 1, 2$, are estimated by OLS using the weekly time-series of emerging market spreads and spread curve factors.[5] In a hierarchical regression approach, we gradually add global macroeconomic factors, $\boldsymbol{G}_t$, and formulate the predictive model

$$s_{i,t+h}(\tau) \ = \ \alpha_i + \gamma_{i0}\hat{\beta}_{i0,t} + \gamma_{i1}\hat{\beta}_{i0,t} + \gamma_{i2}\hat{\beta}_{i2,t} + \boldsymbol{\theta}_i^G \boldsymbol{G}_t + \varepsilon_{i,t+h} \tag{5}$$

and emerging-market specific macroeconomic factors, $\boldsymbol{EM}_{i,t}$, leading to the predictive model

$$s_{i,t+h}(\tau) = \alpha_i + \gamma_{i0}\hat{\beta}_{i0,t} + \gamma_{i1}\hat{\beta}_{i0,t} + \gamma_{i2}\hat{\beta}_{i2,t} + \boldsymbol{\theta}_i^G \boldsymbol{G}_t + \boldsymbol{\theta}_i^{EM} \boldsymbol{EM}_{i,t} + \varepsilon_{i,t+h}, \tag{6}$$

The predictive horizon is one-quarter-ahead ($h = 13$ weeks). We discuss the candidates for global predictors, $\boldsymbol{G}_t$, and domestic predictors, $\boldsymbol{EM}_{i,t}$, in the next section.

[5] Diebold and Li (2006) employ instead a two-step forecasting method by, first, fitting autoregressive models (by OLS) to the estimated weekly factors to capture persistence, and then using the corresponding projections, $\hat{\beta}_{ij,t+h} = f(\hat{\beta}_{ij,t})$, $j = 0, 1, 2$ as predictive variables in eq. (4).

For the in-sample predictability analysis, equations (4)-(6) are estimated using the entire sample (T weeks). For the OOS predictability analysis, we split the latter into an estimation period ($T_0 = 2/3T$ weeks) and a holdout or evaluation period ($T_1 = 1/3T$ weeks). The sequence of OOS forecasts is obtained by recursive estimation. The first estimation window spans week $t = 1$ up to week $t = T_0$ and enables a first h-week-ahead forecast $\hat{s}_{i,t+h|t}\,(\tau)$. The next window, spanning weeks $t = 1$ to $t = T_0 + 1$, enables a second forecast and so forth.

2.3 Evaluation of in- and out-of-sample predictive ability

We gauge the in-sample predictability gains in the hierarchical regression analysis through the adjusted coefficient of determination R^2. A Wald test for block-exclusion restrictions is conducted to assess the significance of any predictability gain; the null hypothesis is $H_0 : \Delta\text{Adj}R^2 = 0$ and the alternative hypothesis is $H_A : \Delta\text{Adj}R^2 > 0$.

We utilize the mean square error (MSE) statistic, which captures the expected value of the squared error loss or quadratic loss, to measure the quality of the quarter-ahead OOS forecasts $\hat{s}_{i,t}(\tau)$. Significance will be assessed through the Clark and West (2007) one-sided *MSE-adjusted* t-test. The relevant question in our hierarchical modeling approach is: Does model B produce superior OOS forecasts than a simpler (nested) model A. Under H_0, model A is assumed to generate the data and therefore model B requires estimating unnecessary parameters which introduces noise in the MSE_B. Hence, the expected value of the differential $MSE_A - MSE_B$ is negative under H_0; the adjustment of the Clark-West test statistic is meant to account for this noise and the test hypotheses are formulated as $H_0 : MSE_A \leq MSE_B$ against $H_A : MSE_A > MSE_B$. Thus, a test rejection indicates that the extended model B produces more accurate OOS forecasts than the nested model A.

A second set of OOS predictability tests is aimed at *benchmarking*. The idea is to assess whether our predictive regressions, eqs. (4)-(6), are able to beat those models employed as benchmarks in the literature. Given the stylized persistence of credit spreads, a widely-used benchmark is the random walk (RW) model $s^{RW}_{i,t+h|t}(\tau) = s_{i,t}(\tau) + \varepsilon_{i,t+h}$. Another natural benchmark (inspired from the riskless bond predictability literature) is a time-series OLS regression of credit spread changes on credit spread slopes, $s_{i,t+h}(\tau) - s_{i,t}(\tau) = c_i + d_i(s_{i,t}(\tau) - s_{i,t}(2)) + \varepsilon_{i,t+h}$, where $s_{i,t}(2)$ denotes the 2-year credit spread. This simple slope regression follows the spirit of the forward-rate regressions of Fama and Bliss (1987) and Cochrane and Piazzesi (2005), and the term spread regression of Campbell and Shiller (1991), that have been deployed as alternative tests of the rational expectations theory in the context of *riskless* interest rates.[6]. Since this benchmarking involves comparing non-nested models, we employ the Diebold and Mariano (1995) two-sided t-test which hypothesizes $H_0 : MSE_b - MSE_j = 0$ against $H_A : MSE_b - MSE_j \neq 0$, with the subscripts j and b denoting the candidate predictive model and the benchmark at hand, respectively. Both sets of OOS predictive ability tests are adjusted for autocorrelation in the weekly OOS forecast error sequence.

3 Credit Spreads and Predictors: Data Description

3.1 Bond market price data and preliminary analysis

The period of analysis is July 1, 2003 to December 31, 2013 and the sampling frequency is weekly. The modeling and forecasting analysis will be conducted separately over a pre-Lehman (268 weeks) period and a post-Lehman (263 weeks) period, for comparison.[7] The data set used for the riskless zero-coupon bond yield extraction and corresponding term-

[6] For further discussion, see Diebold and Li (2006) and Steeley (2014)

[7] The first period is July 1, 2003 to October 14, 2008. Excluding the anomalous weeks immediately following the Lehman Brothers' bankruptcy, the second period is December 1, 2008 to December 31, 2013.

structure curve fitting are midweek bid-ask average price quotes for U.S. Treasury bonds from the *Center for Research in Security Prices.* Over 100 prices are available per week.

In order to collect emerging market bond prices, we establish various eligibility criteria geared towards achieving reliable term-structure estimation. The first requirement is the availability in each sample week of market price data on at least six Eurobond issues across a range of bond maturities (from 1 to 32 years). The minimum amount at issue is $500 million to mitigate illiquidity. Since relatively few emerging market Eurobonds with maturity below 3 years or above 20 years are observed on a trading day, to mitigate illiquidity also the analysis is confined to 3-20 year maturities. The pool of eligible sovereign bonds per country is further filtered to retain only plain vanilla bond issues, with fixed regular coupon payments and without collateral, sink funds or other special contractual aspects.[8]

Thus we end up with histories of midweek bid-ask average price quotes for U.S. dollar denominated Eurobonds of four emerging market sovereigns – Brazil, Mexico, Philippines and Turkey. The primarily data source is *Bloomberg*. We use *Datastream* as supplementary data source to fulfill our requirement of at least six market bond prices observed on any given week; 19% of our emerging-market sovereign bond prices come from *Datastream.* The week-by-week spread curve fitting described in Section 2.1 is thus based on cross-sections of between 9 and 21 (6 and 17) bond prices for Brazil, Mexico and Turkey (Philippines).

The empirical distribution of the bond pricing error (observed bond price minus fitted bond price for a $100 bond) pooled across maturities and weeks has a mean value of less

[8]CDS contracts would be a convenient alternative to obviate the extraction of zero-coupon bond yields. But CDS markets are still relatively illiquid at both short and long maturities for the sovereigns of interest here. Ammer and Cai (2007) provide empirical evidence that the relative liquidity of the two markets is a key determinant of where price discovery occurs and document that bond spreads lead CDS premiums for many emerging sovereign borrowers. CDS contracts include various conditions too and it has been shown, for instance, that the cheapest-to-deliver option affects the CDS spread (Ammer and Cai, 2007). Pan and Singleton (2008) emphasize the liquidity of the underlying bond market as a key determinant of the CDS market liquidity because traders hedge their CDS positions with cash market instruments; a relatively less liquid cash market leads to high hedging costs and, consequently, high bid/ask spreads in the CDS market.

than 2 cents for U.S. Treasuries and between 6 and 13 cents for emerging market bonds. The dispersion of the distribution, given by the standard deviation, is 30 cents for the U.S. market, and between 65 and 130 cents for emerging markets. These pricing errors compare well with those reported in similar studies of speculative and low investment-grade bonds such as Elton et al. (2001) and Khrishnan et al. (2010).

Figure 1 shows the emerging-market spread curves from 3- to 20-year maturity obtained week by week. To preserve space, hereafter the discussion is confined to a short (5-year) maturity and a long (15-year) maturity.[9] Various stylized facts are confirmed by the summary statistics for the weekly credit spreads and spread curve factors given in Table 1.

[Insert Figure 1 around here]

[Insert Table 1 around here]

The credit spread curves exhibit time and cross-section heterogeneity. The common time-variation reflects the global business cycle. For instance, the curves decline during the 2003-2006 period of favorable global financial conditions and ample liquidity. This is followed by a moderate rise in spreads during the turbulent 2007-2008 period. In October 2008 (Lehman Brothers' bankruptcy), all four spread curves shift upwards sharply.

The credit spread curves are mainly upward-sloping. The slope somewhat declines post-Lehman reflecting the start of a global recovery. Consistent with a slow improvement in global fundamentals and relatively stable country-specific economic conditions, the time variation in the credit curve level and slope, captured by the standard deviation of the estimated $\beta_{0,t}$ and $\beta_{1,t}$, also lessens post-Lehman (Table 1). The first-order autocorrelation coefficient of the credit spreads confirms the stylized persistence of credit spreads.[10]

[9] We analyzed the predictability of emerging market sovereign spreads for 3, 10, and 20-year maturity bonds also, and the findings are broadly aligned with those discussed here; details are available upon request.

[10] Credit spreads are theoretically conceptualized as realizations from persistent but stationary processes.

Cross-section heterogeneity in the credit spread curves is also evident, especially, at the beginning of the sample period when the S&P's rating agency assigned a low speculative grade B rating to Brazil and Turkey, a higher speculative grade BB rating to Philippines, while Mexico was rated investment grade BBB. Brazil's rating improved to BB on September 17, 2004 and later to BBB on April 30, 2008. Turkey experienced only a modest upgrade to BB, remaining in the speculative grade whereas Philippines was upgraded to the investment grade BBB on May 2, 2013. Mexico's rating remained unchanged.

3.2 Global macroeconomic predictors

Our hierarchical regression approach starts by constructing quarter-ahead spread predictions from the *credit spread curve* model (4). Then we test the in- and out-of-sample predictability gains, and relative benchmarking ability by augmenting it with various other predictors.

Among the global macroeconomic indicators, the first natural candidates are the *level*, *slope*, and *curvature* factors $(\beta_{f0,t},\beta_{f1,t},\ \beta_{f2,t})'$ that jointly summarize the information content of the global riskless yield curve.[11] The motivation is twofold. First, through its impact on domestic business conditions, the global interest rate influences the emerging economy's future ability to repay external debt. The current global riskless yield curve is thus likely to convey information about the future default-risk related component of the emerging market sovereign spread.[12] Empirically, it has been shown that U.S. interest rate shocks are responsible for about 20% of fluctuations in an emerging economy's aggregate activity, and the transmission mechanism occurs mainly through the country's credit spread that determines

[11]Following Diebold and Li (2006), we fit the Nelson and Siegel (1987) decomposition to the unsmoothed Fama-Bliss yields on zero-coupon U.S. Treasury bonds to obtain the three latent factors.

[12]In the neoclassical growth model of Uribe and Yue (2006), a positive U.S. interest rate shock contracts the emerging economy's output and investment. The small open economy model of Neumeyer and Perri (2005) contends that shocks to the U.S. interest rate influence emerging-market business conditions. The structural sovereign debt model of Gibson and Sundaresan (2005) predicts a counter-cyclical relationship between the global business cycle, which is signaled by the global interest rate, and the credit spread.

the borrowing cost that the country faces in international markets (Uribe and Yue, 2006).

Second, the global interest rate influences global liquidity conditions and investors' risk appetite. These, in turn, affect the demand for emerging-market bonds, and other asset classes, versus riskless bonds and therefore the (non-default) emerging market risk premium component of the spread (Hartelius et al., 2008; Ciarlone et al., 2009; Longstaff et al., 2011). In other words, the U.S. Treasury bond yield reflects the monetary policy path of the Federal Reserve which influences the capital re-allocation among asset classes globally and the net capital flows to emerging markets. For instance, expansionary U.S. monetary policy together with a decrease in investors' risk aversion can fuel the "search for yield" which leads to surges in the global demand for emerging market bonds and lower spreads; tighter monetary conditions in major economies and a drying up of global liquidity can reverse the capital flows and increase the spreads (Hartelius et al., 2008; Ciarlone et al., 2009). It has been shown empirically that the U.S. Treasury yield *curve* contains predictive information for future U.S. Treasury bond yields and for risky corporate credit spreads (Diebold and Li, 2006 and Khrishnan et al., 2010, respectively.)

Our next candidate predictor is the U.S. short-term *interest rate volatility*, denoted $\sigma_{f,t}^{short}$ and measured at the weekly frequency (on each week $t = 1, 2..., T$ of the sample period) as the standard deviation of the daily 1-year U.S. Treasury bond yield over the most recent 10-day trading window. Greater uncertainty about the monetary policy of major economies (global business conditions) as signaled by higher U.S. short-term interest rate volatility, poses a challenge for international investors regarding financial risk allocation decisions (e.g., Hartelius et al., 2008; Arora and Cerisola, 2001). Higher U.S. short-term interest rate volatility also implies greater uncertainty about global liquidity which is likely to widen the emerging market spread. Figure A1 (Panel I) in the on-line Addendum visually illustrates this point through time-series graphs of the weekly 5-year credit spreads, $s_{i,t}(5)$, i=\{Mexico, Turkey\}, alongside the 13-week-lagged U.S. short-term interest rate volatility, $\sigma^{short}_{f,t-13}$. The post-Lehman sample correlation coefficient between the two variables is large and positive ranging across the four countries between 0.60 and 0.80 (0.62 and 0.79) for the 5- (15-) year credit spreads.[13]

The global factors are added to the baseline model in a two-step hierarchical fashion leading to the following formulations of equation (5): model $G1$ with the global predictors $\boldsymbol{G}_t \equiv (\beta_{f0,t}, \beta_{f1,t}, \beta_{f2,t})'$, and model $G2$ with $\boldsymbol{G}_t \equiv \left(\beta_{f0,t}, \beta_{f1,t}, \beta_{f2,t}; \sigma^{short}_{f,t}\right)'$. The sample distribution of all four global macroeconomic indicators is summarized in Table 1.

3.3 Domestic macroeconomic predictors

Extant business cycle theory and evidence suggest that an emerging-market sovereign's external sector conveys information about its economic conditions which, in turn, drives future credit spreads. Traditional wisdom says that the sovereign's trade balance signals its ability to generate funds in hard currencies for servicing external debt and the volatility of trade balance signals uncertainty thereof. The small-open-economy model of Neumeyer and Perri (2005) decomposes the real interest rate into two components, international rate and country risk, and suggests that net exports are more strongly counter-cyclical in emerging markets than in developed ones. There is evidence for emerging-market economies that a greater trade balance is associated with output, consumption and investment contraction (Aguiar and Gopinath, 2007; Neumeyer and Perri, 2005).

In the real business cycle model for an emerging economy of Aguiar and Gopinath (2007), trend shocks to productivity growth are the key driver of economic growth, and the volatility

[13] By contrast, pre-Lehman the correlations between the country spreads and 13-week-lagged volatility of the riskless short-term interest rate are much lower, ranging across countries between -0.32 and -0.13 (-0.22 and -0.05) for the 5- (15-) year bonds.

of trade balance is informative about the relative weight of trend versus temporary shocks. This aligns well with the finding that trend shocks to productivity growth can quantitatively match the frequency of defaults in emerging economies (Aguiar and Gopinath, 2006).

Accordingly, we assess the in- and out-of-sample predictive ability (for the quarter-ahead spread) of the *trade balance*, denoted $TB_{i,t}$, which represents the month t exports minus imports over GDP in US$, and the *volatility of trade balance* ($\sigma_{i,t}^{TB}$) measured as the standard deviation of $TB_{i,t}$ over the most recent 6-month window. The data are obtained from *Datastream*. We interpolate the monthly $TB_{i,t}$ and $\sigma_{i,t}^{TB}$ measures to weekly. The link between country credit spreads, $s_{i,t}(\tau)$, and lagged trade balance volatility, $\sigma_{i,t-13}^{TB}$, can be informally gleaned from the time-series plots in Figure A1 (Panel II) of the on-line Addendum.

It is also known that terms-of-trade shocks affect economic activity mainly through fluctuations in the price of energy and other commodities. In the context of emerging economies, the effect is amplified by specialization in commodity exports, dependence on imported capital goods, and limited access to global financial markets (Chen and Rogoff, 2003; Mendoza, 1995; Sachs, 1981; IMF, 1991). Previous research has linked current *terms-of trade-growth* and future sovereign default risk (Bulow and Rogoff, 1989; Hilscher and Nosbusch, 2010).

The savings-under-uncertainty neoclassical model of Mendoza (1997) formalizes the positive link between terms-of-trade changes and economic growth, and indicates that high terms-of-trade growth variability can impair economic growth and reduce social welfare. Extant empirical research has shown that not only the terms-of-trade growth but also its volatility are significant determinant of future emerging market sovereign default risk (Hilscher and Nosbusch, 2010). These considerations motivate us to examine the in- and out-of-sample forecasting ability of *terms-of-trade growth* ($\Delta TT_{i,t}$) and *volatility of terms-of-trade growth* ($\sigma_{i,t}^{\Delta TT}$) as predictors of the quarter-ahead spreads. $\Delta TT_{i,t}$ is measured on each sample month

t as the annual percentage change in the US$ price of the country's exports relative to the US$ price of its imports; $\sigma_{i,t}^{\Delta TT}$ is the standard deviation of $\Delta TT_{i,t}$ over the most recent 6-month window. The data are from *Datastream.* Again the monthly $\Delta TT_{i,t}$ and $\sigma_{i,t}^{\Delta TT}$ measures are interpolated to weekly. Given that direct measures of emerging-market business conditions are only available to a forecaster with delays, our empirical analysis can shed light on whether the trade balance and terms-of-trade growth (in levels and volatility) are useful proxies of those economic conditions for the real-time prediction of quarter-ahead spreads.

Finally, for completeness, we entertain as predictor the emerging-market *financial risk rating* (referred to as country rating, CR, for simplicity hereafter) provided by the International Country Risk Guide of the Political Risk Services Group which directly signals the more imminent ability of a sovereign to pay off external debt. Not surprisingly, the CR has been contemporaneously linked to the credit spread (e.g., Audzeyeva and Schenk-Hoppe, 2010; Csonto and Ivaschenko, 2013). The CR captures risks related to the deterioration in various foreign debt related indicators: foreign debt to GDP, foreign debt service to exports, current account to exports, official reserves as months of imports and exchange rate stability.[14] These indicators and the resulting CR ought to be quickly impounded into bond prices (and spreads) as they are closely monitored by investors and therefore, they may not convey information for the future spread. Nevertheless, given the prominence of the CR in the empirical emerging-market debt modeling literature, all our predictive equations with emerging-market external sector variables include also the CR as control variable.

Accordingly, we begin by adding the emerging-market *country rating* to the model at hand, $G1$, and formulate model GEM_1. Then we add the *trade balance* to obtain GEM_2,

[14]The foreign debt related indicators behind the CR have been shown to maintain a contemporaneous relationship with credit spreads in Min (1998) and Eichengreen and Mody (1998) inter alia. The CRs are measured in a 0–50 scale and updated monthly. The detailed CR construction is described in Csonto and Ivaschenko (2013) and *http://www.prsgroup.com/about-us/our-two-methodologies/icrg.*

the *volatility of trade balance* to obtain GEM_3. Finally, model GEM_4 adds *terms-of-trade growth*, and GEM_5 adds the *volatility of terms-of-trade growth*. Summary statistics for these emerging-market external sector variables and country rating are provided in Table 1. The full list of predictive models built in this hierarchical fashion is shown in Table 2.

[Insert Table 2 around here]

4 Empirical results

4.1 Within-sample predictive ability

The baseline credit spread factor model and the two successive extensions with global factors, models $G1$ and $G2$, are compared in Table 3 on the basis of their in-sample predictive power.

[Insert Table 3 around here]

On average across countries and both time periods (pre- and post-Lehman), the incremental in-sample predictive power afforded by the U.S. yield curve factors ($\Delta \text{Adj}R^2_{G1} \equiv \text{Adj}R^2_{G1} - \text{Adj}R^2_{base}$) is 10.2 and 7.5 percentage points (pp) for 5- and 15-year maturity bonds respectively, with no discernible difference pre- and post-Lehman. The Wald tests (the null hypothesis is that the coefficients of the additional predictors are jointly zero) suggest that the predictive gains are significant.[15] This finding represents evidence against *Hypothesis* 1 that the credit spread curve is a sufficient statistic to predict the future spread. Adding the volatility of the U.S. short-term interest rate enhances the average in-sample predictive

[15]The Wald tests are based on the standard asymptotic (chi-square) distribution. Hence, they do not account for regressor uncertainty or the fact that the level, slope and curvature factors are estimated. We measured the correlation between the weekly RMSEs of the cross-section fitted Nelson-Siegel equation (3) and the weekly residuals of the time-series regression equation (4). The value is small at 0.089 on average across countries, sub-periods and maturities which indirectly suggests that the test distortions are trivial.

ability ($\Delta\text{Adj}R^2_{G2} \equiv \text{Adj}R^2_{G2} - \text{Adj}R^2_{G1}$) by 2.4pp and 2.7pp, respectively. However, in contrast with the U.S. yield curve factors, a notable contrast pre- and post-Lehman is observed regarding the additional predictive ability afforded by the volatility of the U.S. interest rate; $\Delta\text{Adj}.R^2_{G2}$ reaches only 1.3pp and 0.8pp pre-Lehman but 3.4pp and 4.6pp post-Lehman for the 5- and 15-year bonds, respectively. This evidence supports *Hypothesis* 3 on the "wake-up"effect of the Lehman Brother's bankruptcy.

Next we assess the in-sample predictability gains afforded by domestic macroeconomic variables ($\Delta\text{Adj}R^2_{GEM_j}$) and their significance (Wald test). Table 4 reports the results.

[Insert Table 4 around here]

At both the short- and long-end of the bond maturity spectrum, the country-specific external sector indicators afford significant in-sample predictive gains, especially post-Lehman. Most prominently, on average across countries the *volatility of trade balance* as predictor enhances predictive power ($\Delta\text{Adj}R^2_{GEM3} \equiv \text{Adj}R^2_{GEM3} - \text{Adj}R^2_{GEM2}$) by 0.4pp and 1.2pp pre-Lehman and 1.4pp and 1.9pp post-Lehman for 5- and 15-year maturity bonds, respectively. At country level, *trade balance* is highly informative for Philippines and Turkey, *terms-of-trade growth* for Brazil and Turkey, and *volatility of terms-of-trade growth* for Brazil.

Country rating is the exceptional predictor whose role decreases post-Lehman on average across countries and bond maturities ($\Delta R^2_{GEM1} \equiv \text{Adj}R^2_{GEM1} - \text{Adj}R^2_{G2} < 0$). At country level, this finding is most prominent in Brazil, Mexico and Philippines, and absent in the relatively small Turkish bond market. What is the intuition? First, the CR has predictive content for the quarter-ahead credit spread in the pre-Lehman period which indicates that the CR information is not quickly impounded into bond prices. Second, the quarter-ahead predictive content in the CR vanishes post-Lehman, an indirect reflection of a dramatic change in the emerging-market bond price discovery process which becomes then more efficient; this evidence is also consistent with *Hypothesis* 3. Table A1 in the on-line Addendum reports the OLS estimation results for the baseline model and selected (to preserve space) extensions thereof obtained hierarchically by adding global/domestic macroeconomic predictors.

4.2 Out-of-sample predictive ability

Since in-sample predictive ability does not necessarily translate into out-of-sample (OOS) or real-time predictive ability, the next important task is to assess the latter. In the pre-Lehman analysis, we construct 92 quarter-ahead OOS spread forecasts based on expanding estimation windows; the first forecast (based on an initial estimation window of 163 weeks) corresponds to November 28, 2006 and the last one to October 14, 2008. In the post-Lehman analysis, the number of OOS forecasts is 90; the first forecast (based on an initial estimation window of 160 weeks) is for March 27, 2012 and the last one for December 31, 2013.

Global macroeconomic indicators. The information content in the *global riskless yield curve* enhances the OOS predictive ability as borne out by the small root mean square error ratio of model $G1$ relative to the baseline model (i.e., $RMSE_{G1}/RMSE_{base} < 1$) reported in Table 5. This finding reinforces the in-sample predictive evidence against *Hypothesis* 1. On average across countries, the reduction in forecast errors afforded by the *global riskless yield curve* $(1 - RMSE_{G1}/RMSE_{base})$ is 1.2% and 2.9% pre-Lehman and a remarkably larger 12.1% and 11.5% post-Lehman for the 5- and 15-year bonds, respectively. The one exception is Brazil pre-Lehman where augmenting the model with the riskless yield curve factors adds noise to the predictions ($RMSE_{G1}/RMSE_{base} > 1$). To explain this contrasting finding, we also notice a distinct sharp fall in the Brazilian credit spreads pre-Lehman. Helped by favorable global market conditions and investors' search for yield, the dramatic improvement in Brazil's credit rating from B in 2003 to BBB in 2008 may have resulted in over-confident investor sentiment towards Brazil that somewhat decoupled its spreads from the levels consistent with the global interest rate.

[Insert Table 5 around here]

Further adding the *volatility of the U.S. short-term interest rate* shrinks the forecast errors ($1 - RMSE_{G2}/RMSE_{G1} > 0$) on average across countries by -0.9% and 4.1% pre-Lehman and by 6.4% and 5.6% post-Lehman for the 5- and 15-year bonds, respectively. The Clark and West (2007; CW) tests unambiguously confirm that this global macroeconomic uncertainty indicator adds significant predictive content post-Lehman to the credit-spread curve and riskless yield curve across the bond maturity spectrum.

Next we benchmark the baseline predictive model and its extensions with global macroeconomic indicators (models $G1$ and $G2$) against the random walk and slope-regression. The results are set up in Table 6. Reported RMSE ratios below unity indicate that the candidate model gives more accurate forecasts than the benchmark. Significance is assessed with the Diebold and Mariano (1995) two-sided t-test statistic for non-nested models. A significant and positive DM statistic indicates that the candidate model outperforms the benchmark.

[Insert Table 6 around here]

The *baseline* model (4) almost never beats both benchmarks, neither pre-Lehman nor post-Lehman; the exception is Turkey post-Lehman when both benchmarks are outperformed by the *credit curve* model at the 5% significance level. Exploiting the information in the *global riskless yield curve* reduces the forecast errors enough for model $G1$ to be able to outperform both benchmarks post-Lehman, with some exceptions (Brazil 5-year and 20-year bonds, and Mexico 5-year bonds). It is only when the *volatility of the U.S. short-term interest rate* is added to the predictors set that for all countries and bond maturities the resulting model $G2$ beats both benchmarks post-Lehman. In the pre-Lehman period, in sharp contrast, models $G1$ and $G2$ generally fail to outperform both benchmarks. These findings altogether represent further evidence against *Hypothesis* 1 about the informativeness of the credit spread curve alone, but provide support for the wake-up call *Hypothesis* 3.

As a robustness check, we reformulated the predictive regressions substituting the first three Principal Components (PCs) of the credit spreads and the U.S. Treasury yields, respectively, for the *level*, *slope* and *curvature* of the country credit spread curve and the global riskless yield curve.[16] The resulting RMSE ratios and significance statistics do not challenge the above findings, and are not reported to preserve space (available upon request).

Domestic macroeconomic indicators. Our final task is to elucidate the marginal OOS predictive ability of the country rating and external sector variables. In the spirit of our hierarchical regression approach, we confront model $GEM1$ with the prior (nested) model $G2$, model $GEM2$ with $GEM1$, and so forth. Table 7 reports the results.

[Insert Table 7 around here]

Consistent with the in-sample predictability findings, the *country rating* stands in contrast with the external sector variables due to its weaker OOS predictive power post-Lehman. The error reduction $(1-RMSE_{GEM1}/RMSE_{G2})$ is 5.0% and 6.2% pre-Lehman versus -3.8% and 1.3% post-Lehman on average across countries for the 5- and 15-year bonds, respectively.

The information content in the *volatility of trade balance* significantly improves the OOS forecasts for short- and long-term maturity bond spreads, especially post-Lehman; the only exception is Philippines. On average across Brazil, Mexico and Turkey, a post-Lehman forecast error reduction $(1 - RMSE_{GEM3}/RMSE_{GEM2} > 0)$ of 8.2% and 11.4% is achieved

[16] At weekly frequency, we extract the PCs of credit spreads on zero-coupon bonds of 3, 4,..., 20 year maturity and yields on U.S. zero-coupon bonds of 1, 2,..., 20 year maturity.

for the 5- and 15-year credit spreads, respectively. Again post-Lehman only, the information content in the *volatility of terms-of-trade growth* improves the accuracy of forecasts ($1 - RMSE_{GEM5}/RMSE_{GEM4} > 0$) for the Brazil short- and long-term bond spreads and the Mexico short-term bond spreads. These distinctive results for Brazil and Mexico are plausible given that both countries are highly reliant on commodity exports.

The absence of evidence on the predictive role of external trade *volatility* indicators for Philippines is not surprising. To begin with, terms-of-trade data is unavailable for Philippines over most of the sample period which precludes the study of the predictive models $GEM4$ and $GEM5$; hence, we cannot draw inferences on the predictive content of the Philippines *volatility of terms-of-trade growth* indicator. According to the Eurobond market size, Philippines is notably smaller than Brazil, Mexico and Turkey.[17] Smaller bond market size is generally associated with higher market frictions such as the cost of trading due to lower trading volumes and lesser liquidity, and also with higher information costs. These sovereign bond market frictions may hinder predictability by obscuring the nexus between the current credit spread and past country's macroeconomic fundamentals.

The level of *trade balance* and *terms-of-trade growth* exhibit also less predictive ability pre- than post-Lehman, consistent with *Hypothesis* 3. However, their overall predictive ability is less remarkable than that of the *volatility* of trade balance and terms-of-trade growth. The forecast error change afforded by the *trade balance* level ($1 - RMSE_{GEM2}/RMSE_{GEM1}$) is either positive but statistically insignificant or negative. The information in the level of *terms-of-trade growth* helps to reduce the forecast error ($1 - RMSE_{GEM4}/RMSE_{GEM3} > 0$) for Brazil and Turkey at about 5.0% altogether but only regarding the 15-year bonds.

[17] Many sovereign emerging Eurobond markets, including new or historically small markets, expanded considerably during 2003-2013. For instance, external financing of new bond issuance measured by the four-year total (in billions US$) tripled or even quadrupled from $40.7, $30.3, and $19.2 in 2000-2003 to $168.9, $119.2, and $53.5 in 2010-2013 for Brazil, Mexico and Turkey, respectively (IMF, 2004, and IMF, 2014). In contrast, Philippines' new issuance expanded only very moderately from $12.9 to $18.0 billion.

Finally, we benchmark the OOS predictions. The results are reported in Table 8.

[Insert Table 8 around here]

During the pre-Lehman period, the extended models with country rating and external sector variables generally fail to outperform the two benchmarks. In sharp contrast, post-Lehman the same models beat the benchmarks. The only exception is the Mexico 5-year credit spread for which the model forecasts fail to beat the random-walk post-Lehman. Further investigation suggests that this anomalous result is to a large extent an artefact of the noise introduced by the irrelevant CR variable (which is statistically insignificant according to Wald tests, as shown in the on-line Addendum Table A1). The parallel benchmarking results for the extended models with domestic macroeconomic predictors ($GEM2$ to $GEM5$) but without the CR as control variable are shown in the on-line Addendum Table A2.[18]

5 Conclusions

This paper provides an entirely new perspective on emerging-market sovereign credit spreads by conducting a comprehensive within-sample and out-of-sample predictability analysis. The investigation is organized around three hypotheses which have implications for policy-makers and bond investors. *Hypothesis* 1 states that the current spread curve is a sufficient statistic to predict future spreads. Building on extant theoretical and empirical contributions, we conjecture that the volatility of global and domestic macroeconomic indicators contains valuable information content about future sovereign credit spreads over and above that conveyed by the current sovereign spread curve (*Hypothesis* 2). Building on the notion of

[18] In line with the in-sample analysis, the OOS predictive findings are robust to the use of the first three Principal Components of credit spreads and U.S. bond yields instead of the corresponding Nelson-Siegel *level*, *slope* and *curvature* factors. Detailed results are available from the authors upon request.

"wake-up calls" in financial markets, *Hypothesis* 3 states that emerging-market sovereign credit spreads became more closely aligned with fundamentals post-Lehman.

To formally test these hypotheses, we estimate dynamic models for Brazil, Mexico, Philippines and Turkey with weekly data over two periods surrounding the Lehman Brothers' bankruptcy. Formal statistical tests of a model's out-of-sample forecast performance are conducted by splitting each of the two periods (pre- and post-Lehman) into an in-sample period, used for the initial parameter estimation, and an out-of-sample period, used to evaluate forecast accuracy. The forecast horizon is one quarter (thirteen weeks) ahead and the out-of-sample forecasts are constructed recursively through expanding estimation windows.

The baseline model that exploits solely the information content in the current credit spread curve is unable to outperform the canonical random walk and slope-regression benchmarks. Successively adding global and country-specific macroeconomic variables produces superior forecasts. This novel finding for emerging market debt refutes *Hypothesis* 1 and aligns well with extant evidence for riskless debt, questioning the assumptions of affine term-structure models. We conclude that the predictability of future bond yields cannot be completely ascribed to information latent in the cross-section of current yields.

Volatility measures that signal uncertainty either about the global economic outlook or the borrower's future ability to repay debt carry useful information content about future emerging-market credit spreads, consistent with *Hypothesis* 2. Uncertainty measures therefore should be of concern to policy-makers and market participants. Overall we also see significantly greater predictive ability of global and country-specific macroeconomic indicators post-Lehman which, consistent with the wake-up call *Hypothesis* 3, suggests that the pricing of emerging market bonds became then more closely aligned with fundamentals.

The out-of-sample predictability perspective on emerging-market credit spreads adopted in this paper, namely, the construction and evaluation of forecasts over future time periods not used in the model parameter estimation, is relevant for various reasons. Empirical evidence based on out-of-sample and in-sample forecast performance is generally considered more trustworthy than evidence based on in-sample performance alone, which can be more sensitive to outliers and data mining. Out-of-sample forecasts also better reflect the information available to the forecaster in "real time". Emerging-market spreads, signifying international borrowing costs, influence domestic business conditions which, in turn, feed into spreads via the default-risk component. A deeper understanding of the real-time predictability of country spreads can help world policy-makers to contain excessive business cycle fluctuations in emerging-market sovereigns and assist investors in financial risk allocation.

Our findings endorse policies aimed at promoting emerging-market stability by keeping the volatility of U.S. monetary policy low. They also promote policies aimed at sustaining long-term growth in emerging economies by stabilizing their net exports and terms-of-trade growth. Such long-term macroeconomic risk management via institutional and policy change is promoted in Gray and Malone (2008). Our findings also endorse the proposition made by Hilscher and Nosbusch (2010), Caballero (2003) and Merton (2005) that sovereign borrowers should consider innovative financial instruments to hedge macroeconomic risk exposures.

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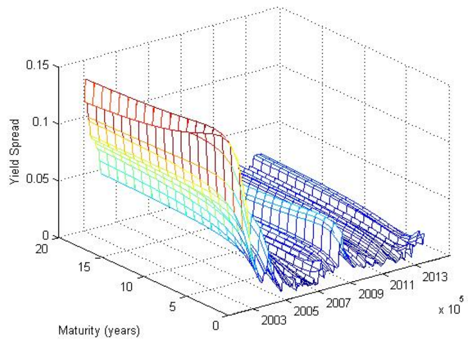
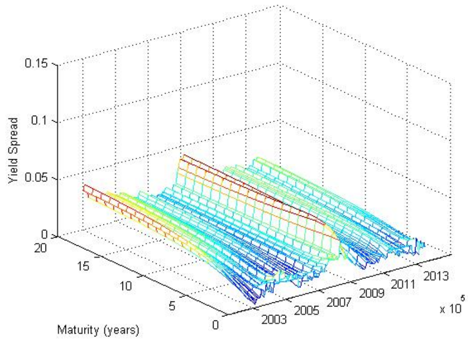
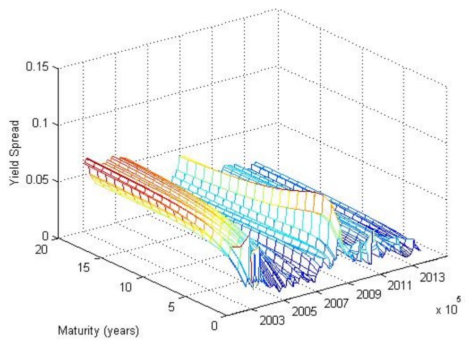


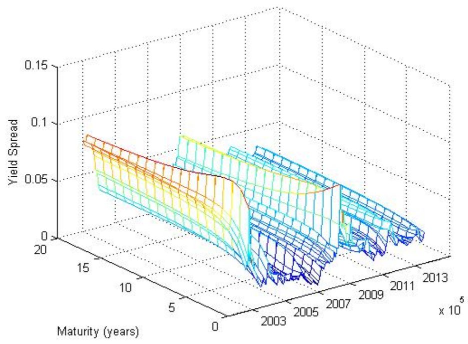
(a) Brazil



(b) Mexico



(c) Philippines



(d) Turkey

FIG.1. Emerging market credit spreads

Each panel plots country credit spread curves estimated at weekly frequency from July 1, 2003 to December 31, 2013 with cross-sections of daily Eurobond prices using the Nelson-Siegel decomposition.

TABLE 1. SUMMARY STATISTICS OF CREDIT SPREADS AND PREDICTIVE VARIABLES

Country Variable	Mean	StDev	Min	Max	AR(1)	Mean	StDev	Min	Max	AR(1)
US	*Panel A: Pre-Lehman*					*Panel B: Post-Lehman*				
$\beta_{f,0}$	0.054	0.005	0.045	0.067	0.978	0.045	0.008	0.029	0.058	0.981
$\beta_{f,1}$	-0.014	0.019	-0.054	0.010	0.994	-0.027	0.015	-0.053	-0.004	0.981
$\beta_{f,2}$	-0.043	0.023	-0.096	-0.006	0.970	-0.091	0.017	-0.139	-0.048	0.942
σ_f^{short}	0.001	0.001	0.000	0.005	0.965	0.000	0.001	0.000	0.004	0.933
Brazil										
s*(5)*	0.028	0.018	0.006	0.080	0.978	0.015	0.008	0.004	0.050	0.939
s(15)	0.036	0.020	0.010	0.096	0.980	0.019	0.007	0.010	0.045	0.938
β_0	0.040	0.022	0.012	0.103	0.980	0.021	0.006	0.012	0.041	0.930
β_1	-0.036	0.025	-0.103	0.017	0.968	-0.014	0.014	-0.041	0.023	0.843
β_2	-0.012	0.032	-0.078	0.090	0.929	-0.010	0.031	-0.107	0.069	0.903
CR	35.951	3.012	29.000	39.500	0.985	39.806	3.247	32.500	45.500	0.972
TB	0.333	0.116	0.055	0.560	0.990	0.079	0.062	-0.112	0.233	0.975
σ_{TB}	0.051	0.017	0.024	0.106	0.980	0.043	0.015	0.021	0.090	0.980
ΔTT	2.393	2.825	-2.834	8.759	0.982	2.793	8.502	-8.580	18.965	0.998
$\sigma_{\Delta TT}$	2.128	0.657	0.969	4.491	0.960	3.277	1.789	0.499	9.054	0.991
Mexico										
s*(5)*	0.010	0.004	0.004	0.020	0.935	0.015	0.007	0.007	0.047	0.933
s(15)	0.017	0.005	0.008	0.031	0.958	0.019	0.006	0.011	0.045	0.923
β_0	0.021	0.006	0.010	0.039	0.958	0.020	0.006	0.013	0.044	0.903
β_1	0.001	0.015	-0.039	0.040	0.848	-0.014	0.011	-0.044	0.008	0.790
β_2	-0.047	0.027	-0.114	0.022	0.852	-0.005	0.020	-0.062	0.063	0.795
CR	40.364	1.750	36.000	42.000	0.985	40.561	1.844	35.500	43.000	0.971
TB	-0.076	0.057	-0.287	0.048	0.964	-0.023	0.061	-0.272	0.085	0.946
σ_{TB}	0.044	0.023	0.010	0.102	0.979	0.052	0.022	0.024	0.131	0.980
ΔTT	3.583	3.487	-3.342	10.567	0.992	-0.117	9.904	-21.839	18.538	0.990
$\sigma_{\Delta TT}$	2.065	0.748	0.909	4.080	0.985	4.788	3.565	0.994	14.547	0.987
Philippines										
s*(5)*	0.026	0.010	0.008	0.045	0.981	0.019	0.011	0.005	0.067	0.947
s(15)	0.035	0.014	0.014	0.058	0.991	0.021	0.008	0.010	0.051	0.947
β_0	0.041	0.017	0.015	0.068	0.991	0.022	0.007	0.010	0.042	0.936
β_1	-0.030	0.026	-0.068	0.064	0.867	-0.007	0.020	-0.042	0.080	0.912
β_2	-0.026	0.036	-0.147	0.058	0.854	-0.006	0.045	-0.151	0.159	0.927
CR	37.535	1.042	36.000	39.000	0.977	42.405	2.208	36.000	45.000	0.978
TB	-0.366	0.191	-0.776	0.039	0.984	-0.275	0.169	-0.585	0.269	0.982
σ_{TB}	0.156	0.061	0.041	0.324	0.985	0.135	0.052	0.077	0.328	0.985
Turkey										
s*(5)*	0.026	0.012	0.011	0.075	0.948	0.026	0.011	0.013	0.073	0.930
s(15)	0.032	0.010	0.020	0.078	0.950	0.028	0.010	0.014	0.062	0.949
β_0	0.035	0.010	0.023	0.079	0.954	0.029	0.009	0.013	0.063	0.952
β_1	-0.026	0.016	-0.079	0.006	0.915	-0.006	0.016	-0.055	0.061	0.747
β_2	-0.011	0.041	-0.113	0.118	0.945	-0.002	0.030	-0.124	0.127	0.757
CR	32.701	0.876	31.000	34.500	0.910	33.363	2.775	27.000	37.000	0.977
TB	-0.774	0.108	-1.065	-0.446	0.978	-0.864	0.239	-1.253	-0.202	0.991
σ_{TB}	0.074	0.030	0.024	0.149	0.985	0.099	0.037	0.042	0.209	0.984
ΔTT	-0.485	3.357	-7.345	5.405	0.994	-0.404	3.976	-8.221	8.399	0.993
$\sigma_{\Delta TT}$	1.869	0.658	0.795	3.391	0.987	2.191	1.309	0.683	5.328	0.993

The table reports mean, standard deviation, minimum, maximum and first-order autocorrelation of credit spreads for 5- and 15-year bonds, and candidate predictors. The *betas* are level, slope and curvature factors of the U.S. yield curve (US) and credit spread curve extracted from daily cross-sections of bond prices sampled at the weekly frequency. σ_f^{short} is the standard deviation of the daily U.S. short-term interest rate over the most recent 10-day period. Monthly macroeconomic data is converted into weekly using linear interpolation. *CR* is country rating. *TB* is trade balance. ΔTT is year-on-year terms of trade growth. σ_{TB} ($\sigma_{\Delta TT}$) is the standard deviation of *TB* (ΔTT) over the most recent 6-month period. The pre-Lehman period is July 1, 2003 to October 14, 2008 (268 weeks) and the post-Lehman period is December 1, 2008 to December 31, 2013 (263 weeks).

TABLE 2. HIERARCHICAL MODELS FOR EMERGING-MARKET SOVEREIGN CREDIT SPREAD PREDICTION

MODELS	PREDICTORS							
	Global predictors			Domestic predictors				
	Credit-spread-curve (Level, Slope, Curvature)	U.S. yield curve factors (Level, Slope, Curvature)	Volatility of U.S. short-term rate	Country risk rating	Trade balance		Terms-of-trade growth	
					Level	Volatility	Level	Volatility
	β_0 β_1 β_2	$\beta_{f,0}$ $\beta_{f,1}$ $\beta_{f,2}$	σ_f^{short}	*CR*	*TB*	σ_{TB}	ΔTT	$\sigma_{\Delta TT}$
Baseline	√							
G1	√	√						
G2	√	√	√					
GEM1	√	√	√	√				
GEM2	√	√	√	√	√			
GEM3	√	√	√	√	√	√		
GEM4	√	√	√	√	√	√	√	
GEM5	√	√	√	√	√	√	√	√

The target variable is the emerging-market sovereign credit spread on week $t+h$ and the predictive variables are the week t measures outlined in columns. The predictive horizon h is 13 weeks (quarter-ahead prediction). The *baseline* model is a regression of spreads on spread curve factors, eq. (4). Models *G1* and *G2* are extensions, eq. (5), obtained by adding the U.S. yield curve factors and the volatility of the US short-term interest rate, respectively. Models *GEM1* to *GEM5* are extensions, eq. (6), obtained by adding country rating, trade balance, volatility of trade balance, terms-of-trade growth, and volatility of terms of trade growth. The credit spread curve factors and U.S. yield curve factors are extracted using the Nelson-Siegel decomposition. The global and country-specific variables are discussed in Sections 3.2 and 3.3, respectively.

TABLE 3. WITHIN-SAMPLE PREDICTIVE ABILITY OF GLOBAL MACROECONOMIC INDICATORS

Model		Brazil		Mexico		Philippines		Turkey	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
		5 years	15 years	5 years	15 years	5 years	15 years	5 years	15 years
Panel A: Pre-Lehman									
Baseline	Adj.R2	0.751	0.841	0.454	0.648	0.736	0.906	0.560	0.588
G1	Adj.R2	0.816	0.864	0.693	0.788	0.853	0.945	0.712	0.668
	Wald stat.	19.45 ***	12.43 ***	89.36 ***	65.58 ***	107.09 ***	61.47 ***	28.87 ***	20.58 ***
G2	Adj.R2	0.842	0.878	0.692	0.792	0.853	0.946	0.741	0.681
	Wald stat.	6.47 **	5.06 **	0.00	2.02	0.22	1.00	5.60 **	3.73 *
Panel B: Post-Lehman									
Baseline	Adj.R2	0.683	0.564	0.684	0.626	0.775	0.675	0.559	0.510
G1	Adj.R2	0.716	0.618	0.720	0.653	0.800	0.783	0.706	0.635
	Wald stat.	8.42 **	16.25 ***	9.33 **	11.28 **	7.88 **	38.06 ***	48.88 ***	31.08 ***
G2	Adj.R2	0.786	0.674	0.770	0.738	0.799	0.794	0.724	0.667
	Wald stat.	54.65 ***	35.67 ***	36.62 ***	61.79 ***	0.20	6.13 **	11.22 ***	20.36 ***

The table reports the adjusted coefficient of determination Adj.R^2 of each model as measure of its in-sample predictive ability, and Wald test statistics for the significance of the predictability gain ΔAdj.R^2 afforded by the global predictors $(\beta_{f0,t}, \beta_{f1,t}, \beta_{f2,t})'$ in model *G1*, and $\sigma_{f,t}^{short}$ in model *G2*; the null hypothesis is that the coefficients of $(\beta_{f0,t}, \beta_{f1,t}, \beta_{f2,t})'$are jointly zero in *G1* model and the coefficient of $\sigma_{f,t}^{short}$ is zero in *G2* model. The *baseline* model, eq. (4), exploits the credit spread factors only. *, ** and *** denote significance of the ΔAdj.R^2 at the 10%, 5% and 1% significance levels, respectively. The estimation period is July 1, 2003 to October 14, 2008 (268 weeks; pre-Lehman) or December 1, 2008 to December 31, 2013 (263 weeks; post-Lehman). See Table 2 for a detailed description of the hierarchical models.

TABLE 4. WITHIN-SAMPLE PREDICTIVE ABILITY OF COUNTRY-SPECIFIC MACROECONOMIC VARIABLES

		Brazil		Mexico		Philippines		Turkey	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
Model		5 years	15 years	5 years	15 years	5 years	15 years	5 years	15 years
				Panel A: Pre-Lehman					
G2	Adj.R2	0.842	0.878	0.692	0.792	0.853	0.946	0.741	0.681
GEM1	Adj.R2	0.870	0.897	0.691	0.804	0.856	0.953	0.741	0.680
	Wald stat.	10.75 ***	10.65 ***	0.14	3.20 *	3.40 *	18.17 ***	0.48	0.04
GEM2	Adj.R2	0.870	0.897	0.693	0.803	0.858	0.953	0.757	0.700
	Wald stat.	0.29	0.69	0.66	0.00	1.74	0.27	6.10 **	5.11 **
GEM3	Adj.R2	0.876	0.897	0.693	0.822	0.861	0.954	0.762	0.727
	Wald stat.	2.99 *	0.20	0.47	11.83 ***	2.78 *	2.89 *	2.30	13.21 ***
GEM4	Adj.R2	0.875	0.899	0.694	0.825			0.788	0.726
	Wald stat.	0.01	1.84	0.93	1.50			13.87 ***	0.16
GEM5	Adj.R2	0.876	0.900	0.694	0.824			0.794	0.735
	Wald stat.	1.06	0.77	0.18	0.08			4.39 **	6.37 **
				Panel B: Post-Lehman					
G2	Adj.R2	0.786	0.674	0.770	0.738	0.799	0.794	0.724	0.667
GEM1	Adj.R2	0.787	0.674	0.775	0.737	0.802	0.798	0.747	0.690
	Wald stat.	0.51	0.19	1.82	0.04	2.44	4.89 **	7.76 ***	7.41 ***
GEM2	Adj.R2	0.791	0.679	0.779	0.736	0.817	0.804	0.793	0.718
	Wald stat.	1.82	1.30	2.33	0.02	9.96 ***	3.41 *	21.64 ***	8.18 ***
GEM3	Adj.R2	0.796	0.695	0.789	0.769	0.827	0.803	0.822	0.744
	Wald stat.	1.73	3.47 *	6.87 ***	15.35 ***	8.27 ***	0.00	17.39 ***	9.99 ***
GEM4	Adj.R2	0.804	0.717	0.791	0.768			0.825	0.757
	Wald stat.	5.21 **	8.87 ***	0.71	0.13			2.07	4.30 **
GEM5	Adj.R2	0.822	0.753	0.793	0.768			0.824	0.758
	Wald stat.	8.36 ***	17.84 ***	1.11	0.06			0.07	0.55

The table reports the adjusted coefficient of determination Adj.R^2 of each model as measure of its in-sample predictive ability, and Wald test statistics for the significance of the predictability gain ΔAdj.R^2 afforded by the country-specific variables; the null hypothesis is that the coefficient of the additional country-specific variable(s) in model GEM_j is zero. Model *G2* includes as predictors the spread curve factors and global variables (U.S. yield curve factors and volatility of the U.S. short-term interest rate). *GEM1* adds country rating, *GEM2* adds trade balance, *GEM3* adds volatility of trade balance, *GEM4* adds terms-of-trade growth, and *GEM5* adds volatility of terms-of-trade growth. *, ** and *** denote significance of the ΔAdj.R^2 at the 10%, 5% and 1% significance levels, respectively. The estimation period is July 1, 2003 to October 14, 2008 (268 weeks; pre-Lehman) or December 1, 2008 to December 31, 2013 (263 weeks; post-Lehman). Table 2 lists the hierarchical models.

TABLE 5. OUT-OF-SAMPLE PREDICTIVE ABILITY OF GLOBAL MACROECONOMIC VARIABLES

Model		Brazil		Mexico		Philippines		Turkey	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
		5-years	15-years	5-years	15-years	5-years	15-years	5-years	15-years
		Panel A: Pre-Lehman							
Baseline	RMSE	59.6	67.3	35.8	29.5	59.4	42.0	40.6	30.9
G1	Ratio RMSE	1.49	1.29	0.76	0.84	0.85	0.80	0.86	0.95
	CW statistic	0.62	0.11	2.54 **	2.72 ***	3.55 ***	4.37 ***	3.19 ***	2.63 ***
G2	Ratio RMSE	0.88	0.92	1.02	0.92	1.07	1.10	1.06	0.90
	CW statistic	1.35 *	1.25	-0.25	1.04	-0.62	-0.53	2.12 **	2.16 **
		Panel B: Post-Lehman							
Baseline	RMSE	33.4	39.8	24.9	26.6	27.50	41.9	48.2	44.3
G1	Ratio RMSE	0.95	0.95	0.82	0.94	0.87	0.71	0.88	0.93
	CW statistic	1.86 **	2.18 **	2.64 ***	2.22 **	2.11 **	2.92 ***	3.71 ***	3.23 ***
G2	Ratio RMSE	0.85	0.95	0.91	0.92	1.01	0.96	0.97	0.95
	CW statistic	3.08 ***	2.22 **	2.82 ***	2.99 ***	-0.94	2.52 ***	1.26	1.81 **

The first row in each panel reports the RMSE of the *baseline* credit spread curve model. The following rows show the ratio of RMSEs of the model at hand and the preceding (nested) model. Ratio RMSE < 1 indicates that the additional global macroeconomic predictors in the extended model bring a forecast error reduction vis-à-vis the preceding model. Significance of the mean error differential is tested with the Clark and West (2007; CW) *t*-statistic for the null hypothesis that the predictive ability of the extended model is not superior to that of the preceding model; $H_0: MSE_{base} \leq MSE_{G1}$ vs. $H_A: MSE_{base} > MSE_{G1}$ for model *G1* and $H_0: MSE_{G1} \leq MSE_{G2}$vs. $H_A: MSE_{G1} > MSE_{G2}$ for model *G2*. ***, ** and * denotes rejection at the 10%, 5% or 1% level, respectively. Model *G1* adds the U.S. yield curve factors. Model *G2* adds the volatility of the U.S. short-term interest rate. Table 2 lists the models. Estimation is based on weekly data and the forecast horizon is *h*=13 weeks (quarter ahead). Bond maturity is $\tau = \{5, 15\}$ years. The forecast evaluation period is November 28, 2006 to October 14, 2008 (92 forecasts; pre-Lehman) and March 27, 2012 to December, 2013 (90 forecasts; post-Lehman).

TABLE 6. BENCHMARKING THE FORECASTING ABILITY OF GLOBAL MACROECONOMIC VARIABLES

Model		Random walk		Slope-regression		Random walk		Slope-regression	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
		5-years	15-years	5-years	15-years	5-years	15-years	5-years	15-years
		Panel A: Pre-Lehman							
		Brazil				Mexico			
Benchmark	RMSE	50.9	48.1	50.9	51.6	40.2	31.6	38.5	30.8
Baseline	Ratio RMSE	1.17	1.40	1.17	1.30	0.89	0.93	0.93	0.96
	DM stat.	-1.28	-2.56	-2.12	-2.91	2.69 ***	1.07	1.41	0.66
G1	Ratio RMSE	1.74	1.80	1.74	1.68	0.67	0.78	0.70	0.80
	DM stat.	-2.07	-2.81	-2.32	-3.13	2.84 ***	1.93 *	3.34 ***	2.53 **
G2	Ratio RMSE	1.53	1.65	1.53	1.54	0.69	0.77	0.72	0.79
	DM stat.	-1.86	-2.90	-2.08	-3.15	2.58 ***	2.09 **	3.04 ***	2.54 **
		Philippines				Turkey			
Benchmark	RMSE	62.2	38.9	59.7	38.4	47.9	34.8	48.0	34.1
Baseline	Ratio RMSE	0.96	1.08	1.00	1.10	0.85	0.89	0.85	0.91
	DM stat.	1.13	-0.73	0.15	-1.00	1.37	0.83	1.12	0.60
G1	Ratio RMSE	0.81	0.87	0.85	0.88	0.73	0.85	0.72	0.87
	DM stat.	2.00 **	1.28	2.21 **	1.24	2.11 **	1.05	2.75 ***	1.00
G2	Ratio RMSE	0.87	0.96	0.91	0.97	0.77	0.76	0.77	0.78
	DM stat.	1.04	0.36	0.91	0.25	2.17 **	1.73 *	1.70 *	1.83 *
		Panel B: Post-Lehman							
		Brazil				Mexico			
Benchmark	RMSE	36.1	44.4	36.3	47.0	26.6	29.0	28.0	32.3
Baseline	Ratio RMSE	0.93	0.90	0.92	0.85	0.93	0.92	0.89	0.82
	DM stat.	0.86	1.16	0.55	1.77 *	1.13	0.96	1.23	2.06 **
G1	Ratio RMSE	0.88	0.86	0.87	0.81	0.77	0.87	0.73	0.78
	DM stat.	0.96	1.44	1.05	2.46 **	1.80 *	1.07	2.54 **	3.48 ***
G2	Ratio RMSE	0.75	0.81	0.74	0.77	0.70	0.79	0.67	0.71
	DM stat.	2.54 **	2.38 **	2.01 **	3.78 ***	2.39 **	1.91 *	2.84 ***	3.76 ***
		Philippines				Turkey			
Benchmark	RMSE	31.9	41.6	38.1	42.0	64.4	58.8	59.5	57.2
Baseline	Ratio RMSE	0.86	1.01	0.72	1.00	0.75	0.75	0.81	0.77
	DM stat.	2.53 **	-0.05	2.38 **	0.03	2.49 **	2.22 **	2.14 **	2.33 **
G1	Ratio RMSE	0.75	0.72	0.62	0.71	0.66	0.70	0.71	0.72
	DM stat.	2.21 **	2.13 **	3.50 ***	2.65 ***	2.69 ***	2.24 **	2.59 ***	2.47 **
G2	Ratio RMSE	0.76	0.68	0.63	0.68	0.64	0.67	0.69	0.69
	DM stat.	2.12 **	2.39 **	3.47 ***	3.01 ***	2.93 ***	2.62 ***	2.86 ***	2.88 ***

The table reports the RMSE of the benchmark (random walk or slope-regression) model and the ratio of RMSEs of the model at hand to the benchmark. Ratio RMSE < 1 indicates that the model brings a forecast error reduction versus the benchmark. Significance of the forecast accuracy gains is assessed with the Diebold and Mariano (1995) *t*-statistic for the null hypothesis of equal mean squared error; $H_0: MSE_{bench} - MSE_m = 0$ vs. $H_A: MSE_{bench} - MSE_m \neq 0$. *, ** and *** denote rejection at the 10%, 5% or 1% level, respectively. The *baseline* model, eq. (4), exploits the credit spread curve factors. Model *G1* adds the U.S. yield curve factors. Model *G2* adds the U.S. short-term interest rate volatility. Table 2 provides details on the models. Estimation is based on weekly data and the forecast horizon is h=13 weeks (quarter-ahead). Bond maturity is $\tau = \{5, 15\}$ years. The forecast evaluation period is November 28, 2006 to October 14, 2008 (92 forecasts; pre-Lehman) and March 27, 2012 to December 31, 2013 (90 forecasts; post-Lehman).

TABLE 7. OUT-OF-SAMPLE PREDICTIVE ABILITY OF DOMESTIC MACROECONOMIC VARIABLES

Model		Brazil		Mexico		Philippines		Turkey	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
		5-years	15-years	5-years	15-years	5-years	15-years	5-years	15-years
					Panel A: Pre-Lehman				
G2	RMSE	77.9	79.5	27.6	24.4	54.1	37.2	37.0	26.6
GEM1	Ratio RMSE	0.81	0.86	1.00	0.95	0.99	0.92	0.99	1.03
	CW statistic	2.57 ***	2.43 ***	-0.12	2.13 **	1.03	2.61 ***	0.93	-1.87
GEM2	Ratio RMSE	1.12	1.08	1.05	1.04	0.99	1.00	1.03	1.10
	CW statistic	-3.93	-2.75	-0.42	-0.48	0.89	-0.15	0.83	0.36
GEM3	Ratio RMSE	0.95	1.01	1.04	1.04	0.98	0.97	1.09	0.93
	CW statistic	2.53 ***	-0.55	-1.66	0.22	1.66 **	1.72 **	-1.77	2.30 **
GEM4	Ratio RMSE	1.01	1.00	1.00	1.00			0.82	1.28
	CW statistic	0.39	1.04	0.47	0.52			3.84 ***	-1.66
GEM5	Ratio RMSE	1.09	1.05	1.00	1.02			1.02	1.02
	CW statistic	-0.69	-0.39	0.15	-1.07			1.32 *	0.52
					Panel B: Post-Lehman				
G2	RMSE	27.0	36.1	18.6	23.0	24.1	28.5	41.2	39.3
GEM1	Ratio RMSE	1.02	1.03	1.09	1.00	0.97	0.97	1.06	1.05
	CW statistic	-0.67	-1.49	-2.39	0.00	2.00 **	2.21 **	1.77 **	1.68 **
GEM2	Ratio RMSE	0.99	0.99	1.07	1.02	1.03	1.01	0.96	0.96
	CW statistic	0.82	0.88	0.02	-1.18	0.19	0.20	1.20	1.16
GEM3	Ratio RMSE	0.98	0.96	0.95	0.83	1.00	1.00	0.82	0.87
	CW statistic	1.40 *	2.03 **	1.69 **	2.71 ***	0.78	-0.27	3.31 ***	2.39 ***
GEM4	Ratio RMSE	1.03	0.95	1.02	1.04			0.99	0.95
	CW statistic	0.37	1.91 **	-0.40	-1.27			1.17	1.91 **
GEM5	Ratio RMSE	0.96	0.94	0.98	1.02			1.03	1.03
	CW statistic	1.49 *	3.11 ***	1.99 **	-2.32			-2.23	-1.62

The first row in each panel reports the RMSE of model *G2* which includes the spread curve factors and global variables (U.S. yield curve factors and U.S. short-term interest rate volatility) as predictors. The following rows report the ratio of RMSEs of the model at hand versus the preceding (nested) model. Ratio RMSE < 1 indicates that the additional country-specific predictor in the extended model brings a forecast error reduction versus the preceding nested model. Significance of the error reduction is assessed with the Clark and West (2007; CW) *t*-test where the null hypothesis is that the predictive ability of the extended model is not superior to that of the preceding nested model; e.g. $H_0{:}\, MSE_{G2} \leq MSE_{GEM1}$ vs. $H_A{:}\, MSE_{G2} > MSE_{GEM1}$ for model *GEM1* and $H_0{:}\, MSE_{GEM1} \leq MSE_{GEM2}$ vs. $H_A{:}\, MSE_{GEM1} > MSE_{GEM2}$ for model *GEM2*. ***, ** and * denote rejection at the 10%, 5% or 1% level, respectively. *GEM1* adds country rating. *GEM2* adds trade balance. *GEM3* further adds volatility of trade balance. *GEM4* adds terms-of-trade growth. *GEM5* adds volatility of terms-of-term growth. Table2 lists all the models. The forecast evaluation period is November 28, 2006 to October 14, 2008 (92 forecasts; pre-Lehman) and March 27, 2012 to December 31, 2013 (90 forecasts; post-Lehman). Models *GEM4* and *GEM5* are not feasible for Philippines due to data unavailability on terms of trade. Estimation is based on weekly data and forecast horizon is *h*=13 weeks (quarter ahead). Bond maturity is $\tau = \{5, 15\}$ years.

TABLE 8. BENCHMARKING THE OOS FORECASTING ABILITY OF DOMESTIC MACRO VARIABLES

Model		Random Walk		Slope Regression		Random Walk		Slope Regression	
		Bond maturity		Bond maturity		Bond maturity		Bond maturity	
		5-years	15-years	5-years	15-years	5-years	15-years	5-years	15-years
				Panel A: Pre-Lehman					
		Brazil				Mexico			
GEM1	Ratio RMSE	1.24	1.42	1.24	1.32	0.69	0.73	0.72	0.75
	DM stat.	-1.21	-2.86	-1.53	-3.34	2.60 ***	2.59 ***	3.03 ***	2.75 ***
GEM2	RMSE Ratio	1.40	1.52	1.40	1.42	0.72	0.76	0.75	0.78
	DM stat.	-2.04	-3.56	-2.66	-4.11	2.33 **	2.25 **	2.81 ***	2.39 **
GEM3	Ratio RMSE	1.33	1.53	1.33	1.43	0.75	0.79	0.78	0.81
	DM stat.	-1.87	-3.52	-2.56	-4.07	2.04 **	2.02 **	2.38 **	2.79 ***
GEM4	Ratio RMSE	1.34	1.54	1.34	1.44	0.75	0.78	0.78	0.81
	DM stat.	-1.87	-3.02	-2.45	-3.38	2.15 **	2.00 **	2.54 **	3.10 ***
GEM5	Ratio RMSE	1.46	1.62	1.46	1.51	0.75	0.80	0.78	0.82 ***
	DM stat.	-2.30	-3.15	-2.68	-3.20	2.07 **	1.81 *	2.39 **	2.65
		Philippines				Turkey			
GEM1	RMSE Ratio	0.86	0.87	0.90	0.89	0.77	0.79	0.77	0.80
	DM stat.	1.15	1.05	1.06	1.01	2.14 **	1.57	1.72 *	1.62
GEM2	Ratio RMSE	0.85	0.88	0.88	0.89	0.79	0.86	0.79	0.88
	DM stat.	1.18	1.00	1.16	0.96	1.69 *	0.91	1.57	0.91
GEM3	Ratio RMSE	0.84	0.85	0.87	0.86	0.87	0.80	0.87	0.82
	DM stat.	1.32	1.24	1.35	1.21	1.06	1.36	1.04	1.79 *
GEM4						0.71	1.03	0.71	1.05
						2.25 **	-0.15	2.01 **	-0.52
GEM5						0.72	1.04	0.72	1.06
						2.16 **	-0.23	2.00 **	-0.51
				Panel B: Post-Lehman					
		Brazil				Mexico			
GEM1	RMSE Ratio	0.76	0.84	0.76	0.79	0.76	0.79	0.7	0.71
	DM stat.	2.63 ***	2.28 **	1.86 *	3.34 ***	2.23 **	1.90 *	2.59 ***	3.80 ***
GEM2	Ratio RMSE	0.75	0.83	0.75	0.78	0.82	0.81	0.8	0.73
	DM stat.	2.78 ***	2.57 **	1.85 *	3.33 ***	1.40	1.75 *	1.83 *	3.54 ***
GEM3	RMSE Ratio	0.74	0.79	0.73	0.75	0.78	0.67	0.7	0.60
	DM stat.	2.88 ***	2.89 ***	1.91 *	3.26 ***	1.59	2.66 ***	1.92 *	3.44 ***
GEM4	Ratio RMSE	0.76	0.75	0.76	0.71	0.80	0.70	0.8	0.63
	DM stat.	2.37 **	2.92 ***	1.72 *	3.32 ***	1.50	2.40 **	1.87 *	3.34 ***
GEM5	Ratio RMSE	0.73	0.71	0.72	0.67	0.78	0.71	0.7	0.64
	DM stat.	2.63 ***	3.12 ***	1.87 *	3.43 ***	1.62	2.32 **	1.95 *	3.28 ***
		Philippines				Turkey			
GEM1	RMSE Ratio	0.73	0.67	0.61	0.66	0.68	0.70	0.74	0.72
	DM stat.	2.37 **	2.52 **	3.69 ***	3.14 ***	2.37 **	2.18 **	2.59 ***	2.84 ***
GEM2	Ratio RMSE	0.76	0.67	0.64	0.66	0.66	0.68	0.71	0.69
	DM stat.	2.19 **	2.51 **	3.82 ***	3.21 ***	2.41 **	2.30 **	2.31 **	2.62 ***
GEM3	RMSE Ratio	0.76	0.67	0.63	0.67	0.54	0.59	0.58	0.60
	DM stat.	2.64 ***	2.53 **	3.68 ***	3.14 ***	2.87 ***	2.63 ***	2.70 ***	2.71 ***
GEM4	Ratio RMSE					0.53	0.56	0.58	0.57
	DM stat.					2.92 ***	2.83 ***	2.72 ***	2.82 ***
GEM5	Ratio RMSE					0.55	0.57	0.59	0.59
	DM stat.					2.88 ***	2.79 ***	2.65 ***	2.73 ***

The table reports the ratio of RMSEs of the model at hand versus the benchmark (random walk or slope-regression model). Significance is assessed through the Diebold and Mariano (1995) t-test for the hypotheses $H_0: MSE_{bench} - MSE_m = 0$ vs. $H_A: MSE_{bench} - MSE_m \neq 0$. *, ** and *** denotes rejection at the 10%, 5% or 1% level, respectively. Estimation is based on weekly data and the forecast horizon is h=13 weeks (quarter ahead). Bond maturity is $\tau = \{5, 15\}$ years. The forecast evaluation period is November 28, 2006 to October 14, 2008 (92 forecasts; pre-Lehman) and March 27, 2012 to December 31, 2013 (90 forecasts; post-Lehman). See note to Table 7 for a description of the models. Table 2 provides the full list of hierarchical models.