Forecasting local currency bond risk premia of emerging markets: The role of cross-country macrofinancial linkages

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ABSTRACT

In this paper, we forecast local currency debt of five major emerging market countries (Brazil, Indonesia, Mexico, South Africa, and Turkey) over the period January 2010 to January 2019 (with an in-sample period: March 2005 to December 2009). We exploit information from a large set of economic and financial time series to assess the importance not only of "own-country" factors (derived from principal component and partial least squares approaches), but also create "global" predictors by combining the country-specific variables across the five emerging economies. We find that, while information on own-country factors can outperform the historical average model, global factors tend to produce not only greater statistical and economic gains, but also enhance market timing ability of investors, especially when we use the target variable (bond premium) approach under the partial least squares method to extract our factors. Our results have important implications not only for fund managers but also for policymakers.

KEYWORDS: bond risk premia, emerging markets, factor extraction methods, out-of-sample forecasting

JEL CLASSIFICATION: C22C53C55G12

1 INTRODUCTION

The data set used in this paper includes a relatively large set of economic indicators, consisting of 97, 87, 121, 114, and 105 economic series for Brazil, Indonesia Mexico, South Africa, and Turkey, respectively. These series are selected to represent a broad range of macroeconomic variables relating to supply-side indicators, such as industrial production indexes, and demand-side indicators, such as electricity consumption and motor vehicle sales. In addition to macroeconomic variables, we also include commonly accepted technical indicators of stock markets, namely the price–earnings ratio, the dividend yield, price to book ratio, etc. All data were downloaded from Bloomberg, and a complete list of variables is available in Tables A1–A5 of the online Appendix (Supporting Information). All variables are subject to preliminary transformations to induce stationarity as needed.

Theoretically, the yield on a long-term nominal government bond can be expressed as the sum of expectations of future short-term rates over the maturity of the bond and a maturity-specific term premium. Since long-term bonds have a greater duration to maturity than short-term debt, investors typically demand a risk premium. In this regard, although a large number of studies have investigated the determinants of bond premia for advanced economies (see; Cepni, Demirer, Gupta, & Pierdzioch, 2019; Cepni, Gupta, & Wohar, 2019; Cochrane & Piazzesi, 2005; Gargano, Pettenuzzo, & Timmermann, 2019; Ghysels, Horan, & Moench, 2018; Laborda & Olmo, 2014; Ludvigson and Ng, 2009, 2011; Zhu, 2015),[1] the corresponding literature on emerging market local currency bonds is scarce, with the existing studies primarily dealing with in-sample predictability (see, e.g., Akgiray, Baronyan, Sener, & Yilmaz, 2016; Cepni, Gul, & Gupta, 2019; Cepni & Güney, 2019; Gadanecz, Miyajima, & Shu, 2018; Miyajima, Mohanty, & Chan, 2015). Miyajima et al. (2015) show that, while resilient to global risk aversion shocks, forecasts of the domestic short-term interest rate, output growth, and the fiscal balance explain a large part of the local currency bond yields of emerging markets. Akgiray et al. (2016) looked at predictability of local currency excess bond returns in the emerging markets of Brazil, Mexico, South Africa, and Turkey. As in Ludvigson and Ng (2009, 2011), using a dynamic factor approach based on a large panel of economic and financial time series, these authors detected strong predictable variation in bond premia derived from macroeconomic activity. Gadanecz et al. (2018), based on a large sample of emerging countries, found that when the volatility and expected depreciation of the exchange rate increased, investors required a larger yield compensation for holding local currency bonds. While Cepni and Güney (2019) highlight the role of credit ratings besides macroeconomic and financial (including exchange rate volatility) variables, Cepni et al. (2019) document the importance of uncertainty related to economic policies in driving local currency bond premia of emerging countries.

Realizing that real-time forecasts are more important for fund managers than information of in-sample predictability (Welch & Goyal, 2008), and also the fact that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors used) is in its out-of-sample performance (Campbell, 2008), we build on the in-sample-based evidence of Akgiray et al. (2016) in several directions when conducting a full-fledged out-of-sample forecasting exercise. First, we not only extract common factors from a large data set using principal component analysis, but we also rely on partial least squares. The latter approach also constructs a set of latent factors from a large set of variables, but unlike principal components analysis it estimates factors that are specifically valuable for forecasting a given target, which in our case is the local currency bond premia of emerging markets. Second, when extracting factors, we not only consider “own-country” variables but also create factors by combining the country-specific variables across the five emerging economies. This resulting set of “Global” predictors, and its global subsets of “Macroeconomic” and “Financial” factors, are used individually to specify new factors, which are then combined with the own-country factor model. Note that the motivation for doing this emanates from the widespread evidence of spillovers (comovements) across sovereign bond markets of emerging countries due to common underlying cross-country factors (Bunda, Hamann, & Lall, 2009; Subramaniam & Prasanna, 2017; Subramaniam, Prasanna, & Bhaduri, 2016). Third, given that forecasts for which conventional prediction error statistics outperform the benchmark models might not result in profitable investment strategies, we employ a directional accuracy test that analyzes market timing ability by constructing the hit ratio with the assumption related to the probability of independence between predictions and realizations. Fourth, since directional predictive ability does not ensure economic significance, we also analyze the economic value of active trading strategies formed on the local currency bond risk premium forecasts by utilizing the setting for a mean–variance investor aiming to optimally allocate wealth across risky and risk-free instruments using a utility-based metric. Finally, as a minor addition to the work of Akgiray et al. (2016), we also include Indonesia in our analysis besides Brazil, Mexico, South Africa, and Turkey, as analyzed by these authors. Note that we select these five major emerging sovereign bond markets by notional amount outstanding.[2] These countries, as pointed out by Akgiray et al. (2016), share three essential features: (a) they belong to the J. P. Morgan Government Bond Index—Emerging Markets (GBI-EM), which is an investable index for emerging market local currency bonds; (b) they have large and liquid local currency bond markets in which search and trading costs are low; and (c) they offer long-term local bonds. Moreover, as of the first quarter of 2019, these five economies comprise 26.7% of the total market size of local currency bonds of (18)[3] emerging markets in the GBI-EM index (Debt Securities Database, Bank of International Settlements), with Mexico (10.3%) leading the pack and followed by Turkey (5.7%), Indonesia (4.7%), Brazil (4.5%), and South Africa (1.5%).

To the best of our knowledge, this is the first paper to incorporate the role of local and global factors in forecasting the local currency bond risk premia of five important emerging countries over the period January 2010 to January 2019 (given the in-sample period of March 2005 to December 2009) from not only a purely statistical perspective but also based on aspects of investment strategies and economic significance. The remainder of the paper is organized as follows: Section 2 discusses the data; Section 3 outlines the econometric methodologies; Section 4 presents the results; and Section 5 concludes the paper.

2 DATA

The data set used in this paper includes a relatively large set of economic indicators, consisting of 97, 87, 121, 114, and 105 economic series for Brazil, Indonesia Mexico, South Africa, and Turkey, respectively. These series are selected to represent a broad range of macroeconomic variables relating to supply-side indicators, such as industrial production indexes, and demand-side indicators, such as electricity consumption and motor vehicle sales. In addition to macroeconomic variables, we also include commonly accepted technical indicators of stock markets, namely the price–earnings ratio, the dividend yield, price to book ratio, etc. All data were downloaded from Bloomberg, and a complete list of variables is available in Tables A1–A5 of the online Appendix (Supporting Information). All variables are subject to preliminary transformations to induce stationarity as needed.

More specifically, the data set covers the period March 2005 to January 2019 and can be classified into seven categories:

- *Housing and order variables*: house price index, completed buildings recorded, and new orders;
- *Labor market variables*: employment, labor participation rate, and unemployment rate;
- *Prices*: producer prices and consumer prices;
- *Financial variables*: interest rates, exchange rates, implied volatility, and stock prices;
- *Money, credit and quantity aggregates*: money supply, mortgage loans, time and sight deposits;
- *Real economic activity*: PMI survey, industrial production, retail sales and consumer confidence;
- *Technical indicators*: price to book ratio, total debt to total assets and dividend payout ratio.

In addition to the above set of macroeconomic and financial indicators, which are used in our construction of local and global factors, we collect monthly observations of 1-year, 2-year, 3-year, 4-year, and 5-year zero coupon bond prices for Brazil, Indonesia, Mexico, South Africa, and Turkey. We follow (Cochrane & Piazzesi, 2005) for the notation of excess bond returns and yields. Let $p_t^{(n)}$ be the log-price of n-year discount bond at time t, then the log-yield is $y_t^{(n)} = \frac{-1}{n} p_t^{(n)}$. We denote the log-holding period return from buying an n-year bond at time t and selling an $n-1$ year bond at time $t+1$ as: $r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$. Finally, the excess returns are computed using the following equation:

$$rx_{t+1}^{(n)} = r_{t+1}^{(n)} - y_t^{(1)}, \tag{1}$$

where $rx_{t+1}^{(n)}$ denotes the continuously compounded excess bond returns on an n-year zero coupon bond in period $t+1$. Put differently, the risk premium on an n-year discount bond over a short-term bond is the difference between the holding returns of the n-year and the 1-year bonds.

3 EMPIRICAL METHODOLOGY

3.1 Extraction of common factors

We estimate the common factors from a large data set of macroeconomic variables to explore the relevance of incorporating richer information sets into the analysis of a local currency bond risk premium. Since using a large set of predictors exacerbates parameter estimation uncertainty, standard least squares or other estimation methods seem to be infeasible given problems like multicollinearity and degrees of freedom. Thus we employ widely used dimensionality reduction techniques, namely principal component analysis and partial least squares.

3.1.1 Principal component analysis (PCA)

PCA is the most popular multivariate statistical method utilized for data reduction and size compression. It aims to extract the important information from a large data set by expressing it as a set of new orthogonal variables called principal components. In this context, the factor representing the highest proportion of the total variation across variables is termed the first principal component, which captures the common movements. Technically, the PCA method identifies the directions in the data with most variation (which are called eigenvectors) by conducting spectral decomposition of the correlation (or covariance) matrix of the data. Let D represent the $p \times p$ correlation matrix to be analyzed. The eigendecomposition of D can be illustrated as follows, in which v_i terms represent eigenvectors (principal components):

$$
\begin{aligned}
D &= V\Lambda V' \sum_{i=1}^{p} \Lambda_i v_i v_i', \\
v_i v_i' &= \delta_{ij}, \\
\Lambda_1 &\geq \Lambda_2 \geq \ \ldots \ \Lambda_p \geq 0.
\end{aligned}
\tag{2}
$$

The widespread use of the PCA method in financial economics and forecasting practices is discussed in Stock and Watson (2002, 2002), Bai and Ng (2002), Diebold and Li (2006), and Ludvigson and Ng (2009), Ludvigson and Ng (2011). Moreover, it is also preferred particularly in regarding stock return predictabilities. Some recent works in the literature show that prediction about excess stock returns can be improved by exploiting the factors obtained from a large set of macroeconomic and financial variables through factor models, as argued by Bai (2010), Neely, Rapach, Tu, and Zhou (2014), and Çakmaklı and van Dijk (2016).

3.1.2 Partial least squares

As discussed by Bai and Ng (2008) and Boivin and Ng (2006), the performance of PCA may be poor in forecasting the target variable when other factors dominate the predictive ability of a target-relevant factor. In static factor models, it might be the case that the included factors do not reflect the most relevant information for the excess bond returns that we want to forecast. In order to overcome this issue, we utilize the partial least squares (PLS) method of Wold (1966). This technique also constructs a set of latent factors from a large set of variables but, unlike the PCA, it estimates factors that are specifically valuable for forecasting a given target. Although Kelly and Pruitt (2015) show that PLS and PCA extract asymptotically similar factors when the data have a strong factor structure, Groen and Kapetanios (2016) demonstrate that PLS outperforms PCA in forecasting the target variable in the presence of a weak factor structure for the predictor variables, for which PCA is known to be inconsistent.

The PLS method is applied by following the two-step procedure explained in Friedman, Hastie, and Tibshirani (2001). The algorithm starts by standardizing each candidate predictor variable x_j $(j = 1, \dots, p)$ to have zero mean and unit variance. Then, univariate regression coefficients $\widehat{\gamma_{1j}} = \langle x_j, y\rangle$ are stored for each j. From this, the first PLS direction $z_1 = \sum_j \widehat{\gamma_{1j}} x_j$ is obtained as the weighted sum of the vector of univariate regression coefficients and original set of predictor variables. Thus the construction of the PLS direction includes the degree of association between excess bond returns and common factors. In the following step, the "target" variable y is regressed on z_1, resulting in a coefficient θ_1, and then all inputs are orthogonalized with respect to z_1. This process is iterated until PLS produces a sequence of $l < p$ orthogonal directions.

Since PLS uses the excess bond returns to construct the directions, its solution path is a nonlinear function of excess bond returns. As stated in Bianchi, Buchner, and Tamoni (2019), it differs from PCA in the sense that, while PCA seeks directions that maximize only the variance, PLS aims for the directions that have high variance and high correlation with the target variable simultaneously. In particular, the m th PLS direction $\widehat{\gamma_m}$ solves the following optimization problem:

$$\begin{aligned} &\max_{\alpha} && \mathrm{corr}^2(y, X_\alpha)\mathrm{var}(X_\alpha), \\ &\text{subject to} && \|\alpha\| = 1, \quad \alpha' S \widehat{\gamma_l} = 0, \quad l = 1, \dots, m-1, \end{aligned} \tag{3}$$

where S represents the sample covariance matrix of x_j.

3.2 Factor-augmented predictive regressions

The approach that we consider in this paper is based on the assumption that the large set of macroeconomic variables available obey a factor structure of the form

$$X_t = \Lambda F_t + \xi_t, \quad \xi_t \sim N(0, \Sigma_e), \tag{4}$$

where F_t is an $n \times 1$ vector of unobserved common factors ($n \leqslant N$) with zero mean and unit variance, which reflects "most" of the comovements in the variables; Λ is a corresponding $n \times 1$ vector of factor loadings; and the idiosyncratic disturbances, ξ_t, are uncorrelated with F_t at all leads and lags, and have a diagonal covariance matrix, Σ_e. Given such estimates of common factors, we consider a factor-augmented predictive regression for excess bond returns of the following form:

$$rx_{t+h}^{(n)} = \mu + \beta' f_t + \varepsilon_{t+h}, \tag{5}$$

where the dimension of f_t is $r \times 1$, with $r \leq n$; μ is an intercept term; β is an $r \times 1$ -dimensional vector of slope parameters; and ε_{t+h} is again an unobserved disturbance term with mean zero. Nevertheless, the excess bond return itself does not need to be dependent on the full set of F_t; it is important to select the number of factors r to be included in predictive regressions. In order to select the number of factors (r) in Equation 5, we search across all combinations, for $r = 1, \ldots, 5$, and choose the model for each country by comparing the out-of-sample performance for all combinations of parameters.[4]

3.3 Forecasting experiment

We carry out two types of experiment. In our first set of experiments, we investigate the forecasting performances of factor-augmented predictive regressions where the factors are constructed using both PCA and PLS methods based on only local or "own-country" variables of a specific country. We label this specification (1) as the "local factor model." Our second set of experiments includes combining the country-specific variables used in our first set of experiments across all five countries. This resulting set of "global" predictors (which includes all variables) is then partitioned into two sets of variables: "macroeconomic" (which includes only macroeconomic variables) and "financial" (which includes only financial variables). These subsets of variables are then used individually to specify new factors that are combined with our local factor model. In particular, we add three new specifications (2–4) as follows:

- *Specification 1*: Local factor model $rx_{t+h}^{(n)} = \mu + \beta' f_t^{\text{Local}} + \varepsilon_{t+h}$
- *Specification 2*: EM macro factor model $rx_{t+h}^{(n)} = \mu + \beta' f_t^{\text{Local}} + \vartheta' f_t^{\text{EM macro}} + \varepsilon_{t+h}$
- *Specification 3*: EM financial factor model $rx_{t+h}^{(n)} = \mu + \beta' f_t^{\text{Local}} + \theta' f_t^{\text{EM financial}} + \varepsilon_{t+h}$
- *Specification 4*: EM global factor model $rx_{t+h}^{(n)} = \mu + \beta' f_t^{\text{Local}} + \delta' f_t^{\text{EM global}} + \varepsilon_{t+h}$

We evaluate the forecasting performance of the above factor-augmented regression models by using a recursive forecasting scheme—that is, by expanding the model estimation sample prior to the construction of each new forecast. The estimation sample starts on March 2005, and our out-of-sample evaluation period is January 2010 to January 2019, with the start of the forecast evaluation corresponding to the turmoil in the global bond markets as a result of the European sovereign debt crisis. For each month, we produce a sequence of six h -month-ahead forecasts; that is, $h = 1$, 2, 3, 6, 9, 12. Finally, we use the mean squared forecast error (MSFE)-adjusted test of Clark and West (2007) to compare forecast performance relative to the random walk (RW) model. While comparison with the RW model is a standard exercise in most forecasting applications, as it allows us to quantify the accuracy gains associated with models that incorporate additional exogenous (own-country) information, evaluation relative to the the specification types 2–4 allows us to quantify the importance of cross-country macrofinancial linkages when forecasting the excess bond returns.

3.4 Market timing

As argued by Leitch and Tanner (1991) and Pesaran and Timmermann (1995), among others, traditional statistical measures might ignore the implications of predictive models in terms of investors. Put differently, forecasts for which conventional prediction error statistics turn out to outperform the benchmark models might not result in profitable investment strategies. To fill this gap, we employ the directional accuracy test of Pesaran and Timmermann (1992). This nonparametric test analyzes the market timing ability by constructing the hit ratio with the assumption related to the probability of independence between predictions and realizations. In this context, the hit ratio can be defined as the share of periods (months), for which the sign of excess bond returns is predicted correctly, in the entire sample period. The null hypothesis of this test is specified as the lack of relationship between the actual and the predicted directional changes. In our case, the null hypothesis is formulated as the nonexistence of market timing ability, and is tested with the empirical hit ratio by examining whether or not the empirical indicator is significantly larger than the expected hit ratio.

Given that $\hat{P}$ and $\hat{P}*$ represent actual and expected hit ratios (under independence assumption), respectively, we can provide the following representations:

$$\hat{P} = \frac{1}{n}\sum_{t=0}^{n-1} I[r_{b,t+1}\hat{r}_{b,t+1}],$$
$$\hat{P}^{*} = \hat{P}_r\hat{P}_{\hat{r}} + (1-\hat{P}_r)(1-\hat{P}_{\hat{r}}), \tag{6}$$

where $I[.]$ is the indicator function, which takes the value one when the multiplication of realized excess bond return ($r_{b,t+1}$) with forecast excess bond return ($\hat{r}_{b,t+1}$) is positive, whereas it takes the value zero otherwise. In a similar manner, expected hit ratio is a function of the proportion of time periods for which actual ($\hat{P}_r = \frac{1}{n}\sum_{t=1}^{n} I[r_{b,t+1}]$) and predicted ($\hat{P}_r = \frac{1}{n}\sum_{t=1}^{n} I[\hat{r}_{b,t+1}]$) local currency bond risk premia are positive. The directional accuracy (DA) statistic can then be formulated as follows:

$$\mathrm{DA} = \frac{\hat{P} - \hat{P}_*}{\sqrt{\hat{V}(\hat{P}) - \hat{V}(\hat{P}_*)}}, \tag{7}$$

where $\hat{V}(\hat{P})$ and $\hat{V}(\hat{P}_*)$ stand for estimates of variances of $\hat{P}$ and $\hat{P}_*$, respectively.

3.5 Economic value analysis

Since directional predictive ability does not ensure economic significance, our methodological framework also incorporates the economic value of active trading strategies formed on the local currency bond risk premium forecasts. To this end, we utilize the setting for a mean–variance investor, who optimally allocates the wealth across a “risky asset” and “risk-free instrument.” In particular, this setting is constructed based on a myopic risk-averse investor with one-period horizon. We develop a utility-based metric to assess the willingness of the investor, in terms of return-based values, for switching from passive investment strategy to an active one, given the informative content of our bond risk premia predictions. The employed procedure is frequently used to determine the economic value of dynamic investment strategies (de Pooter, Martens, & van Dijk, 2008; Fleming, Kirby, & Ostdiek, 2001), and is widely preferred for analyzing the superiority of factor-augmented predictions in the equity risk premia literature (Buncic & Tischhauser, 2017; Çakmaklı & van Dijk, 2016; Campbell & Thompson, 2008; Ferreira & Santa-Clara, 2011; Neely et al., 2014). Economic value analysis also paves the way for the calculation of certainty equivalent return (CER), as well as the incorporation of risk aversion behavior, lack of which is the weakness of many empirical studies.

In general, the mean–variance investor is assumed to maximize the expected utility from his or her ass et allocation decision with the following objective function:

$$\max_{w_{t+1}} U(R_{p,t+1}) = E_t(R_{p,t+1}) - \frac{1}{2}\gamma \ \mathrm{var}_t(R_{p,t+1}), \tag{8}$$

where $R_{p,t+1}$ stands for the return on investor's portfolio. $E_t(R_{p,t+1})$ and $\mathrm{var}_t(R_{p,t+1})$ represent the expected value and the variance of the portfolio return, with respect to time period $t+1$ conditional on the information set available in time period t. Furthermore, γ measures the investor's degree of relative risk aversion. At the end of period t, the investor is assumed to optimally allocate a portion of the funds w_t to a risky asset, which is the local currency sovereign bond, while the remaining part is invested in a risk-free instrument during period $t+1$. Thus the portfolio return can be represented as follows:

$$R_{p,t+1} = r_{f,t+1} + w_{t+1} r_{b,t+1}, \tag{9}$$

where $r_{f,t+1}$ and $r_{b,t+1}$ denote risk-free return and excess bond return, respectively. Assuming that the risk-free rate of return is fixed at the end of period, the solution of the investor to the utility maximization problem yields the following portfolio variance and optimal portfolio weight for long-term bonds as follows:

$$\begin{aligned} \mathrm{var}_t(R_{p,t+1}) &= w_{t+1}^2 \mathrm{var}_t(r_{b,t+1}), \\ w_{t+1}^* &= \frac{1}{\gamma} \frac{E_t(r_{b,t+1})}{\mathrm{var}_t(r_{b,t+1})}. \end{aligned} \tag{10}$$

In this case, the optimal ass et allocation decision is performed by considering the forecast of bond risk premia, and its variance is given the information available up to time t. Hence we assume that the representative investor utilizes recursive excess bond return predictions as an estimate of conditional expected returns. On the other hand, our framework includes several assumptions. First, a 3-year rolling window of past returns is used to estimate the forecast variance of the bond risk premia. Secondly, the portfolio share of the risky asset is constrained with an interval of 0 and 1.5 following (Neely et al., 2014). This assumption is deemed to be realistic given that it not only allows for short-sale, but it also embodies the restriction on the leverage of portfolio with 50% threshold. Lastly, the coefficient of relative risk aversion γ is set to 5.

The CER for the portfolio is then calculated as follows:

$$\mathrm{CER}_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}_p^2, \tag{11}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the sample mean and variance for the portfolio return $R_{p,t+1}$ over the forecast evaluation period. This indicator can be interpreted as the absolute fixed return for which an investor will be willing to abandon the investment in the risky portfolio. In line with this, CER gains can be defined as the difference between the CER indicator calculated for an investor who uses the informative nature of the predictive regression forecasts, and CER for an investor who takes input from the historical average forecasts into consideration for making investment decisions as a benchmark strategy. This difference is multiplied by 1,200 to be interpreted as the annual percentage portfolio management fee that would be paid to use the predictive factor-augmented regression forecasts. Similarly to (Neely et al., 2014), we assume the portfolio transaction cost to be equal to 50 basis points. The following equation determines the change in CER based on the discussion above:

$$\Delta\text{CER}^{\text{factor-augmented}} = 1,200 * (\text{CER}^{\text{factor-augmented}} - \text{CER}^{\text{benchmark}}). \tag{12}$$

4 EMPIRICAL RESULTS

4.1 Out-of-sample forecasting results

Tables 1-5 summarize the results of our experiments, in which we compare the four different specification types that are used for forecasting excess bond returns. Additionally, each of these specification types is estimated using both PCA and PLS. The tables are partitioned vertically into four sets of results for 2-year, 3-year, 4-year, and 5-year excess bond returns across five emerging market economies, respectively. In each of the tables, entries in the first row correspond to MSFEs associated with forecasts constructed using the RW model. All other entries in the tables are MSFEs of the other models relative to the RW model.

The results in Tables 1-5 reveal various interesting observations. First, we observe that MSFE values generally increase with the forecast horizons. Second, virtually all of the entries in Tables 1-5 are less than unity, indicating that the factor-augmented predictive regressions generally produce quite accurate predictions relative to the benchmark RW model. Third, this observation is further supported by the test of Clark and West (2007), noting that entries with "stars" indicate rejection of the null hypothesis of equal predictive accuracy, indicating statistically significant improvements in forecast accuracy compared to the RW model.

Fourth, our results indicate that there are notable decreases in MSFE for a number of countries when "macro" and "global" factors extracted from our pooled data set across the emerging market countries included in the predictive regressions, especially for Brazil, Indonesia, and Mexico. For example, note that in Table 1 (i.e., the case of Brazil) the inclusion of emerging market global factors results in best MSFE models in 10 out of the 24 cases.[0] For Indonesia (see Table 2), the model that includes the emerging market macro factors attains the top rank in 14 out of 24 cases. The predictive power of emerging market macro factors is particularly notable for longer maturity of excess bond returns, and also for longer forecast horizons. Since the risk premia on long-term bonds are subject to more sizable price fluctuations than short-term bonds, investors are more likely to require a higher risk premium for holding long-duration assets. Moreover, this result provides further evidence supporting the main finding of Ludvigson and Ng (2009) on the forecasting power of broad macro factors for excess bond returns. The picture is equally clear for Mexico, in which

Table 1. Out-of-sample forecasting of excess bond returns based on alternative model specifications: Brazil

	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
$rx_{t+1}^{(2)}$						
RW	2.66	2.69	2.73	2.81	2.86	2.88
Local-PCA	0.75***	0.84***	0.90***	1.01***	1.02***	1.03***
EM macro-PCA	**0.66*****	**0.75*****	0.83***	0.96***	1.05***	1.10**
EM financial-PCA	0.70***	0.80***	0.87***	0.98***	1.01***	1.04***
EM global-PCA	0.81***	0.89***	0.96***	1.05***	1.01***	1.01***
Local-PLS	0.82***	0.85***	0.86***	0.86***	0.89***	0.82***
EM macro-PLS	0.79***	0.82***	0.84***	0.83***	0.85***	**0.82*****
EM financial-PLS	0.77***	0.81***	0.83***	0.84***	0.89***	0.88***
EM global-PLS	0.77***	0.79***	**0.82*****	**0.82*****	**0.85*****	0.83***
$rx_{t+1}^{(3)}$						
RW	5.34	5.41	5.47	5.62	5.70	5.71
Local-PCA	0.72***	0.80***	0.86***	0.97***	0.98***	0.97***
EM macro-PCA	**0.60*****	**0.71*****	**0.79*****	0.92***	1.03***	1.14***
EM financial-PCA	0.70***	0.79***	0.86***	0.98***	1.02***	1.04***
EM global-PCA	0.77***	0.85***	0.92 ***	1.00***	0.98***	0.96***
Local-PLS	0.82***	0.85***	0.87***	0.87***	0.87***	0.86***
EM macro-PLS	0.79***	0.82***	0.83***	0.84***	0.86***	0.88***
EM financial-PLS	0.74***	0.78***	0.80***	0.82***	**0.85*****	0.87***
EM global-PLS	0.80***	0.83***	0.80***	**0.76*****	0.86***	**0.85*****
$rx_{t+1}^{(4)}$						
RW	7.67	7.76	7.85	8.06	8.15	8.13
Local-PCA	0.77***	0.84***	0.91***	1.02***	1.03***	1.00***
EM macro-PCA	**0.57*****	**0.67*****	**0.74*****	0.91***	1.07***	1.18***
EM financial-PCA	0.74***	0.83***	0.90***	1.05***	1.11***	1.12***
EM global-PCA	0.80***	0.89***	0.96***	1.06***	1.05***	1.00***
Local-PLS	0.86***	0.88***	0.89***	0.89***	0.88***	0.91**
EM macro-PLS 0.82***	0.85***	0.86***	0.86***	0.87***	0.92**	
EM financial-PLS	0.77***	0.80***	0.82***	0.83***	0.84***	0.90**
EM global-PLS	0.78***	0.81***	0.81***	**0.80*****	**0.82*****	**0.87*****
$rx_{t+1}^{(5)}$						
RW	10.50	10.62	10.73	11.00	11.14	11.10
Local-PCA	0.77***	0.85***	0.93***	1.06***	1.08***	1.05***
EM macro-PCA	**0.55*****	**0.64*****	**0.73*****	0.93***	1.09***	1.16***
EM financial-PCA	0.94***	0.96***	0.99***	1.04	1.05	1.04
EM global-PCA	0.69***	0.79***	0.89***	1.07***	1.15***	1.20***
Local-PLS	0.86***	0.88***	0.89***	0.89***	0.89***	0.93*
EM macro-PLS	0.78***	0.83***	0.85***	0.87***	0.87***	**0.88*****
EM financial-PLS	0.77***	0.80***	0.82***	0.82***	0.85***	0.92**
EM global-PLS	0.78***	0.81***	0.82***	**0.81*****	**0.84*****	0.91***

Note. Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, whereas the rest are relative MSFEs. Hence a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (***1% level; **5% level; *10% level) are significantly superior to the RW model, based on the Clark and West (2007) predictive accuracy test.

Table 2. Out-of-sample forecasting of excess bond returns based on alternative model specifications: Indonesia

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx_{t+1}^{(2)}$						
RW	1.81	1.83	1.84	1.89	1.96	2.01
Local-PCA	1.15	1.13	1.13	1.13	1.12	1.12
EM macro-PCA	1.09	1.08	1.09	1.10	1.10	1.10
EM financial-PCA	0.97***	1.03***	1.09***	1.07***	1.11*	1.13
EM global-PCA	1.06	1.06	1.06	1.07	1.07	1.07
Local-PLS	0.73***	0.75***	0.77***	0.82***	0.92***	1.00**
EM macro-PLS	0.72***	0.75***	0.77***	**0.80*** **	0.91***	1.00***
EM financial-PLS	0.81***	0.86***	0.89***	0.99***	1.13*	1.29
EM global-PLS	**0.71*** **	**0.75*** **	**0.76*** **	0.80***	**0.91*** **	**1.00*** **
$rx_{t+1}^{(3)}$						
RW	3.62	3.65	3.68	3.79	3.94	4.08
Local-PCA	1.16	1.15	1.14	1.12	1.11	1.11
EM macro-PCA	1.12***	1.12***	1.12***	1.10***	1.09**	1.08**
EM financial-PCA	0.98***	1.02***	1.07***	1.07***	1.10**	1.10**
EM global-PCA	**0.69*** **	0.79***	0.90***	1.07***	1.26***	1.23***
Local-PLS	0.73***	**0.76*** **	**0.79*** **	0.86***	0.97***	1.06
EM macro-PLS	0.80***	0.82***	0.85***	**0.86*** **	**0.88*** **	**0.89*** **
EM financial-PLS	0.83***	0.88***	0.93***	1.03***	1.17*	1.31
EM global-PLS	0.80***	0.82***	0.85***	0.86***	0.88***	0.89***
$rx_{t+1}^{(4)}$						
RW	5.38	5.43	5.47	5.64	5.88	6.12
Local-PCA	1.14	1.13	1.13	1.11	1.10	1.09
EM macro-PCA	1.11	1.11	1.11	1.09	1.08	1.07
EM financial-PCA	0.97***	1.01***	1.05***	1.06***	1.08***	1.07***
EM global-PCA	**0.69*** **	0.78***	0.88***	1.09***	1.28***	1.22***
Local-PLS	0.72***	**0.76*** **	**0.78*** **	0.87***	0.98***	1.06*
EM macro-PLS	0.79***	0.81***	0.83***	**0.84*** **	**0.86*** **	**0.87*** **
EM financial-PLS	0.82***	0.87***	0.91***	1.01***	1.14*	1.27
EM global-PLS	0.79***	0.81***	0.83***	0.84***	0.86***	0.87***
$rx_{t+1}^{(5)}$						
RW	6.90	6.97	7.02	7.24	7.57	7.89
Local-PCA	1.15	1.13	1.13	1.11	1.09	1.08
EM macro-PCA	1.12	1.11	1.12	1.09	1.08	1.06
EM financial-PCA	0.97***	1.01***	1.05***	1.07***	1.08***	1.07**
EM global-PCA	1.10	1.10	1.10	1.09	1.08	1.07
Local-PLS	0.89***	0.90***	0.92***	0.91***	0.91***	0.88***
EM macro-PLS	**0.79*** **	**0.81*** **	**0.84*** **	**0.83*** **	**0.86*** **	**0.86*** **
EM financial-PLS	0.80***	0.85***	0.89***	1.00***	1.13**	1.26
EM global-PLS	0.79***	0.81***	0.84***	0.83***	0.86***	0.86***

Note. See note to Table 1.

Table 3. Out-of-sample forecasting of excess bond returns based on alternative model specifications: Mexico

	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
$rx_{t+1}^{(2)}$						
RW	1.07	1.09	1.11	1.18	1.25	1.32
Local-PCA	0.86***	0.90***	0.93***	0.92***	0.81***	0.70***
EM macro-PCA	0.71***	0.72***	0.74***	0.77***	0.79***	0.80***
EM financial-PCA	0.82***	0.87***	0.91***	0.86***	0.76***	0.84***
EM global-PCA	0.77***	0.79***	0.80***	0.83***	0.84***	0.84***
Local-PLS	0.69***	0.70***	0.70***	0.71***	0.70***	0.71***
EM macro-PLS	0.68***	0.69***	0.68***	0.67***	0.64***	0.64***
EM financial-PLS	**0.67*****	**0.68*****	**0.68*****	0.70***	0.69***	0.68***
EM global-PLS	0.68***	0.68***	0.68***	**0.67*****	**0.64*****	**0.64*****
$rx_{t+1}^{(3)}$						
RW	2.00	2.02	2.06	2.20	2.37	2.52
Local-PCA	0.92***	0.96***	1.00***	1.00***	0.91***	0.83***
EM macro-PCA	**0.62*****	**0.65*****	**0.67*****	**0.67*****	**0.63*****	**0.61*****
EM financial-PCA	0.90***	0.98***	1.02***	0.94***	0.74***	0.74***
EM global-PCA	0.73***	0.75***	0.77***	0.80***	0.79***	0.79***
Local-PLS	0.76***	0.75***	0.75***	0.75***	0.73***	0.74***
EM macro-PLS	0.73***	0.72***	0.72***	0.70***	0.66***	0.67***
EM financial-PLS	0.74***	0.75***	0.75***	0.75***	0.70***	0.68***
EM global-PLS	0.69***	0.70***	0.73***	0.70***	0.66***	0.63***
$rx_{t+1}^{(4)}$						
RW	2.63	2.66	2.70	2.90	3.12	3.35
Local-PCA	0.83***	0.88***	0.89***	0.87***	0.93***	1.15***
EM macro-PCA	**0.71*****	0.75***	0.78***	0.79***	0.72***	0.65***
EM financial-PCA	0.90***	0.97***	1.01***	0.97***	0.80***	0.85***
EM global-PCA	0.77***	0.82***	0.86***	0.89***	0.85***	0.81***
Local-PLS	0.77***	0.77***	0.77***	0.76***	0.73***	0.74***
EM macro-PLS	0.74***	0.74***	0.74***	0.71***	0.66***	**0.65*****
EM financial-PLS	0.76***	0.77***	0.77***	0.77***	0.73***	0.74***
EM global-PLS	0.72***	**0.72*****	**0.72*****	**0.69*****	**0.65*****	0.66***
$rx_{t+1}^{(5)}$						
RW	3.35	3.39	3.44	3.67	3.96	4.25
Local-PCA	0.86***	0.92***	0.94***	0.90***	0.87***	1.02***
EM macro-PCA	0.79***	0.85***	0.89***	0.91***	0.82***	**0.71*****
EM financial-PCA	0.98***	0.98***	0.98***	0.98***	0.97***	0.96***
EM global-PCA	0.87***	0.89***	0.89***	0.90***	0.89***	0.89***
Local-PLS	0.80***	0.80***	0.80***	0.79***	0.75***	0.74***
EM macro-PLS	0.73***	0.73***	0.75***	0.74***	0.72***	0.74***
EM financial-PLS	0.83***	0.84***	0.85***	0.84***	0.80***	0.79***
EM global-PLS	**0.71*****	**0.71*****	**0.73*****	**0.70*****	**0.69*****	0.75***

Note. See note to Table 1.

Table 4. Out-of-sample forecasting of excess bond returns based on alternative model specifications: South Africa

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx_{t+1}^{(2)}$						
RW	0.82	0.83	0.83	0.84	0.85	0.86
Local-PCA	**0.72***	**0.76***	**0.79***	0.97***	1.09***	1.16***
EM macro-PCA	0.80***	0.85***	0.89***	1.02***	1.18***	1.34***
EM financial-PCA	0.99***	1.00**	1.00**	1.02*	1.03	1.03
EM global-PCA	1.01***	1.03***	1.03**	1.06	1.08	1.04
Local-PLS	0.95***	0.96***	0.96***	**0.95***	**0.95***	**0.98***
EM macro-PLS	1.03***	1.04***	1.04***	1.01**	1.04*	1.05
EM financial-PLS	1.02**	1.03**	1.03**	1.03**	1.03*	1.09
EM global-PLS	0.91***	0.89***	0.91***	1.02***	0.98***	0.99***
$rx_{t+1}^{(3)}$						
RW	2.05	2.05	2.05	2.06	2.07	2.06
Local-PCA	**0.60***	**0.66***	**0.71***	0.86***	0.94***	1.00***
EM macro-PCA	0.75***	0.80***	0.83***	0.96***	1.08***	1.09***
EM financial-PCA	0.99***	1.00**	1.01**	1.04	1.06	1.06
EM global-PCA	0.99***	1.00***	1.01***	1.07	1.10	1.07
Local-PLS	0.92***	0.94***	0.96***	0.96***	0.93***	**0.99**
EM macro-PLS	0.95***	1.00**	1.02*	1.08*	1.03**	1.05
EM financial-PLS	0.94***	0.96***	0.96***	0.97***	0.98***	1.15**
EM global-PLS	0.89***	0.88***	0.87***	**0.85***	**0.86***	1.00**
$rx_{t+1}^{(4)}$						
RW	3.57	3.57	3.58	3.59	3.61	3.58
Local-PCA	**0.63***	**0.72***	**0.79***	1.01***	1.05***	1.03***
EM macro-PCA	0.69***	0.76***	0.81***	**0.93***	0.99***	**0.97***
EM financial-PCA	0.97***	0.98**	0.99**	1.02	1.04	1.04
EM global-PCA	0.76***	0.83***	0.88***	1.05***	1.12***	1.12***
Local-PLS	0.92***	0.95***	0.98***	0.94***	**0.91***	1.03
EM macro-PLS	1.01***	1.03***	1.02***	1.04***	1.03***	1.09***
EM financial-PLS	1.00**	1.00**	1.00**	1.01**	1.02	1.07
EM global-PLS	0.93***	0.94***	0.94***	0.97***	0.98**	1.10
$rx_{t+1}^{(5)}$						
RW	4.63	4.65	4.68	4.75	4.80	4.77
Local-PCA	0.97***	0.98***	0.98**	1.00*	1.01	1.01
EM macro-PCA	**0.73***	**0.80***	**0.85***	0.96***	1.02***	**1.00***
EM financial-PCA	0.98***	0.99**	1.00**	1.02	1.03	1.03
EM global-PCA	0.85***	0.90***	0.93***	1.05***	1.09***	1.04***
Local-PLS	0.98***	0.99***	0.99**	1.00	1.01	1.01
EM macro-PLS	0.92***	0.97***	0.95***	0.96***	1.02***	1.10***
EM financial-PLS	0.97***	0.98***	0.98***	0.99***	1.01*	1.04
EM global-PLS	0.90***	0.90***	0.90***	**0.92***	**0.94***	1.06

Note. See note to Table 1.

Table 5. Out-of-sample forecasting of excess bond returns based on alternative model specifications: Turkey

	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
$rx_{t+1}^{(2)}$						
RW	2.96	3.00	3.05	3.42	4.29	4.49
Local-PCA	0.76***	0.84***	0.90***	0.92***	0.96***	1.02***
EM macro-PCA	0.88***	0.92***	0.95***	0.97***	0.96***	0.99***
EM financial-PCA	0.83***	0.90***	0.97***	1.00***	1.02***	1.08***
EM global-PCA	0.89***	0.89***	0.90***	0.89***	0.89***	0.93***
Local-PLS	0.58***	0.59***	0.60***	0.58***	0.58***	0.71***
EM macro-PLS	**0.48*****	**0.51*****	**0.53*****	**0.54*****	0.55***	0.68***
EM financial-PLS	0.54***	0.56***	0.57***	0.55***	**0.47*****	**0.62*****
EM global-PLS	0.57***	0.60***	0.61***	0.58***	0.54***	0.68***
$rx_{t+1}^{(3)}$						
RW	4.73	4.79	4.87	5.65	7.59	7.90
Local-PCA	0.84***	0.91***	0.99***	0.97***	1.00***	1.05***
EM macro-PCA	1.03***	1.04***	1.04***	1.01***	0.98***	1.01***
EM financial-PCA	0.88***	0.97***	1.04***	1.07***	1.05***	1.11***
EM global-PCA	1.00***	1.00***	1.00***	0.97***	0.95***	0.98***
Local-PLS	0.59***	0.60***	0.61***	0.57***	0.57***	0.72***
EM macro-PLS	0.57***	0.59***	0.61***	0.60***	0.60***	0.74***
EM financial-PLS	**0.54*****	**0.55*****	**0.56*****	**0.50*****	**0.45*****	**0.60*****
EM global-PLS	0.61***	0.63***	0.65***	0.59***	0.52***	0.70***
$rx_{t+1}^{(4)}$						
RW	6.07	6.15	6.24	7.44	10.27	10.66
Local-PCA	0.94***	1.00***	1.06***	1.02***	1.02***	1.06***
EM macro-PCA	1.10***	1.11***	1.11***	1.05***	1.01***	1.03**
EM financial-PCA	1.09***	1.10***	1.11***	1.11***	1.08***	1.11**
EM global-PCA	1.12***	1.11***	1.11***	1.04***	1.00***	1.03***
Local-PLS	0.59***	0.60***	0.60***	0.56***	0.55***	0.70***
EM macro-PLS	0.60***	0.63***	0.65***	0.63***	0.61***	0.75***
EM financial-PLS	**0.54*****	**0.55*****	**0.54*****	**0.45*****	**0.43*****	**0.58*****
EM global-PLS	0.63***	0.65***	0.67***	0.58***	0.50***	0.70***
$rx_{t+1}^{(5)}$						
RW	7.42	7.52	7.63	9.09	12.75	13.14
Local-PCA	0.98***	1.05***	1.11***	1.06***	1.05***	1.09***
EM macro-PCA	1.11***	1.12***	1.11***	1.06***	1.01***	1.04**
EM financial-PCA	1.07***	1.08***	1.09***	1.09***	1.07***	1.10**
EM global-PCA	1.16***	1.15***	1.14***	1.08***	1.02***	1.05***
Local-PLS	0.58***	0.60***	0.60***	0.55***	0.53***	0.68***
EM macro-PLS	0.61***	0.64***	0.66***	0.63***	0.59***	0.73***
EM financial-PLS	**0.54*****	**0.56*****	**0.57*****	**0.48*****	**0.41*****	**0.59*****
EM global-PLS	0.61***	0.63***	0.64***	0.56***	0.48***	0.69***

Note. See note to Table 1.

emerging market global factors yield substantial predictive gains in 12 out of 24 cases. This implies that global factors contain information about future excess bond returns beyond what is captured by local factors.

Fifth, if one delves more deeply into the findings for South Africa, a different pattern emerges. In particular, note that for South Africa the specification types that include only local factors yield the best MSFEs in 14 out of 24 cases. Thus global information appears to lose its predictive content, relative to local information. Since South Africa's sovereign credit has one of the highest investment ratings[1] among the emerging markets, the share of nonresidents' holding of the country's bonds is 38% as of the last quarter of 2018, according to the Government and Debt Contingent Liabilities database of the South African National Treasury.[2] This result provides evidence that global investors differentiate meaningfully between emerging markets regarding local macroeconomic fundamentals, and do not view the local currency debt markets as a single asset class. On the other hand, emerging market financial factors play a key role in forecasting Turkish excess bond returns. Comparing the various model specifications, we observe that the model embodying local and emerging market financial factors attain the top rank in 20 out of 24 cases. This result is consistent with the argument that the low level of domestic savings and heavy reliance on capital inflows to finance new investment projects in Turkey reflect the importance of financial factors due to the global swings in investor sentiment (Cepni, Güney, & Swanson, 2019).

Lastly, an inspection of Tables 1-5 also reveals that taking into account the specific target when constructing factors improves the out-of-sample forecasting performance of factor-augmented models further. This is because we extract orthogonal PLS factors sequentially, utilizing the remaining covariances of the target and the predictor variables. Since the PCA method uses only the predictor variables ignoring the target to extract common components, there is no guarantee that they are in any way close to the best factors that include valuable information for predicting the excess bond returns.

Overall, our findings suggest that global investors (and policymakers) should consider the cross-country linkages across emerging markets when predicting the excess bond returns. Putting it differently, we have substantial evidence that global emerging market factors have useful predictive content, suggesting that macrofinancial linkages across emerging markets can be accurately modeled using dimension reduction methods. This is in line with the growing integration of emerging markets economies, which is likely to result in transmission of economic shocks via trade and financial linkages.

4.2 Market timing ability

In Tables 6-10, we present the results of the market timing ability analysis for the excess bond return forecasts of all specification types considered. Hit ratios and statistical significance of the directional predictive ability of the competing models are shown for the same out-of-sample period of January 2010 to January 2019. A quick inspection of Tables 6-10 indicates several interesting results. First, the factor-augmented predictive regressions achieve hit ratios of 0.52–0.91%, 0.54–0.85%, 0.61–0.96%, 0.51–0.86%, and 0.38–0.89%, respectively for Brazil, Indonesia, Mexico, South Africa, and Turkey. Second, with a limited number of exceptions, all of the hit ratios of the factor-augmented models are significantly higher than those expected under independence according to the directional accuracy test.

Table 6. Market timing abilities of the monthly excess bond return forecasts: Brazil

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx_{t+1}^{(2)}$						
RW	0.62^{NA}	0.62^{NA}	0.62^{NA}	0.62^{NA}	0.62^{NA}	0.62^{NA}
Local-PCA	0.81^{***}	0.82^{***}	0.80^{***}	0.73^{***}	0.71^{***}	0.67^{***}
EM macro-PCA	0.81^{***}	0.79^{***}	0.79^{***}	0.71^{***}	0.64^{*}	0.61
EM financial-PCA	0.79^{***}	0.73^{***}	0.68^{***}	0.68^{***}	0.67^{***}	0.68^{***}
EM global-PCA	0.86^{***}	0.86^{***}	0.86^{***}	0.84^{***}	0.78^{***}	0.78^{***}
Local-PLS	0.67^{***}	0.67^{***}	0.69^{***}	0.72^{***}	0.75^{***}	0.69^{***}
EM macro-PLS	0.76^{***}	0.76^{***}	0.81^{***}	0.80^{***}	0.81^{***}	0.76^{***}
EM financial-PLS	0.85^{***}	0.82^{***}	0.84^{***}	0.81^{***}	0.74^{***}	0.72^{***}
EM global-PLS	0.76^{***}	0.75^{***}	0.79^{***}	0.79^{***}	0.84^{***}	0.74^{***}
$rx_{t+1}^{(3)}$						
RW	0.64^{NA}	0.64^{NA}	0.64^{NA}	0.64^{NA}	0.64^{NA}	0.64^{NA}
Local-PCA	0.79^{***}	0.78^{***}	0.75^{***}	0.73^{***}	0.69^{***}	0.73^{***}
EM macro-PCA	0.87^{***}	0.84^{***}	0.84^{***}	0.81^{***}	0.79^{***}	0.64^{*}
EM financial-PCA	0.73^{***}	0.69^{***}	0.66^{**}	0.68^{***}	0.67^{***}	0.66^{**}
EM global-PCA	0.86^{***}	0.86^{***}	0.86^{***}	0.85^{***}	0.82^{***}	0.75^{***}
Local-PLS	0.68^{***}	0.68^{***}	0.68^{***}	0.66^{**}	0.71^{***}	0.71^{***}
EM macro-PLS	0.78^{***}	0.78^{***}	0.75^{***}	0.78^{***}	0.74^{***}	0.68^{***}
EM financial-PLS	0.76^{***}	0.78^{***}	0.78^{***}	0.76^{***}	0.72^{***}	0.71^{***}
EM global-PLS	0.78^{***}	0.76^{***}	0.79^{***}	0.79^{***}	0.78^{***}	0.79^{***}
$rx_{t+1}^{(4)}$						
RW	0.67^{NA}	0.67^{NA}	0.67^{NA}	0.67^{NA}	0.68^{NA}	0.68^{NA}
Local-PCA	0.80^{***}	0.79^{***}	0.72^{***}	0.64	0.64	0.62
EM macro-PCA	0.91^{***}	0.91^{***}	0.89^{***}	0.81^{***}	0.69^{***}	0.62
EM financial-PCA	0.73^{***}	0.67^{**}	0.65	0.52	0.58	0.61
EM global-PCA	0.91^{***}	0.85^{***}	0.84^{***}	0.75^{***}	0.74^{***}	0.73^{***}
Local-PLS	0.72^{***}	0.68^{**}	0.69^{**}	0.69^{**}	0.67^{**}	0.71^{**}
EM macro-PLS	0.73^{***}	0.74^{***}	0.71^{***}	0.68^{***}	0.68^{***}	0.67^{**}
EM financial-PLS	0.73	0.71	0.71	0.75	0.74	0.72
EM global-PLS	0.73^{***}	0.72^{***}	0.74^{***}	0.76^{***}	0.78^{***}	0.73^{***}
$rx_{t+1}^{(5)}$						
RW	0.67^{NA}	0.67^{NA}	0.67^{NA}	0.67^{NA}	0.67^{NA}	0.67^{NA}
Local-PCA	0.81^{***}	0.76^{***}	0.74^{***}	0.66	0.61	0.61
EM macro-PCA	0.89^{***}	0.87^{***}	0.85^{***}	0.79^{***}	0.64^{**}	0.61
EM financial-PCA	0.61	0.59	0.58	0.58	0.54	0.55
EM global-PCA	0.81^{***}	0.74^{***}	0.73^{***}	0.69^{***}	0.72^{***}	0.69^{***}
Local-PLS	0.71^{***}	0.69^{**}	0.67^{*}	0.66	0.64	0.66
EM macro-PLS	0.76^{***}	0.72^{***}	0.68^{***}	0.68^{***}	0.66^{**}	0.67^{***}
EM financial-PLS	0.71^{***}	0.72^{***}	0.66^{***}	0.74^{***}	0.68^{**}	0.68^{**}
EM global-PLS	0.73^{***}	0.72^{***}	0.74^{***}	0.73^{***}	0.71^{***}	0.67^{**}

Note. The table presents the market timing abilities of the different model specifications that are defined in Section 3.3. Entries are the proportions of signs predicted correctly. Entries superscripted with an asterisk (***1% level; **5% level; *1% level) have significantly superior market timing ability compared to the benchmark RW model, based on the directional accuracy test of Pesaran and Timmermann (1992) as defined in Equation 7. NA indicates that the test could not be computed.

Table 7. Market timing abilities of the monthly excess bond return forecasts: Indonesia

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx^{(2)}_{t+1}$						
RW	0.75^{NA}	0.75^{NA}	0.75^{NA}	0.75^{NA}	0.73^{NA}	0.69^{NA}
Local-PCA	0.72	0.73	0.74	0.75	0.73	0.69
EM macro-PCA	0.72	0.73	0.73	0.75	0.73	0.69
EM financial-PCA	0.72	0.71	0.71	0.69	0.68	0.67
EM global-PCA	0.72	0.73	0.74	0.75	0.73	0.69
Local-PLS	0.81***	0.79***	0.79***	0.81***	0.74**	0.68
EM macro-PLS	0.80***	0.78***	0.80***	0.81***	0.74***	0.71**
EM financial-PLS	0.79***	0.78***	0.75***	0.72	0.72	0.69
EM global-PLS	0.82***	0.80***	0.79***	0.82***	0.75***	0.68
$rx^{(3)}_{t+1}$						
RW	0.73^{NA}	0.73^{NA}	0.73^{NA}	0.72^{NA}	0.68^{NA}	0.65^{NA}
Local-PCA	0.69	0.69	0.71	0.71	0.68	0.65
EM macro-PCA	0.69	0.68	0.68	0.58	0.55	0.55
EM financial-PCA	0.69	0.68	0.68	0.58	0.55	0.55
EM global-PCA	0.82***	0.81***	0.81***	0.81***	0.81***	0.80***
Local-PLS	0.84***	0.84***	0.82***	0.78***	0.71**	0.66
EM macro-PLS	0.79***	0.78***	0.76***	0.75***	0.69**	0.66*
EM financial-PLS	0.79***	0.76***	0.73**	0.66	0.66	0.64
EM global-PLS	0.79***	0.78***	0.76***	0.76***	0.68*	0.66*
$rx^{(4)}_{t+1}$						
RW	0.72^{NA}	0.72^{NA}	0.72^{NA}	0.69^{NA}	0.66^{NA}	0.62^{NA}
Local-PCA	0.68	0.68	0.69	0.68	0.66	0.62
EM macro-PCA	0.67	0.68	0.68	0.68	0.66	0.62
EM financial-PCA	0.68	0.67	0.64	0.54	0.54	0.59
EM global-PCA	0.81***	0.82***	0.82***	0.79***	0.79***	0.78***
Local-PLS	0.85***	0.84***	0.82***	0.78***	0.69**	0.65*
EM macro-PLS	0.79***	0.79***	0.76***	0.74***	0.65	0.65**
EM financial-PLS	0.78***	0.78***	0.74***	0.67	0.71***	0.64*
EM global-PLS	0.79***	0.79***	0.76***	0.74***	0.65	0.65**
$rx^{(5)}_{t+1}$						
RW	0.72^{NA}	0.72^{NA}	0.72^{NA}	0.69^{NA}	0.66^{NA}	0.62^{NA}
Local-PCA	0.67	0.68	0.68	0.68	0.66	0.62
EM macro-PCA	0.67	0.67	0.68	0.67	0.64	0.62
EM financial-PCA	0.71	0.69	0.66	0.58	0.54	0.60
EM global-PCA	0.67	0.68	0.69	0.68	0.66	0.62
Local-PLS	0.74**	0.72	0.74**	0.71*	0.66	0.65*
EM macro-PLS	0.76***	0.75***	0.78***	0.75***	0.66**	0.66**
EM financial-PLS	0.84***	0.78***	0.76***	0.69**	0.69**	0.62
EM global-PLS	0.78***	0.75***	0.78***	0.75***	0.66**	0.67***

Note. See note to Table 6.

Table 8. Market timing abilities of the monthly excess bond return forecasts: Mexico

	$h = 1$	$h = 2$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
$rx_{t+1}^{(2)}$						
RW	0.79^{NA}	0.78^{NA}	0.76^{NA}	0.73^{NA}	0.69^{NA}	0.66^{NA}
Local-PCA	0.84^{***}	0.84^{***}	0.84^{***}	0.84^{***}	0.86^{***}	0.88^{***}
EM macro-PCA	0.93^{***}	0.87^{***}	0.81^{***}	0.78^{***}	0.68	0.61
EM financial-PCA	0.88^{***}	0.88^{***}	0.86^{***}	0.86^{***}	0.86^{***}	0.79^{***}
EM global-PCA	0.84^{***}	0.81^{***}	0.82^{***}	0.78^{***}	0.71^{*}	0.66
Local-PLS	0.92^{***}	0.92^{***}	0.93^{***}	0.92^{***}	0.92^{***}	0.91^{***}
EM macro-PLS	0.88^{***}	0.88^{***}	0.88^{***}	0.88^{***}	0.88^{***}	0.87^{***}
EM financial-PLS	0.93^{***}	0.94^{***}	0.94^{***}	0.93^{***}	0.92^{***}	0.91^{***}
EM global-PLS	0.88^{***}	0.88^{***}	0.88^{***}	0.88^{***}	0.88^{***}	0.87^{***}
$rx_{t+1}^{(3)}$						
RW	0.80^{NA}	0.79^{NA}	0.78^{NA}	0.74^{NA}	0.71^{NA}	0.67^{NA}
Local-PCA	0.87^{***}	0.86^{***}	0.86^{***}	0.85^{***}	0.82^{***}	0.79^{***}
EM macro-PCA	0.96^{***}	0.96^{***}	0.95^{***}	0.89^{***}	0.85^{***}	0.79^{***}
EM financial-PCA	0.87^{***}	0.88^{***}	0.86^{***}	0.86^{***}	0.86^{***}	0.84^{***}
EM global-PCA	0.86^{***}	0.85^{***}	0.85^{***}	0.82^{***}	0.81^{***}	0.79^{***}
Local-PLS	0.94^{***}	0.94^{***}	0.95^{***}	0.94^{***}	0.93^{***}	0.92^{***}
EM macro-PLS	0.92^{***}	0.92^{***}	0.92^{***}	0.93^{***}	0.91^{***}	0.91^{***}
EM financial-PLS	0.96^{***}	0.95^{***}	0.93^{***}	0.91^{***}	0.91^{***}	0.89^{***}
EM global-PLS	0.92^{***}	0.91^{***}	0.91^{***}	0.91^{***}	0.91^{***}	0.87^{***}
$rx_{t+1}^{(4)}$						
RW	0.82^{NA}	0.81^{NA}	0.80^{NA}	0.76^{NA}	0.73^{NA}	0.69^{NA}
Local-PCA	0.75^{**}	0.74^{**}	0.73^{**}	0.73^{**}	0.72^{**}	0.76^{***}
EM macro-PCA	0.95^{***}	0.95^{***}	0.95^{***}	0.89^{***}	0.86^{***}	0.84^{***}
EM financial-PCA	0.81^{***}	0.81^{***}	0.81^{***}	0.81^{***}	0.84^{***}	0.80^{***}
EM global-PCA	0.89^{***}	0.86^{***}	0.86^{***}	0.85^{***}	0.82^{***}	0.82^{***}
Local-PLS	0.92^{***}	0.93^{***}	0.94^{***}	0.94^{***}	0.94^{***}	0.94^{***}
EM macro-PLS	0.92^{***}	0.91^{***}	0.92^{***}	0.92^{***}	0.92^{***}	0.91^{***}
EM financial-PLS	0.95^{***}	0.95^{***}	0.96^{***}	0.96^{***}	0.96^{***}	0.95^{***}
EM global-PLS	0.92^{***}	0.92^{***}	0.92^{***}	0.92^{***}	0.92^{***}	0.91^{***}
$rx_{t+1}^{(5)}$						
RW	0.77^{NA}	0.76^{NA}	0.75^{NA}	0.71^{NA}	0.68^{NA}	0.64^{NA}
Local-PCA	0.73^{**}	0.71^{*}	0.71^{**}	0.75^{***}	0.74^{***}	0.74^{***}
EM macro-PCA	0.92^{***}	0.92^{***}	0.87^{***}	0.84^{***}	0.81^{***}	0.81^{***}
EM financial-PCA	0.78^{NA}	0.76^{NA}	0.75^{NA}	0.72^{NA}	0.68^{NA}	0.65^{NA}
EM global-PCA	0.78^{NA}	0.76^{NA}	0.75^{NA}	0.72^{NA}	0.68^{NA}	0.65^{NA}
Local-PLS	0.95^{***}	0.95^{***}	0.95^{***}	0.93^{***}	0.92^{***}	0.91^{***}
EM macro-PLS	0.87^{***}	0.87^{***}	0.87^{***}	0.87^{***}	0.88^{***}	0.89^{***}
EM financial-PLS	0.92^{***}	0.92^{***}	0.92^{***}	0.91^{***}	0.91^{***}	0.89^{***}
EM global-PLS	0.89^{***}	0.88^{***}	0.88^{***}	0.89^{***}	0.88^{***}	0.88^{***}

Note. See note to Table 6.

Table 9. Market timing abilities of the monthly excess bond return forecasts: South Africa

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx^{(2)}_{t+1}$						
RW	0.80^{NA}	0.80^{NA}	0.80^{NA}	0.79^{NA}	0.76^{NA}	0.76^{NA}
Local-PCA	0.85^{***}	0.80^{*}	0.79^{*}	0.78^{***}	0.71	0.72
EM macro-PCA	0.84^{***}	0.80^{***}	0.78^{***}	0.79^{***}	0.73^{**}	0.67
EM financial-PCA	0.80	0.80	0.80	0.79	0.76	0.76
EM global-PCA	0.80	0.80	0.80	0.79	0.76	0.76
Local-PLS	0.69	0.69	0.69	0.72	0.72	0.71
EM macro-PLS	0.74	0.75	0.74	0.79^{*}	0.72	0.68
EM financial-PLS	0.78	0.78	0.79	0.76	0.74	0.72
EM global-PLS	0.73^{*}	0.74^{**}	0.74^{**}	0.76^{***}	0.75^{***}	0.75^{**}
$rx^{(3)}_{t+1}$						
RW	0.78^{NA}	0.78^{NA}	0.78^{NA}	0.76^{NA}	0.74^{NA}	0.74^{NA}
Local-PCA	0.82^{***}	0.82^{***}	0.82^{***}	0.73^{***}	0.73^{**}	0.74^{**}
EM macro-PCA	0.80^{***}	0.80^{***}	0.79^{***}	0.72^{***}	0.71^{**}	0.72^{***}
EM financial-PCA	0.78	0.78	0.78	0.76	0.74	0.74
EM global-PCA	0.76	0.78	0.78	0.76	0.73	0.74
Local-PLS	0.79^{***}	0.76^{***}	0.75^{**}	0.71	0.71^{*}	0.66
EM macro-PLS	0.76^{***}	0.72^{**}	0.72^{**}	0.65	0.68	0.68^{**}
EM financial-PLS	0.86^{***}	0.85^{***}	0.86^{***}	0.85^{***}	0.82^{***}	0.73^{***}
EM global-PLS	0.82^{***}	0.80^{***}	0.80^{***}	0.84^{***}	0.80^{***}	0.72^{**}
$rx^{(4)}_{t+1}$						
RW	0.75^{NA}	0.75^{NA}	0.75^{NA}	0.73^{NA}	0.71^{NA}	0.71^{NA}
Local-PCA	0.82^{***}	0.81^{***}	0.81^{***}	0.66	0.61	0.61
EM macro-PCA	0.79^{***}	0.79^{***}	0.75^{***}	0.69	0.65	0.69^{*}
EM financial-PCA	0.75	0.75	0.75	0.73	0.71	0.71
EM global-PCA	0.78^{***}	0.76^{***}	0.75^{**}	0.67	0.61	0.65
Local-PLS	0.74^{**}	0.75^{***}	0.69	0.71^{**}	0.73^{***}	0.60
EM macro-PLS	0.73^{***}	0.69^{***}	0.69^{***}	0.73^{***}	0.69^{***}	0.68^{**}
EM financial-PLS	0.69	0.69	0.68	0.69	0.68	0.65
EM global-PLS	0.69^{**}	0.71^{***}	0.74^{***}	0.64^{*}	0.56	0.48
$rx^{(5)}_{t+1}$						
RW	0.68	0.68	0.68	0.69	0.71^{***}	0.65
Local-PCA	0.73^{NA}	0.73^{NA}	0.73^{NA}	0.71^{NA}	0.67^{NA}	0.67^{NA}
EM macro-PCA	0.80^{***}	0.78^{***}	0.74^{***}	0.68	0.64	0.69^{**}
EM financial-PCA	0.73	0.73	0.73	0.69	0.64	0.64
EM global-PCA	0.72^{***}	0.71^{**}	0.68^{**}	0.56	0.52	0.56
Local-PLS	0.61	0.58	0.56	0.54	0.48	0.51
EM macro-PLS	0.73^{***}	0.72^{***}	0.72^{***}	0.74^{***}	0.72^{***}	0.65
EM financial-PLS	0.64	0.62	0.61	0.61	0.62	0.59
EM global-PLS	0.73^{***}	0.75^{***}	0.74^{***}	0.68^{**}	0.65^{**}	0.51

Note. See note to Table 6.

Table 10. Market timing abilities of the monthly excess bond return forecasts: Turkey

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
$rx_{t+1}^{(2)}$						
RW	0.47^{NA}	0.46^{NA}	0.45^{NA}	0.41^{NA}	0.38^{NA}	0.36^{NA}
Local-PCA	0.66^{***}	0.62^{***}	0.61^{***}	0.60^{***}	0.58^{***}	0.56^{***}
EM macro-PCA	0.67^{***}	0.66^{***}	0.62^{***}	0.56^{*}	0.54^{*}	0.52
EM financial-PCA	0.66^{***}	0.64^{***}	0.61^{**}	0.59^{*}	0.54	0.52
EM global-PCA	0.53	0.52	0.51	0.42	0.44	0.42
Local-PLS	0.78^{***}	0.78^{***}	0.79^{***}	0.73^{***}	0.74^{***}	0.65^{***}
EM macro-PLS	0.87^{***}	0.82^{***}	0.78^{***}	0.82^{***}	0.76^{***}	0.73^{***}
EM financial-PLS	0.79^{***}	0.75^{***}	0.74^{***}	0.74^{***}	0.78^{***}	0.74^{***}
EM global-PLS	0.80^{***}	0.78^{***}	0.76^{***}	0.75^{***}	0.74^{***}	0.66^{***}
$rx_{t+1}^{(3)}$						
RW	0.47^{NA}	0.46^{NA}	0.45^{NA}	0.41^{NA}	0.38^{NA}	0.36^{NA}
Local-PCA	0.69^{***}	0.65^{***}	0.60^{**}	0.61^{***}	0.60^{***}	0.60^{***}
EM macro-PCA	0.51	0.48	0.46	0.41	0.40	0.40
EM financial-PCA	0.68^{***}	0.62^{**}	0.61^{**}	0.60^{**}	0.54	0.53
EM global-PCA	0.49	0.48	0.46	0.42	0.41	0.41
Local-PLS	0.81^{***}	0.82^{***}	0.82^{***}	0.76^{***}	0.73^{***}	0.65^{***}
EM macro-PLS	0.85^{***}	0.84^{***}	0.81^{***}	0.79^{***}	0.75^{***}	0.69^{***}
EM financial-PLS	0.79^{***}	0.76^{***}	0.76^{***}	0.78^{***}	0.79^{***}	0.73^{***}
EM global-PLS	0.82^{***}	0.80^{***}	0.80^{***}	0.76^{***}	0.73^{***}	0.66^{***}
$rx_{t+1}^{(4)}$						
RW	0.48^{NA}	0.47^{NA}	0.46^{NA}	0.42^{NA}	0.40^{NA}	0.39^{NA}
Local-PCA	0.72^{***}	0.67^{***}	0.66^{***}	0.66^{***}	0.67^{***}	0.65^{***}
EM macro-PCA	0.44	0.44	0.46	0.38	0.39	0.39
EM financial-PCA	0.58^{*}	0.56^{*}	0.54	0.56^{**}	0.53^{**}	0.52^{**}
EM global-PCA	0.52	0.49	0.48	0.45	0.44	0.41
Local-PLS	0.86^{***}	0.87^{***}	0.85^{***}	0.81^{***}	0.75^{***}	0.68^{***}
EM macro-PLS	0.89^{***}	0.88^{***}	0.86^{***}	0.85^{***}	0.78^{***}	0.75^{***}
EM financial-PLS	0.85^{***}	0.84^{***}	0.80^{***}	0.84^{***}	0.79^{***}	0.74^{***}
EM global-PLS	0.82^{***}	0.82^{***}	0.81^{***}	0.78^{***}	0.75^{***}	0.65^{***}
$rx_{t+1}^{(5)}$						
RW	0.47^{NA}	0.46^{NA}	0.45^{NA}	0.41^{NA}	0.39^{NA}	0.39^{NA}
Local-PCA	0.68^{***}	0.67^{***}	0.67^{***}	0.66^{***}	0.64^{***}	0.69^{***}
EM macro-PCA	0.52	0.49	0.46	0.41	0.44	0.42
EM financial-PCA	0.62^{***}	0.62^{***}	0.61^{***}	0.56^{**}	0.56^{***}	0.54^{***}
EM global-PCA	0.53	0.53	0.53	0.48	0.47	0.44
Local-PLS	0.82^{***}	0.82^{***}	0.82^{***}	0.81^{***}	0.78^{***}	0.75^{***}
EM macro-PLS	0.87^{***}	0.85^{***}	0.85^{***}	0.84^{***}	0.79^{***}	0.78^{***}
EM financial-PLS	0.82^{***}	0.80^{***}	0.78^{***}	0.81^{***}	0.76^{***}	0.76^{***}
EM global-PLS	0.84^{***}	0.82^{***}	0.82^{***}	0.80^{***}	0.75^{***}	0.67^{***}

Note. See note to Table 6.

Third, in general, the market timing ability of the factor-augmented models seems to be fairly stable over time, as the hit ratios for short- and long-forecast horizons are quite similar for short-term excess bond returns. However, the directional accuracy (DA) results show that the significance of the market timing ability diminishes slightly for the forecast horizons longer than 6 months ahead. Fourth, including emerging market macro, financial, and global factors in the predictive regressions lead to improved market timing ability. This suggests that the factors extracted from pooled data sets across emerging markets contain additional information that is of relevance to market timing, relative to the historical mean benchmark and local factor model. Specifically, we see that the hit ratios of models that include emerging market factors improve more than 90% in the case of Brazil and Mexico. This confirms the superior ability of these models compared to the lack of market timing ability of the historical mean return. However, it is important to state that evaluating the hit ratios of the RW model is somewhat odd and the DA test results confirm this. In particular, the DA statistic cannot be even computed for all predictions of the RW model, indicating that the RW model does not have any market timing ability. The reason is that only a small percentage of excess bond return forecasts from the RW model is negative, and hence it is always optimal to invest in long-term bonds without trying to time the market.

Fifth, in essence, the market timing ability is enhanced by taking into account the specific target when constructing factors. Comparing the hit ratios and level of significance, it is seen that the performance of the specification types that use the PLS approach for extracting the factors is better than that of the PCA, especially for Indonesia, Mexico, and Turkey.

4.3 Assessing the economic value

In the previous section we investigated the market timing ability of the factor-augmented predictive regressions using hit ratios. Although hit ratios provide some indication of model performance, as discussed, the superior market timing ability does not necessarily imply that investment strategies based on the excess return forecasts will be profitable. In order to assess the economic value explicitly, we compute the certainty equivalent return for a mean–variance investor who uses excess return forecasts to decide on weights of ass et allocation.

Tables 11 and 12 report averages of Sharpe ratios and utility gain (annual percentage portfolio management) for all maturities across emerging markets for h-step-ahead forecasts, where $h = 1$, 2, 3, 6, 9, 12.[2] From the results in Table 11, we can say that ass et allocation strategies based on the factor-augmented predictive regressions outperform those of the random walk model, with a few exceptions. This conclusion holds regardless of the forecast horizon. For instance, the portfolios based on the factor-augmented regressions achieve annualized Sharpe ratios in the range 0.44–0.97, compared to 0.22–0.52 for the benchmark model for Mexico. On the other hand, Sharpe ratios are based on portfolios constructed from the local-PCA and EM macro-PCA factor models are noticeably smaller when compared to the benchmark model for Indonesia. This lower result in terms of Sharpe ratios is due to the overall weaker out-of-sample forecast performance of PCA-based factor models in Indonesia. In general, the average of Sharpe ratios decreases with the forecast horizons. The reduction in Sharpe ratios is slightly less dramatic for PLS-based factor models. This confirms that the forecasts of PLS-based factor models are more stable compared to those of the PCA-based factor-augmented models.

Table 11. Performance of active trading strategies: Sharpe ratios

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
Brazil						
RW	0.19	0.20	0.22	0.29	0.37	0.44
Local-PCA	0.70	0.69	0.69	0.68	0.67	0.59
EM macro-PCA	0.70	0.69	0.69	0.64	0.57	0.46
EM financial-PCA	0.58	0.55	0.54	0.48	0.45	0.40
EM global-PCA	0.68	0.67	0.68	0.72	0.71	0.61
Local-PLS	0.54	0.54	0.53	0.52	0.48	0.43
EM macro-PLS	0.55	0.54	0.53	0.52	0.50	0.47
EM financial-PLS	0.58	0.58	0.58	0.56	0.53	0.53
EM global-PLS	0.56	0.55	0.55	0.55	0.55	0.51
Indonesia						
RW	0.41	0.42	0.44	0.44	0.38	0.32
Local-PCA	0.29	0.29	0.29	0.27	0.23	0.20
EM macro-PCA	0.36	0.34	0.33	0.29	0.24	0.21
EM financial-PCA	0.51	0.45	0.40	0.30	0.25	0.22
EM global-PCA	0.56	0.56	0.56	0.60	0.54	0.48
Local-PLS	0.67	0.67	0.67	0.63	0.47	0.34
EM macro-PLS	0.58	0.58	0.59	0.57	0.47	0.38
EM financial-PLS	0.71	0.70	0.70	0.60	0.44	0.30
EM global-PLS	0.58	0.59	0.60	0.57	0.47	0.37
Mexico						
RW	0.52	0.51	0.49	0.41	0.31	0.22
Local-PCA	0.79	0.78	0.77	0.73	0.67	0.57
EM macro-PCA	0.92	0.88	0.85	0.74	0.64	0.55
EM financial-PCA	0.87	0.85	0.82	0.76	0.70	0.58
EM global-PCA	0.86	0.79	0.74	0.63	0.54	0.44
Local-PLS	0.95	0.95	0.95	0.90	0.85	0.77
EM macro-PLS	0.88	0.87	0.86	0.83	0.80	0.74
EM financial-PLS	0.97	0.97	0.97	0.89	0.82	0.72
EM global-PLS	0.89	0.87	0.86	0.84	0.80	0.73
South Africa						
RW	0.49	0.49	0.49	0.49	0.50	0.52
Local-PCA	0.73	0.70	0.69	0.67	0.57	0.56
EM macro-PCA	0.77	0.74	0.72	0.66	0.59	0.62
EM financial-PCA	0.55	0.54	0.53	0.50	0.46	0.47
EM global-PCA	0.66	0.64	0.63	0.57	0.52	0.55
Local-PLS	0.58	0.57	0.56	0.54	0.51	0.47
EM macro-PLS	0.61	0.61	0.62	0.60	0.57	0.53
EM financial-PLS	0.62	0.61	0.61	0.57	0.54	0.47
EM global-PLS	0.65	0.67	0.68	0.64	0.59	0.51
Turkey						
RW	-0.32	-0.35	-0.38	-0.42	-0.45	-0.45
Local-PCA	0.10	0.06	0.03	0.02	0.01	0.09
EM macro-PCA	0.15	0.11	0.08	0.00	-0.04	-0.08
EM financial-PCA	0.06	0.01	-0.02	-0.11	-0.08	-0.06
EM global-PCA	0.19	0.16	0.14	0.07	0.02	-0.04
Local-PLS	0.37	0.38	0.38	0.34	0.29	0.21
EM macro-PLS	0.40	0.39	0.38	0.36	0.31	0.25
EM financial-PLS	0.37	0.36	0.35	0.34	0.33	0.23
EM global-PLS	0.38	0.38	0.37	0.37	0.31	0.21

Note. The table reports the average of the Sharpe ratios across maturities and emerging markets for h-step-ahead forecasts, where $h = 1$, 2, 3, 6, 9, and 12 based on the model specifications defined in Section 3.3. The results are based on portfolio performances for a mean–variance investor with relative risk aversion coefficient of five who selects portfolio weights based on the forecasts of the corresponding model.

Table 12. Performance of active trading strategies: utility gain

	$h=1$	$h=2$	$h=3$	$h=6$	$h=9$	$h=12$
Brazil						
Local-PCA	77.62	58.30	47.89	43.23	54.04	7.62
EM macro-PCA	66.01	46.16	41.27	3.96	-18.85	-97.86
EM financial-PCA	39.35	21.12	8.39	-22.97	-32.81	-53.81
EM global-PCA	49.37	28.82	24.19	44.38	52.25	-27.64
Local-PLS	61.56	57.71	53.75	28.41	-2.99	-45.03
EM macro-PLS	55.51	49.34	41.84	16.37	1.11	-31.03
EM financial-PLS	73.11	68.18	65.21	42.97	9.19	-10.52
EM global-PLS	57.58	50.21	47.92	28.72	15.60	-22.52
Indonesia						
Local-PCA	-17.98	-23.58	-28.94	-39.19	-36.39	-28.47
EM macro-PCA	-4.73	-12.37	-19.86	-35.17	-34.48	-26.21
EM financial-PCA	17.86	6.90	-4.82	-28.96	-31.31	-24.94
EM global-PCA	31.64	27.23	20.23	33.00	41.72	50.24
Local-PLS	48.32	46.26	44.32	40.75	26.30	8.06
EM macro-PLS	30.27	27.71	26.83	20.29	13.17	11.65
EM financial-PLS	45.32	40.59	36.93	16.04	-10.40	-49.02
EM global-PLS	29.97	27.56	26.69	19.94	13.14	11.37
Mexico						
Local-PCA	18.47	18.44	19.15	32.87	42.18	41.56
EM macro-PCA	51.45	50.22	49.93	59.04	72.38	85.83
EM financial-PCA	43.63	43.42	42.70	54.72	72.95	83.07
EM global-PCA	57.49	53.57	50.91	55.46	69.44	81.61
Local-PLS	58.18	63.49	68.16	81.88	100.58	113.02
EM macro-PLS	40.17	40.95	43.14	59.28	80.89	99.47
EM financial-PLS	65.53	71.58	76.43	88.07	103.52	113.86
EM global-PLS	42.20	41.76	42.36	59.53	81.10	95.89
South Africa						
Local-PCA	23.17	17.49	13.25	1.72	-16.29	-12.88
EM macro-PCA	22.02	18.71	11.66	-15.49	-35.73	-24.92
EM financial-PCA	-6.86	-8.51	-10.03	-14.31	-21.76	-22.93
EM global-PCA	9.45	6.45	1.58	-16.78	-33.39	-29.50
Local-PLS	9.78	7.19	3.97	1.07	-4.44	-24.17
EM macro-PLS	-7.85	-7.83	-14.36	-18.96	-23.66	-43.43
EM financial-PLS	8.48	6.81	6.87	1.62	-1.54	-15.25
EM global-PLS	9.54	12.11	12.88	5.10	-5.97	-18.82
Turkey						
Local-PCA	35.79	34.97	34.32	23.40	-12.16	12.26
EM macro-PCA	50.16	48.46	47.56	37.11	2.41	1.83
EM financial-PCA	40.90	38.45	34.96	22.24	-1.31	15.81
EM global-PCA	52.95	52.84	52.28	39.31	0.21	-1.20
Local-PLS	86.50	89.07	91.54	88.96	57.20	37.39
EM macro-PLS	88.03	90.97	93.44	93.24	63.14	41.71
EM financial-PLS	78.76	78.57	79.42	72.74	42.46	24.24
EM global-PLS	86.31	88.43	91.03	89.05	58.91	29.78

Note. The table displays the performance measure for the active mean–variance with relative risk aversion coefficient of five, which decides portfolio weights based on the forecasts of the corresponding model. Entries are the performance fees in annualized basis points for switching from the strategy indicated by the benchmark model to the corresponding factor-augmented predictive regression.

The results in Table 12 show that the performance fees reveal a similar pattern. When the EM macro-PLS model is considered, the performance fee against the benchmark portfolio drops on average from 88 to 41 basis points for Turkey. Put differently, investors will be willing to pay an average performance fee up to 88 basis points annually to switch from the benchmark model to the emerging market macro-PLS model. This confirms the results of the previous sections, namely that the macroeconomic factors add relevant information concerning excess bond returns. However, an interesting observation from Table 12 is that the factor-augmented models generally have higher performance fees when the long-term forecast horizons are considered in the case of Mexico. In particular, the performance fees range between 18.47 and 113.86 basis points for Mexico. Despite the overall success of our factor-augmented predictive regressions, the utility gains are slightly negative in certain cases for Indonesia and South Africa. A similar pattern can be observed when we consider results for Turkey, albeit in a somewhat less pronounced manner.

Overall, the ass et allocation exercise results seem to be compatible with the argument that substantial economic value can be achieved by combining information from cross-country macroeconomic and financial variables.

5 CONCLUSION

In this paper we forecast the local currency debt of five major emerging market countries —Brazil, Indonesia, Mexico, South Africa, and Turkey—over the period January 2010 to January 2019, based on an in-sample period of March 2005 to December 2009. We exploit information from a large set of economic and financial time series to assess the importance not only of "own-country" factors (derived from principal component and partial least squares approach), but also create factors by combining country-specific variables across the chosen emerging economies. These "global" predictors, and their subsets of "macroeconomic" and "financial" factors, are then used individually to specify new factors, and are combined with the own-country factor model. To evaluate the forecasting performance of our models, we not only pursue the standard statistical approach based on prediction errors, but also undertake a directional accuracy test required to devise profitable investment decisions, as well as analyzing the economic value of active trading strategies formed on the local currency bond risk premium forecasts using a utility-based metric.

We find that, while information on own-country factors can outperform the historical average model, global factors tend to produce not only greater statistical and economic gains, but also enhance the market timing ability of investors. In this regard, we also find that when factors are extracted based on the target variable of bond premium using partial least squares, forecasting gains are higher relative to the case when the common predictors are derived from standard principal component analysis. In sum, our findings suggest that global investors should consider the cross-country linkages across emerging markets when forecasting the excess bond returns, as this will allow them to create optimal investment portfolios. In addition, our findings have important implications for policymakers, since information on not only own macroeconomic and financial variables (risks), but also that of other emerging countries, can be used to predict the future path of their local currency bond premium, and in the process reduce the probability of a sovereign debt crisis.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Bloomberg Terminal. Restrictions apply to the availability of these data, which were used under license for this study. However, we shared the corresponding tickers in Tables A1–A5 of the online Appendix. Hence anyone who has a Bloomberg account can easily download the same data.

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