Forecasting and Nowcasting Emerging Market GDP Growth Rates: The Role of Latent Global Economic Policy Uncertainty and Macroeconomic Data Surprise Factors*

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Abstract

In this paper, we assess the predictive content of latent economic policy uncertainty and data surprises factors for forecasting and nowcasting GDP using factor-type econometric models. Our analysis focuses on five emerging market economies, including Brazil, Indonesia, Mexico, South Africa, and Turkey; and we carry out a forecasting horse-race in which predictions from various different models are compared. These models may (or may not) contain latent uncertainty and surprise factors constructed using both local and global economic datasets. The set of models that we examine in our experiments includes both simple benchmark linear econometric models as well as dynamic factor models (DFMs) that are estimated using a variety of frequentist and Bayesian data shrinkage methods based on the least absolute shrinkage operator (LASSO). We find that the inclusion of our new uncertainty and surprise factors leads to superior predictions of GDP growth, particularly when these latent factors are constructed using Bayesian variants of the LASSO. Overall, our findings point to the importance of spillover effects from global uncertainty and data surprises, when predicting GDP growth in emerging market economies.

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1. Introduction

In many countries, initial real GDP estimates are released at least three weeks after the calendar quarter to which the data pertains. For example, in the Euro area and the U.S., GDP reporting lags are three and four weeks, respectively; and in Turkey, first release GDP data are available only after as many as 10 to 12 weeks. At the same time, tracking economic activity in real-time is crucial to the decision-making process of macroeconomic policymakers. Fortunately, there is now an abundance of both real-time and big datasets available to researchers, allowing for the construction of ever more accurate early forecasts and nowcasts (i.e., signals) of the current state of the economy. In this context, as pointed out by Giannone et al. (2008), dynamic factor models (DFMs) have become one of the workhorses for short-term forecasting, and are now widely used in central banks and research institutions for both forecasting and nowcasting. For further discussion, see, Artis et al. (2005) - for the UK; Schumacher (2010) - for Germany; Bessec (2013) - for France, Girardi et al. (2015) - the Euro Area; Modugno et al. (2016) - Turkey; Bragoli (2017) - Japan; Kim and Swanson (2018a) - for the USA, Kim and Swanson (2018b) - for Korea; Luciani et al. (2018) - for Indonesia; and Bragoli and Fosten (2018) - for India).

In this paper, we contribute to the literature on nowcasting and forecasting real GDP growth in emerging economies by empirically assessing the importance of economic policy uncertainty and data surprises in factor-type econometric forecasting models for five emerging market economies, including Brazil, Indonesia, Mexico, South Africa, and Turkey. Our analysis centers around the use of DFMs for constructing GDP predictions, although we also evaluate benchmark linear autoregressive (AR) models. Importantly, our DFMs are specified both with and without uncertainty and data surprise factors constructed using both local and global economic variables. Moreover, in addition to standard econometric estimation methods, we estimate factors using a variety of data shrinkage methods including the standard LASSO, the adaptive LASSO, the Bayesian LASSO, and the Bayesian adaptive LASSO.

As mentioned above, we utilize both local and global datasets when constructing the factors used in our prediction models. Although there are many empirical papers that focus on using only local macroeconomic data in the context of GDP forecasting, the importance of uncertainty regarding policymakers' decisions on international economic policies has received increasing attention since the beginning of 2018. For example, concerns over US-China trade tensions, Brexit negotiations with the EU, Italy's' fiscal planning, and how the Federal Reserve Board of the USA will determine the timing and pace of policy normalization all weigh heavily on the global economy. These sorts of international spillovers are particularly important for emerging markets, in particular those with high foreign portfolio ownership and weak macroeconomic balance sheets. For this reason, it is crucial to assess the relevance of uncertainty and data surprises in the context of forecasting emerging market GDP. Needless to say, the impact of uncertainty on economic activity has received considerable attention in the economics literature in recent years (see, e.g. Bloom (2014)). For example, Bontempi et al. (2016) propose uncertainty indicators based on Google Trends. Their results suggest that online search data can provide early signals of uncertainty, and can be used in macroeconomic forecasting. Baker et al. (2016) construct an index of economic policy uncertainty (EPU) based on newspaper coverage frequency. They find that economic policy innovations foreshadow declines in investment, output, and employment, using a panel vector autoregressive (VAR) model for 12 major economies. Thorsrud (2018) develops a new coincident index of business cycle activity based on quarterly GDP and textual information contained in a daily business newspaper.

In addition to the above proxies for economic policy "uncertainty", a growing strand of the literature uses consensus forecasts to disentangle macroeconomic uncertainty from more "general" uncertainty. In particular, it is argued in this literature that professional forecasters (e.g. those forecasters contributing to the Survey of Professional Forecasters in the USA) closely monitor macroeconomic data and often base their predictions on sophisticated econometric models. Thus, departures of their (consensus) predictions from actual realizations can be viewed as data "surprises", which are themselves measures of macroeconomic uncertainty. There are different proxies for this sort of macroeconomic uncertainty that are proposed in the empirical literature. For example, Rossi and Sekhposyan (2015) construct a macroeconomic uncertainty index based on comparing the realized forecast error of a variable of interest with the sample distribution of the forecast errors of that variable. If the realization is in the tail of the distribution, they conclude that the macroeconomic environment is more uncertain. Carriero et al. (2016) develop a model to identify uncertainty by modeling the common component of the volatility of the forecast errors of a large set of macroeconomic and financial variables. Finally, Scotti (2016) proposes a macroeconomic surprise index that exploits the difference between actual releases of data and Bloomberg forecasts to capture economic agents' expectations about the state of the economy. In this paper, we construct global economic policy uncertainty and surprise indices based on a variety of different local and global datasets. More specifically, we incorporate uncertainty into our prediction models in three different ways. First, as our benchmark we utilize only local macroeconomic data. Using this approach, we estimate both DFMs and simple AR models; but do not explicitly include any uncertainty or surprise indexes. Second, we augment our DFMs with "surprise" indices constructed using professional forecasters' expectations. Finally, we additionally augment our DFMs with factors extracted from a wide variety of uncertainty indices of economic policy, trade policy, monetary policy, and migration.

It should be noted that we focus on the prediction of GDP growth in emerging markets (EM) for two main reasons. First, official releases of EM GDP figures are subject to significant publication lags and data revision, as discussed above. Second, again as discussed above, it is likely that the effects of uncertainty on economic activity are particularly significant in environments characterized by large budget deficits, high current account/GDP ratios, and high external funding needs. As a case in point, note that Carriere et al. (2013) investigate the effects of an uncertainty shock from the USA on developed and developing countries. They find that emerging markets suffer much more severe falls in investment and private consumption when there are credit constraints that lead to increases in the uncertainty index. Gauvin et al. (2014) also point out that elevated policy uncertainty in advanced countries may lead to an increase in capital outflows from emerging markets, because of rising global risk aversion. At the same time, it is important to note that low-quality emerging market data presents distinct challenges when forecasting GDP growth. However, our dataset contains a very large number of variables, allowing us to mitigate this effect to some degree by "pre-selection" of key variables for use in our DFMs. Namely, we argue that a small set indicators from our dataset may be sufficient to identify the most informative uncertainty indexes. Indeed, the idea that a small set of indicators, when chosen appropriately, can improve forecasting performance of factor models is supported by evidence presented in various papers, including Boivin and Ng (2006), Schumacher (2007), Bai and Ng (2008), Banbura and Rünstler (2011), Kim and Swanson (2014, 2018a), Bulligan et al. (2015), and references cited therein. For this reason, we utilize variable selection methods to pre-select indicators before the construction of factors. To this end, we apply a number of LASSO methods for data shrinkage, as discussed above. Of course, we also use standard DFM methods where the entire dataset is used in factor construction. In this way, our analysis adds to our understanding not only of GDP forecasting using uncertainty indices, but also to the usefulness of shrinkage methods in DFM modeling.

Our empirical findings can be summarized as follows. First, as expected, there is a substantial reduction in mean square forecast error (MSFE), as more data related to the current quarter become available and is incorporated into our models. Thus, the forecast accuracy of our DFM models generally increases by incorporating the latest information. Second, uncertainty indexes are quite useful for predicting GDP growth in emerging market economies. More specifically, benchmark AR models, as well as dynamic factor models that utilize only local macroeconomic data yield inferior predictions for Indonesia, South Africa, and Turkey. For these three countries, both “surprise” and “uncertainty” indexes matter. Third, constructing surprise and uncertainty indexes using LASSO shrinkage methods leads to more accurate forecasts than when factors are constructed without variable pre-selection. Indeed, across all ten forecast horizons (including forecasts, nowcasts, and backcasts), and across all five countries the “globally best” models include factors constructed using targeted variable pre-selection in 47 of the 50 cases.[1] Finally, augmenting the DFMs utilized in our analysis regression with lags of the dependent variable (i.e., including an AR component in the DFM) yields forecasting gains relative to models without AR terms only for Indonesia and South Africa. This result is interesting given the preponderance of evidence in the time series forecasting literature concerning the importance of including AR components when forecasting economic variables, and serves to underscore the importance of uncertainty and surprise variables when predicting EM GDP.

Summarizing, we find strong evidence that using targeted predictors in combination with global uncertainty indices as well as global surprise indices based on expectations of professional forecasters leads to more precise GDP predictions for emerging market economies. These findings suggest that when assessing macroeconomic conditions, policymakers and central bankers may increasingly need to take into account the level of economic policy uncertainty originating from other countries, as well as related macroeconomic forecasts formulated by professional forecasters.

The rest of the paper is structured as follows. In Section 2, we present the main features of the datasets used in our empirical investigation. In Section 3, we outline the econometric methodology used in the papers. In Section 4, we discuss our empirical findings. Concluding remarks are gathered in Section 5. Finally, the Appendices include supplementary tables as well as additional details describing the datasets analyzed in the sequel.

2. Data

We analyze a relatively large set of economic indicators consists of 97, 87, 116, 109, 102 economic variables for Brazil, Indonesia, Mexico, South Africa, and Turkey, respectively. The dataset is composed of both “hard indicators” and survey data. Among the hard indicators, we have both supply-side variables, such

[1] A globally best model is one that yields the lowest MSFE across all five data selection methods including (i) Use all data in DFM construction; (ii) use the standard LASSO for dataset reduction; (iii) use the adaptive LASSO for dataset reduction; (iv) use the Bayesian LASSO for dataset reduction; and (v) use the Bayesian adaptive LASSO for dataset reduction.

as industrial production indexes, and demand-side variables, such as electricity consumption. Among the survey variables, we have the Market PMI survey, one of the most watched indicators of the business cycle. Given the sensitivity of EM economies to external conditions, we also include current account balance and volume indices of exports and imports, as well as real effective exchange rates. The dataset can be divided into six categories: *Housing and Order Variables*: House price index, real estate units sold and new orders. *Labor Market Variables*: Employment and unemployment. *Prices*: Producers prices and consumer prices. *Financial Variables*: Treasury bond yields, credit default swaps, exchange rates, and stock prices. *Money, Credit and Quantity Aggregates*: Money supply, commercial bank loans, time and sight deposits. *Real Economic Activity*: PMI survey, industrial production, retail sales, vehicle production and capacity utilization. In general, the survey variables and nominal indicators are released during the reference month (i.e., the calendar month to which the data pertains), whereas real and labor variables are announced with a publication lags of 1-3 months.

In addition to the above collection of macroeconomic and financial indicators, which are used in our baseline DFM model (this DFM model is called Specification 1 in Section 3.3), we examine an uncertainty dataset that contains a wide variety of uncertainty indices pertaining to economic policy, trade policy, monetary policy and migration. These variables are largely the same as those constructed by Baker et al. (2016) for major economies and are called economic policy uncertainty (EPU) indices. Their data construction approach is based on computing the proportion of newspaper articles referring to a specific type of uncertainty over a given period. In particular, the EPU indices reflect the frequency of articles that include terms related to three categories, i.e., economy (E), policy (P) and uncertainty (U)[2]. In total, we utilize 45 "uncertainty" indices from various fully and less developed countries when constructing our "uncertainty" factors for use in our DFM forecasting models (see Specifications 2 and 4 in Section 3.3).

We now turn to a discussion of our "surprise" indices. Understanding how economic data evolve, relative to consensus expectations, is important for gauging potential shifts in macroeconomic sentiment, for a given country. For this purpose, we collect a large set of surprise indices across key regions and countries. Our dataset consists of Citi and Goldman Sachs surprise indices, which are constructed based on similar methodologies. These indices are designed to summarize the degree of surprise inherent in a data release, relative to the associated Bloomberg median forecast of the variable in question. Multiplying the so-called relevance score for a variable by the surprise score allows us to track whether the economic data

[2]More details on the EPU indices can be found at http://www.policyuncertainty.com/index.html.

in a country are "outperforming" or "under-performing" consensus expectations. Since units of measurement vary across variables, the surprise scores are normalized by dividing by sample standard deviation of the corresponding variables.[3] In total, we have 74 surprise indices across different regions and countries, including the USA, UK, Euro Area, Japan, Asia Pacific region, and Latin America. These indices are then used to construct our "surprise" factors for use in our DFM forecasting models (see Specifications 3 and 4 in Section 3.3).

All datasets were collected from Bloomberg, and are for the period January 2003 - June 2018. The complete list of Blomberg tickers is provided in Tables B1-B7 in Appendix B. Finally, all series are transformed to stationarity by differencing or log-differencing, as needed.

3. Econometric Methodology

3.1. Dynamic Factor Models

In our analysis, we separately extract potentially useful forecasting information from our three datasets (i.e., our macroeconomic indicator dataset, surprise dataset, and uncertainty index dataset). To do this, we employ the widely used dynamic factor model (DFM) of Giannone et al. (2008). In this framework, the dynamics of individual variables is represented as the sum of a component that is common to all variables in the economy and an orthogonal idiosyncratic residual. Formally, the DFM can be written as a system with two types of equation: a measurement equation (Eq. (1)) that links the observed variables to the unobserved common factor to be estimated, and the transition equations ((Eq. (2) and Eq.(3)) that describe the dynamics of the common factors and the residuals of the measurement equation. Once Eqs. (1)-(3) are written in state space form, the Kalman filter and smoother are applied to extract common factors and generate forecasts for all of the variables in the model.

More specifically, we consider a panel of observable economic variables, $X_{i,t}$, where i indicates the cross-section unit, $i = 1, ..., N$, and t denotes the time index, $t = 1, ..., T$. Each variable in the dataset can be decomposed into common part and idiosyncratic components, where the common component capture comovement in the data, and is driven by a small number of shocks. The DFM model can be written as:

$$X_t = \Lambda F_t + \xi_t, \qquad \xi_t \sim N(0, \Sigma_e), \tag{1}$$

[3]Note that relevance scores are defined as the absolute value of the contemporaneous correlation between each variable and real GDP growth.

$$F_t = \sum_{i=1}^{k} \Psi_i F_{t-i} + u_t, \qquad u_t \sim N(0, Q), \tag{2}$$

where F_t is an $r \times 1$ vector of unobserved common factors with zero mean and unit variance, Λ is a corresponding $N \times r$ factor loading matrix, and the idiosyncratic disturbance, ξ_t, is uncorrelated with F_t at all leads and lags, and has a diagonal covariance matrix Σ_e. It is assumed that the common factors, F_t, follow a stationary VAR(p) process driven by the common shocks, $u_t \sim N(0, Q)$, and that the Ψ_i are $r \times r$ matrices of autoregressive coefficients. Also, the common shocks (u_t) and idiosyncratic components (ξ_t) are orthogonal. To handle missing observations at the end of the sample due to the non-synchronous flow of data, we characterize the variance of the idiosyncratic component as an extremely large variance. In this way, we ensure that the Kalman filter will put no weight on missing observations in the extraction of the common factors. Finally, in order to construct forecasts of our quarterly GDP target series, say y_t, in our monthly DFM framework, we express each quarterly variable in terms of a partially observed monthly counterpart following the approach of Mariano and Murasawa (2003). Put differently, the general form of the forecasting model can be described as follows:

$$y_t = \mu + \beta' F_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{3}$$

where ε is a stochastic disturbance term. In order to select the optimal number of factors (r), one may use various methods suggested in the the literature. A non-exhaustive list of possible methods are discussed in the following papers: Bai and Ng (2002), Onatski (2009), Alessi et al. (2010), and Ahn and Horenstein (2013). Although the Bai and Ng (2002) criteria is frequently used in the empirical literature, we find that it generally chooses too many factors, resulting in deterioration in forecast accuracy. Hence, we adopt the Onastki (2009) approach that is based on testing the null of $r - 1$ common factors against the alternative of r common factors. Optimal lag length is selected using the Schwarz information criterion (SIC)[4]. In summary, we find that simple model specifications, with one or two factors and one or two lags often yield best out of sample forecast performance. Specification of a parsimonious one or two factor model is also consistent with the literature on factor models, which has shown that heavily parametrized models with many factors usually lead to poor forecasting performance (see Forni et al. (2000), Stock and Watson (2002), and Bragoli (2017)).

[4]The list of selected r and p pairs are (2,2), (1,2), (1,3), (3,3), (1,2) for Brazil, Indonesia, Mexico, South Africa, and Turkey, respectively.

3.2. *Identifying targeted predictors: LASSO - based approaches*

Since dynamic factor models do not explicitly incorporate knowledge of the target variable being forecast, factor extraction is called "un-targeted". Needless to say, targeted forecasting, in which factors with information specific to the target variable are constructed and used in subsequent model specification may yield superior predictions, relative to predictions constructed using factors based on un-targeted methods. These issues are discussed at length in Boivin and Ng (2006), Bai and Ng (2008), Schumacher (2010), Caggiano et al. (2011), Medeiros and Vasconcelos (2016), Kapetanios et al. (2016), Kim and Swanson (2014, 2018b), and many others. In the sequel, we utilize both un-targeted and targeted methods to construct factors. For un-targeted forecasting, we simply use the DFM model outlined in the previous section. For targeted forecasting, we note that one of the most commonly used variable selection and parameter shrinkage method is the LASSO. This method can be thought of as a type of penalized regression, related to classical ridge regression. However, in the case of ridge regression, an ℓ_2-norm penalty is imposed, while under the LASSO, an ℓ_1-norm penalty function is added to the usual least squares minimization problem. Interestingly, the ℓ_1-norm penalty function induces shrinkage to 0 of coefficients associated with "irrelevant" variables.[5] For our purposes, since we are interested in selecting a targeted subset of the original variables in our dataset when constructing shrinkage type factors, we use the LASSO. In particular, we analyze factors constructed using the standard LASSO, the adaptive LASSO, the Bayesian LASSO and the Bayesian adaptive LASSO.

Turning again to our empirical setup, we consider a panel of observable economic variables, $X_{i,t}$, where i indicates the cross-section unit, $i = 1, ..., N$, and t denotes the time index, $i = 1, ..., T$, as discussed above. Following the notation of Hastie et al. (2009), we consider the problem of selecting a subset of X, where X is a $T \times N$ matrix to be used for forecasting quarterly GDP growth, say Y, for $i = 1, ..., T$.

3.2.1. *Least absolute shrinkage operator (LASSO)*

We implement the LASSO, as developed in Tibshirani (1996). This shrinkage operator performs both variable selection and regularization, using a regularization parameter, λ. The idea is to impose an ℓ_1-norm penalty on the regression coefficients, thus allowing for cases where $N > T$. This penalty also results in

[5] As an example of the coefficients referred to in the previous statement, consider coefficients that are defined to be the weights in a linear combination of variables forming a latent factor, when principal component analysis (PCA) is used to construct F_t. When using the LASSO, various of these factor loadings may be identically zero. On the other hand, the classical ridge regression penalty function results in all coefficients being nonzero, for each latent factor, under PCA.

(possible) shrinkage of coefficients (called $\hat{\beta}^{LASSO}$) to zero, as discussed above. The LASSO estimator is defined as:

$$\hat{\beta}^{LASSO} = \arg\min_{\beta} \quad ||Y - X\beta||_2 + \lambda \sum_{j=1}^{N} |\beta_j|, \tag{4}$$

where λ is a tuning (regularization) parameter that controls the strength of the ℓ_1-norm penalty. We choose the tuning parameter λ via cross-validation, which is a data-driven method that is designed to maximize expected out of sample forecasting performance. Since the objective function in the LASSO is not differentiable, numerical optimization must be used when constructing $\hat{\beta}^{LASSO}$. For example, an efficient iterative algorithm called the "shooting algorithm" is proposed in Fu (1998). One of the limitations of the LASSO approach is that the sample size bounds the number of selected variables. For example, if $N > T$, the LASSO yields at most T non-zero coefficients (see Swanson (2016) for further discussion). The variables associated with these non-zero coefficients constitute our set of targeted predictors when using the LASSO method.

3.2.2. Adaptive LASSO (AdaLASSO)

Although the LASSO can perform automatic variable selection because of the ℓ_1-norm penalty, it may yield biased estimates when coefficients are large. Fan and Li (2001) conjecture that LASSO does not have oracle properties and may yield an inconsistent set of selected variables in some cases. In order to address these issues, Zou (2006) introduces a new version of the LASSO, called the adaptive LASSO, where adaptive weights are used for penalizing different coefficients in the ℓ_1-norm penalty. They show that adaptive LASSO enjoys oracle properties. Moreover, Medeiros and Mendes (2016) show that the adaptive LASSO estimator maintains its' consistency, under very general conditions; and performs well even when the number of variables increases faster than the number of observations.

The adaptive LASSO estimator can be written as follows:

$$\hat{\beta}^{AdaLASSO} = \arg\min_{\beta} \quad ||Y - X\beta||_2 + \lambda \sum_{j=1}^{N} w_j |\beta_j|, \tag{5}$$

where $w_j = |\hat{\beta_j^*}|^{-\tau}$ represents different weights on the penalization of each variable, $|\hat{\beta_j^*}|$ is an initial estimator, such as the OLS or ridge estimator (which is estimated in a first step), and $\tau > 0$ controls the difference in weights. Since the adaptive LASSO is still an ℓ_1-norm penalization method, the algorithms for solving the LASSO can be employed for constructing adaptive LASSO estimates.

3.2.3. *Bayesian LASSO (BLASSO)*

Tibshirani (1996) suggested that LASSO estimates can be interpreted as the posterior mode of the Bayes estimate, under the Laplace priors. While the LASSO attributes a value of exactly zero to regression coefficients of irrelevant variables, redundant Bayesian LASSO coefficient modes are not precisely zero. Instead, the BLASSO provides a posterior distribution of coefficients. In our BLASSO estimator, we implement a conditional Laplace prior of the form:

$$\pi\left(\beta|\sigma^2\right) = \prod_{j=1}^{p} \frac{\lambda}{2\sqrt{\sigma^2}} e^{\frac{-\lambda|\beta_j|}{\sqrt{\sigma^2}}}. \tag{6}$$

Park and Casella (2008) show that conditioning on error variance, σ^2, ensures a unimodal full posterior. Otherwise, expensive simulation methods lead to slow convergence of the Gibbs sampler and result in less meaningful point estimates. Since the Laplace distribution can be represented as a scale mixture of normal densities with an exponential mixing density, Park and Casella (2008) propose the following hierarchical BLASSO model:

$$\begin{aligned} y|X,\beta,\sigma^2 &\sim N_n(X\beta,\sigma^2 I_n) \\ \beta|\sigma^2,\{\tau_1{}^2,...,\tau_p{}^2\} &\sim N_p(0_p,\sigma^2 D_\tau) \\ D_\tau &= diag\{\tau_1{}^2,...,\tau_p{}^2\} \end{aligned} \tag{7}$$

with the following priors on σ^2 and $\tau = \{\tau_1{}^2, ..., \tau_p{}^2\}$:

$$\sigma^2,\tau_1{}^2,...,\tau_p{}^2 \sim \pi\left(\sigma^2\right) d\sigma^2 \prod_{j=1}^{p} \frac{\lambda^2}{2} e^{\frac{-\lambda^2\tau_j^2}{2}} d\tau_j^2, \qquad \sigma^2,\tau_1{}^2,...,\tau_p{}^2 > 0, \tag{8}$$

where D_τ is the prior covariance matrix, and λ is a rate parameter of the exponential distribution. Korobilis (2013) compares the forecasting performance of hierarchical Bayesian shrinkage and factor models, and finds that Bayesian shrinkage serves as a valuable addition to existing methods, in the presence of many predictor variables. Our approach is to use this BLASSO method and store the posterior distributions of all coefficients. Thereafter we calculate the 95% confidence intervals, and set a coefficient equal to zero if its interval includes zero. The remaining variables constitute our set of targeted predictors, when using the Bayesian LASSO.

3.2.4. *Bayesian Adaptive LASSO (BaLASSO)*

As discussed in Section 3.2.2, the AdaLASSO uses weighted shrinkage for consistent estimation of regression coefficients, while retaining the attractive convexity property of the LASSO. However, the AdaLASSO requires consistent and informative initial estimates of the regression coefficients, which are generally not available when the number of regressors is larger than the number of observations. Since Bayesian Adaptive LASSO does not require any informative initial estimates of the regression coefficients, this motivates us to replace equation (8) in the Bayesian LASSO section to allow for a more adaptive penalty, as follows:

$$\sigma^2, {\tau_1}^2, ..., {\tau_p}^2 \sim \pi\left(\sigma^2\right) d\sigma^2 \prod_{j=1}^{p} \frac{\lambda_j^2}{2} e^{\frac{-\lambda_j^2 \tau_j^2}{2}} d\tau_j^2 \tag{9}$$

Similar to the BLASSO, we select variables such that their corresponding 95% confidence intervals do not include zero.

3.3. Factor Augmented Prediction Models

To evaluate the forecasting performance of dynamic factor models based on different factor specification types, we run a recursive pseudo out of sample forecasting exercise over the period July 2008 to June 2018. For each reference quarter, we produce a sequence of ten forecasts, starting with the forecast based on the information available in the first month of the two previous quarters, and stopping on the first of the month of the subsequent quarter, before GDP is released. Put differently, we construct three monthly forecasts (for quarterly forecast horizon, $h = 1, 2$), three monthly nowcasts (for quarterly forecast horizon, $h = 0$), and one monthly backcast (for quarterly forecast horizon, $h = -1$).

We apply the dynamic factor model to extract the leading common factors in our large set of uncertainty and surprise indices. We called these new factors our "Global Economic Policy Uncertainty" (GEPU) and "Global Macro-Surprise" (GMS) factors. Earlier, we referred to these variables as our "uncertainty" and "surprise" variables, respectively. These factors can be interpreted as measures of common variation in economic policy uncertainty (uncertainty) and macroeconomic data uncertainty (surprise) across countries. These variables are individually "added" to our DFM model. In particular, noting that "Local" refers to factors that are constructed using only "own" country variables, we construct predictions using the following specifications, where Specification 1 is the model used in Giannone et al. (2008), and Specifications 2-4 are extensions that incorporate our new uncertainty and surprise factors.[6]

- **Specification 1**: Local factor model

  $y_{t+h} = \mu + \beta' F_t^{Local} + \varepsilon_{t+h}$

[6]In addition to estimating Specifications 1-4 using the methods of Section 3.1, variations are estimated using the shrinkage approaches discussed in Sections 3.2.1-3.2.4.

- **Specification 2**: Uncertainty factor model
  $y_{t+h} = \mu + \beta' F_t^{Local} + \vartheta' F_t^{GEPU} + \varepsilon_{t+h}$
- **Specification 3**: Macro-Surprise factor model
  $y_{t+h} = \mu + \beta' F_t^{Local} + \theta' F_t^{GMS} + \varepsilon_{t+h}$
- **Specification 4**: Global factor model
  $y_{t+h} = \mu + \beta' F_t^{Local} + \theta' F_t^{GEPU} + \delta' F_t^{GMS} + \varepsilon_{t+h}$

An additional set of models is also used to construct predictions, in which each of the above DFM models is augmented with lags of the dependent variable (where the lag number is selected using the SIC). Finally, we also construct forecasts using a straw-man AR model, with lags selected using the SIC. We assess the precision of the different sequences of forecasts using mean square forecast error (MSFE), which is measured as the average of the squared differences between predicted and actual GDP values for the ten year period from July 2008 to June 2018. In order to assess the statistical significance of differences in MSFE across specification types, pairwise Diebold-Mariano (DM: 1995) tests of equal predictive accuracy are implemented. In this test, the null hypothesis that of equal predictive accuracy. For a discussion of the test, which is normally distributed under non-nestedness, and has a nonstandard distribution if models are nested, see Kim and Swanson (2018a,b). When carrying out DM tests, the benchmark against which each of our Specification Type 1-4 models are compared with our straw-man AR model.

4. Empirical Results

4.1. Global Economic Policy Uncertainty and Macroeconomic Surprise Factors

Before describing our prediction results, it is of interest to investigate how global economic policy uncertainty and macroeconomic surprise factors are related to macroeconomic fluctuations across our EM economies. As seen in Figure 1, the global uncertainty factor captures the crucial events and spikes near elections in the USA, effects likely associated with Brexit, global financial crises, and major uncertainty surrounding fiscal policy in the USA. Given the pivotal role of uncertainty on world trade volume, spill-overs from elevated global uncertainty to emerging markets likely affect economic activity through a number of channels. For example, the uncertainty about whether the USA will place tariffs on steel or other goods that are imported from China is likely to undermine export oriented investments that are allocated to these sectors. This in turn puts pressure on Chinese GDP growth. Also, in the era of Brexit, we have seen that many firms have stopped hiring and are restricting production until the fallout from Brexit becomes more clear. This has a negative impact on GDP growth in countries with high exports to the UK. These sorts of linkages are precisely what we are trying to capture with our uncertainty and surprise factors.

As shown in Figure 2, the global macroeconomic surprise factor tracks the world GDP growth quite closely and captures the sharp contraction in economic activity over the crisis period around 2008. While we might indeed expect markets to move in response to the "surprise" factor, it is noteworthy that the global macroeconomic surprise factor fails to track world GDP growth rates since the beginning of 2017. One reason might be that over this period, post-US election, economic agents' expectations were more pessimistic about the economy than warranted, given elevated global uncertainty in this period.

The below table reports correlation coefficients between the global economic uncertainty factor (called "Uncertainty"), the global macroeconomic surprise factor (called "Surprise") and country-specific (local) factors. The correlation coefficients between "Uncertainty" and country-specific factors range from -0.17 to -0.57, showing that the global economic uncertainty factor and economic activity is negatively correlated, except for Indonesia. A reason for this might be that an increase in uncertainty regarding economic policy is likely to trigger recessionary effects, including delays in investment and increases in unemployment. Furthermore, Carriere et al. (2013) show that the impact of exogenous uncertainty shocks on emerging economies is to increase the burden of foreign currency denominated debt, due to credit constraints. This may also have an adverse effect on economic growth. On the other hand, the positive relation between "Surprise" and country-specific factors shows that, in general, the macroeconomic data and market expectations move synchronously, as expected. Finally, note that country-specific factors are positively correlated, across countries, likely because of trade linkages.

Correlation Coefficients Between Local and Global Factors

	Brazil	*Indonesia*	*Mexico*	*S.Africa*	*Turkey*	*Surprise*	*Uncertainty*
Brazil	1	0.52	0.34	0.67	0.38	0.48	-0.27
Indonesia	0.52	1	0.18	0.32	-0.02	0.04	0.14
Mexico	0.34	0.18	1	0.63	0.70	0.40	-0.17
S.Africa	0.67	0.32	0.63	1	0.51	0.31	-0.57
Turkey	0.38	-0.02	0.70	0.51	1	0.51	-0.20
Surprise	0.43	0.04	0.40	0.31	0.51	1	-0.25
Uncertainty	-0.27	0.14	-0.17	-0.57	-0.20	-0.25	1

In order to provide insight into the evolution of country-specific factors (local factors), Figure 3 plots GDP growth against estimated common factors. As is evident from inspection of the plots in this figure, local common factors track GDP growth quite well; and also capture the GDP dynamics in these countries during the global financial crisis.

4.2. Forecasting Experiment Results

Tables 1-5 summarize the results of our prediction experiments, for each of Brazil, Indonesia, Mexico, South Africa, and Turkey, respectively. As discussed above, there are eight main DFM varieties in our experiment, including Specifications 1-4 (called "Local", "Uncertainty", "Surprise", and "Global", respectively, in the tables), as well as Specifications 1-4 with AR terms (called "Local-AR", "Uncertainty-AR," "Surprise-AR", and "Global-AR", respectively). Additionally, each of these eight DFM models is estimated using five different types of shrinkage, including "All Sample", in which all country-specific variables are used in the DFM specification, "LASSO", "AdaLASSO", "Bayesian LASSO", and "Bayesian AdaLASSO". For complete details, refer to Section 3. In each of the tables, entries in the first row correspond to MSFEs associated with forecasts constructed using our straw-man AR model. All other entries in the tables are relative MSFEs, where the numeraire is MSFE of the AR model. Thus, entries that are less than unity indicate point MSFEs that are lower than that of the AR model. For each of two quarterly h-step ahead forecast horizons, (under the headers "$h = 1$" and "$h = 2$"), MSFEs from three monthly forecasts (denoted as months "1", "2", and "3") are reported. Results are also reported for three monthly nowcasts, under the header "$h = 0$", and one monthly backcast (under the header "$h = -1$"). For each country, entries denoted in bold indicate the MSFE-"best" model, across all specification types, for a given forecast horizon and shrinkage method. Additionally, for each country, entries denoted in bold and subscripted with "GB" (for "globally-best") indicate the MSFE-best models across all specification types and shrinkage methods, for a given forecast horizon.

The results in Table 1-5 reveal various interesting insights. First, there is a substantial reduction in MSFE as one moves from left to right along each row in the tables (i.e., as more data related to the current quarter become available). This increase in forecast accuracy is as expected, and indicates that the DFM models are able to correctly revise GDP prediction by effectively exploiting the flow of monthly data releases (see, Giannone et al. (2008), Banbura and Runstler (2011) and Li and Chen (2014) for further discussion).

Second, virtually all of the entries in Tables 1-5 are less than unity, indicating that the DFM model generally produces smaller point MSFEs than our straw-man or benchmark AR model. Additionally, noting that starred entries indicate rejection of the null of equal predictive accuracy (when comparing a given model against the AR benchmark), it is apparent upon inspection of the tabulated results that many of these MSFEs are significantly lower than that of the AR model.

Third, recall that there are ten forecast horizons and five shrinkage methods so that there are a total of 50 specification types for each country. Our results indicate that there are notable decreases in MSFE for a number of countries when "uncertainty" and "surprise" factors extracted from our uncertainty and surprise index datasets are included in the DFM.[7] Thus, latent factors that capture uncertainty and macro data surprise appear to contain significant marginal predictive content for country-specific growth prediction. For example, note that in Table 1 (i.e., the case of Brazil) the inclusion of factors extracted from uncertainty and/or surprise index datasets results in the globally MSFE-best models for 4 of 10 forecast horizons, across all shrinkage methods. For Indonesia (see Table 2), we see that for 7 of 10 forecast horizons, the inclusion of uncertainty and/or surprise factors results in the globally MSFE-best models. For Mexico, South Africa, and Turkey, the number of analogous "wins" for our global factors are 3 of 10, 10 of 10, and 9 of 10, respectively. Overall, thus globally MSFE-best models include our global uncertainty and surprise factors in 33 of 50 cases, across all five countries. In summary, there is strong evidence that global factors play a key role in GDP growth for Indonesia, South Africa, and Turkey; while the evidence is mixed for Brazil and Mexico.

Fourth, if one digs more deeply into the findings concerning Brazil, a further pattern emerges. In particular, note that for Brazil, 3 of the 4 "wins" discussed above occur when forecasting, while only 1 of 4 "wins" occur when nowcasting or backcasting. Thus, for this country, global information appears to lose its predictive content, relative to local information, as the calendar date of available monthly data becomes closer to (or surpasses) the calendar date of the GDP value being predicted. For Mexico, the story is different, as local information remains the most useful, regardless of forecast horizon. One reason for this might be that our global factors do not adequately account for shocks that are important to Mexico. This may in turn be due, in part, to the fact that Mexico has approximately the 15th largest economy in the world, in nominal terms, and exhibits a surprising level of macroeconomic stability. Moreover, Mexico has a largely export oriented economy with manufactured products accounting for approximately 90% of all exports.

In order to determine whether the above findings are apparent upon visual inspection of DFM predictions, we have plotted nowcasts against actual GDP growth for the 5 countries (see Figure 4). In this figure, the "Actual GDP" plot is of actual GDP growth rates, "AR" corresponds to nowcasts made with our AR

[7]Recall that entries labeled "Uncertainty" in the tables correspond to DFMs with "uncertainty" factors (i.e. Specification 2), entries labeled "Surprise" correspond to DFMs with "surprise" factors (i.e. Specification 3), and entries labeled "Global" correspond to DFMs with "uncertainty" and "surprise" factors (i.e. Specification 4).

model using all available data (i.e., no shrinkage), and "Local corresponds to DFM nowcasts made using all available data. Finally, for each country, we also include a "Local", "Surprise", or "Global" plot, corresponding to nowcasts made with the MSFE-best DFM model that includes "uncertainty" and/or "surprise" factors. Examination of these plots indicates that specification types based on uncertainty and macroeconomic data surprises tend to predict turning points relatively well, and outperform the "Local" factor model in volatile episodes, particularly for Brazil, South Africa, and Turkey. However, broad rankings of the variety available by summarizing the data in Tables 1-5 cannot be made by inspecting the plots in Figure 4. For this reason, we provide an alternative summary of the information given in Tables 1-5. This summary is given in Table A1 in Appendix A. In this table, the number of model "wins" is tabulated by model specification type, across all forecast horizons. Results in this table corroborate the findings above concerning the usefulness of our global factors for predicting GDP growth in EM countries.

Summarizing, our findings with respect to the importance of "uncertainty" factors are consistent with business cycle synchronization studies that focus on the growing financial and trade integration of world economies, and note that this integration is likely to result in stronger spillovers of shocks across economies. Additionally, our findings with regard to the importance of "surprise" factors underscore the importance of expectations of economic agents, which in turn reflect the importance of the ever greater amount of "soft" news that is available to agents, and that may not be reflected in the timely release of macroeconomic data.

We now turn to a discussion of the usefulness of data shrinkage in our experiments. Even casual inspection of the findings in Tables 1-5 indicates that pre-selection of indicators using shrinkage delivers models with more accurate forecasts than when DFMs are estimated without pre-selection. In particular, when comparing the "globally MSFE-best" models in Table 1-5, which we have defined to be the MSFE-best models for each country across all specification and shrinkage methods, we see that 47 of the 50 "globally best" models utilize shrinkage[8]. This suggests that the selection of relevant predictors from a large dataset mitigates data noisiness, and model (and coefficient estimator) imprecision due to multicollinearity, as might be expected. This result corroborates that of Boivin and Ng (2006), where it is suggested that the possibility of correlated errors increase as more series from the same "category" are included in a dataset, and creates a situation where more data might not be desirable. Among the different shrinkage methods that we utilize in our experiment, the Bayesian methods (Bayesian LASSO and Bayesian AdaLASSO) perform surprisingly well, as they attain the top rank in 36 out of 50 cases. This evidence strongly supports the use of Bayesian

[8]Recall that there are ten forecast horizons and five countries, so that we have total of 50 cases.

shrinkage methods for variable selection.[9] These results are summarized in Table A2 of Appendix A.

5. Concluding Remarks

Dynamic factor models (DFMs) are widely used in the forecasting literature. In this paper, we add to this literature by utilizing these models to predict emerging market (EM) GDP growth rates. Moreover, we augment the standard DFM type models that we examine with global "uncertainty" and "surprise" factors that are meant to capture the deepening interdependencies among all countries in the world. To do this, we construct three new datasets, one focusing on country specific data, and two focusing on worldwide uncertainty, sentiment, and so-called "surprise" data, from which global latent factors are extracted. These factors are constructed using both standard estimation methods as well as via implementation of a number of LASSO type shrinkage methods. We find that our new global economic "uncertainty" and macroeconomic data "surprise" factors are indeed useful, in the sense that they contain substantial marginal predictive content for real GDP growth in numerous EM economies, as shown through a series of real-time forecasting experiments. Moreover, the data shrinkage methods employed in our experiments are found to significantly improve the predictive content of the latent factors used in our DFMs.

This paper is meant as a starting point, as many questions remain unanswered. For example, it will be of interest to investigate the regime-dependent impact of uncertainty shocks on growth by distinguishing effects associated with phases of the business cycle. Also, it remains to analyze the impacts of possible changes in information rigidities in consensus forecasts (such as those used in the construction of our global "surprise" factors) when the economy moves from one phase of the business cycle to another. It also remains to asymptotically analyze extant shrinkage methods, with an eye to the development of new and improved estimation algorithms.

[9] See De Mol et al. (2008), where it is found that a few appropriately selected variables often capture the bulk of the covariation in large macroeconomic dataset that are characterized by collinearity, and use of these small groups of variables often yields comparable forecasting performance, relative to the case where all variables are used when constructing predictions.

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Figure 1: Global economic uncertainty factor

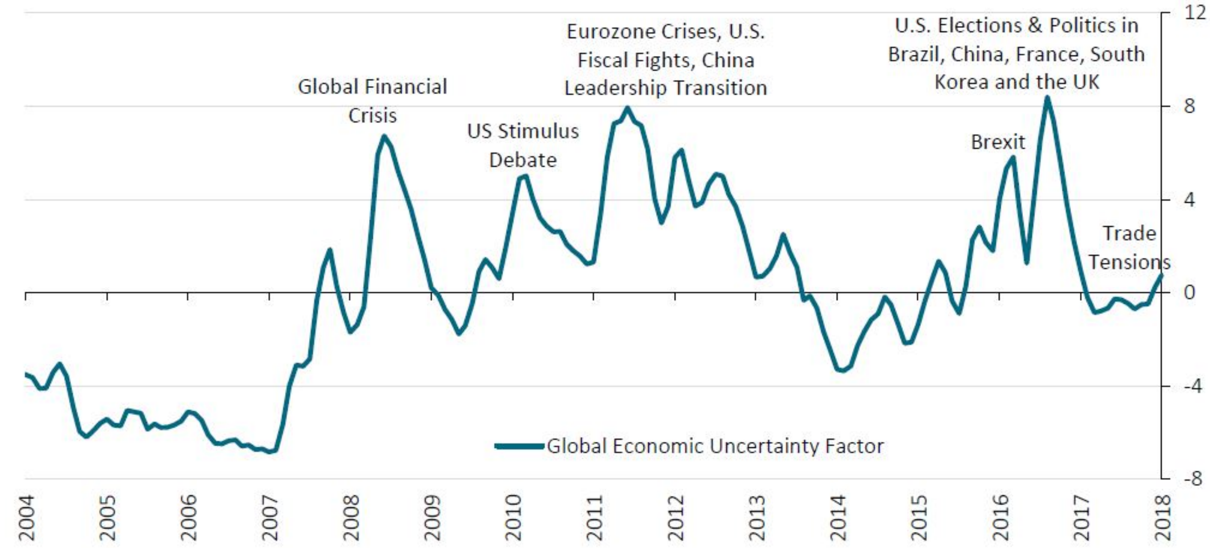

Figure 2: World GDP growth rates plotted against global macro-surprise factor

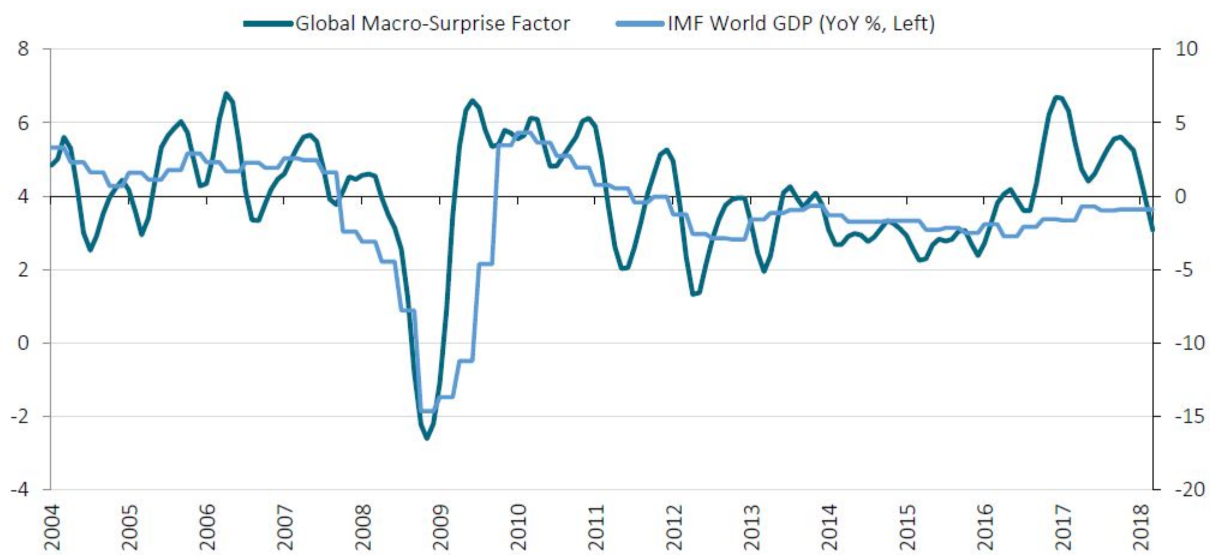

Figure 3: GDP growth rates plotted against local (country-specific) factors

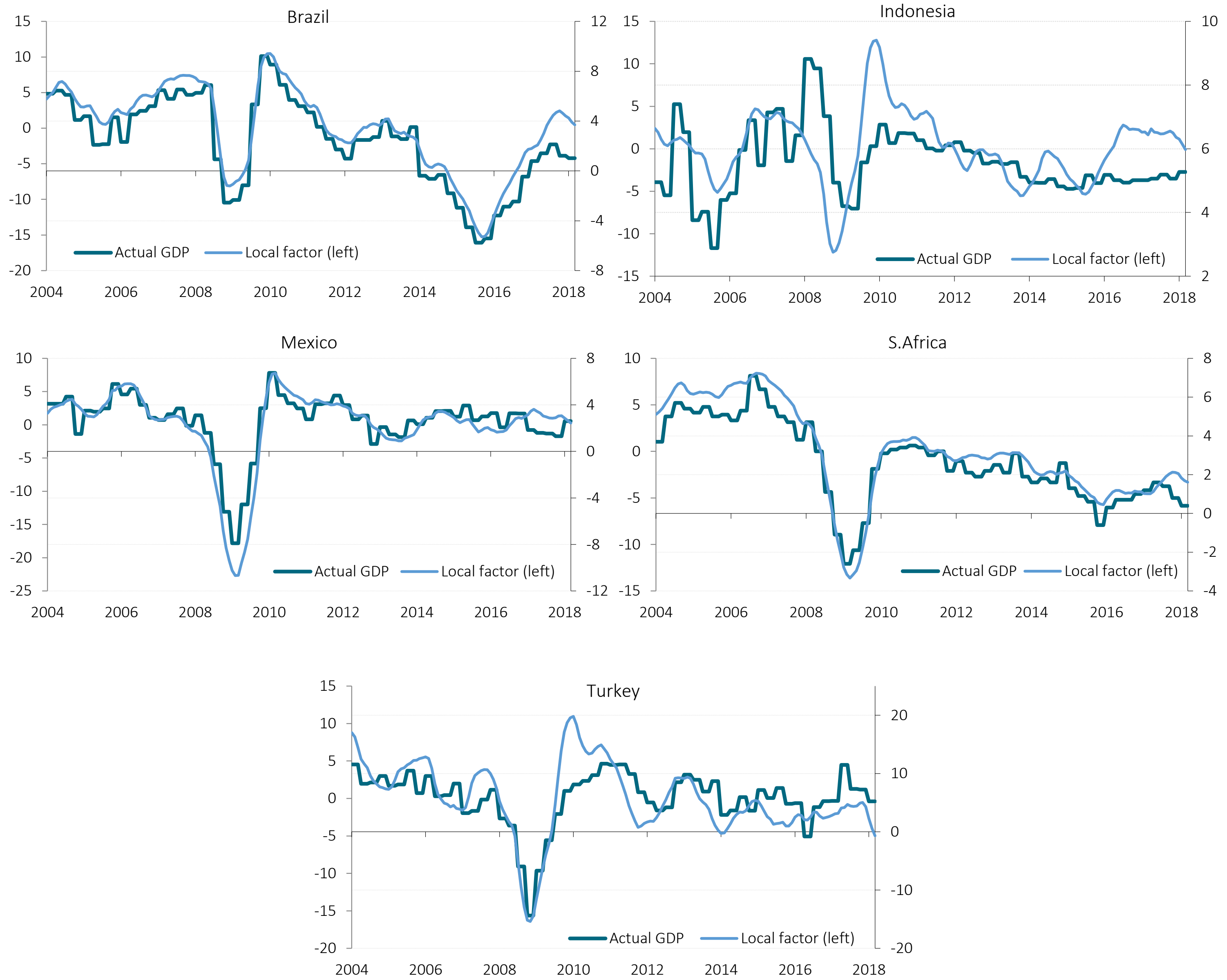

Figure 4: Comparison of actual GDP growth rates with nowcasts based on an AR benchmark, local factor model and MSFE-best models

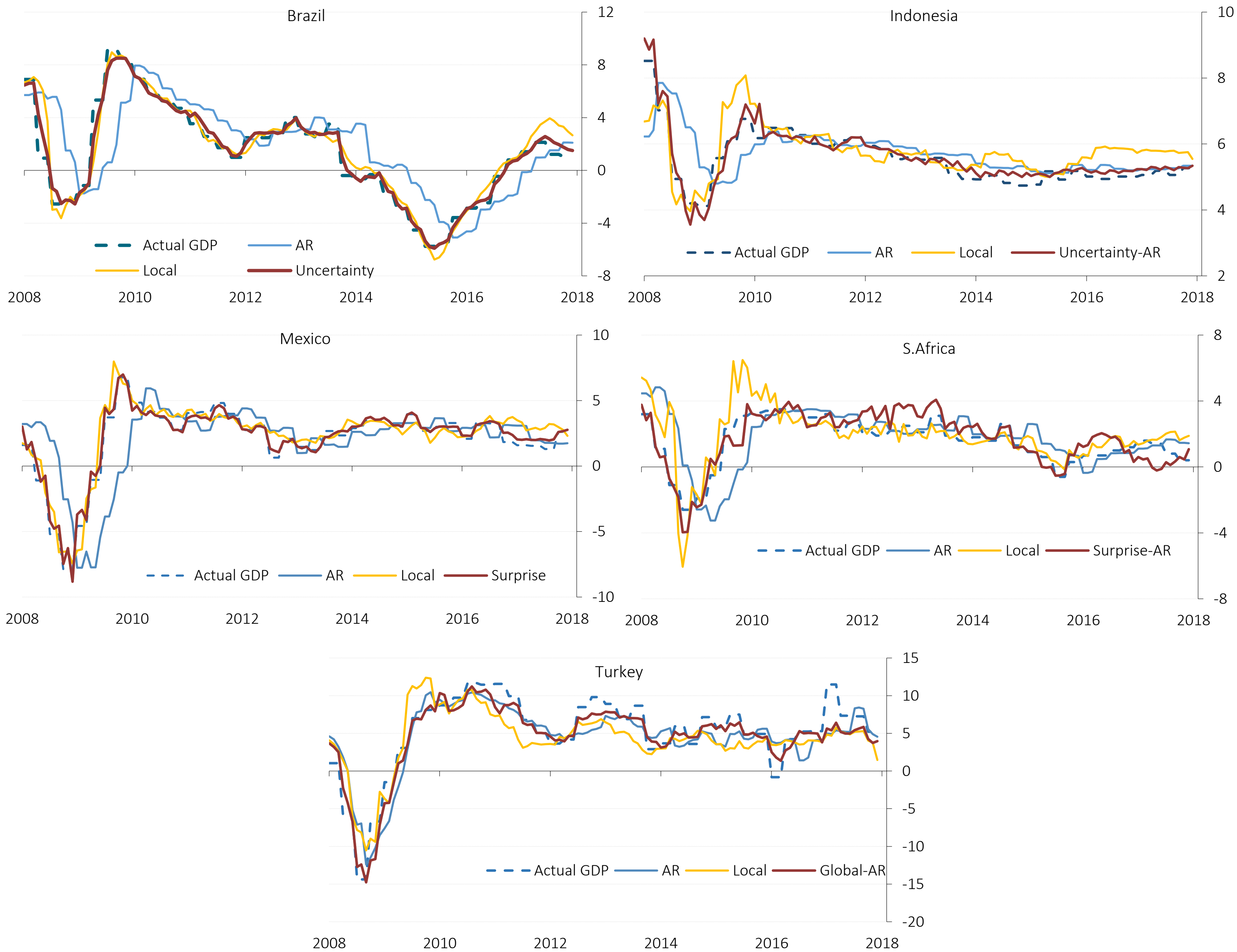

Table 1: MSFEs based on the use of different dimension reduction and shrinkage methods with added global diffusion indexes

Panel A: Brazil

All Sample	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
AR	4.43	4.43	4.20	3.85	3.85	3.52	2.99	2.99	2.62	2.62
Local	0.96	0.88	0.85	0.77	0.67*	0.62*	0.50*	0.39*	0.33*	0.43**
Uncertainty	0.94	0.85	0.83	0.72*	0.60*	0.57*	0.44*	0.30*	0.30*	0.46**
Suprise	0.96	0.89	0.85	0.78	0.68	0.60*	0.51*	0.39*	0.28*	0.39**
Global	0.92	$\mathbf{0.84}$	$\mathbf{0.83}$	0.72*	0.60*	0.57*	0.45*	0.30*	0.28*	0.44**
Local-AR	0.96	0.89	0.86	0.78	0.68	0.63*	0.51*	0.39*	0.31*	0.38**
Uncertainty-AR	0.93	0.85	0.84	0.72*	0.60*	0.57*	0.44*	$\mathbf{0.29^{*}}$	$\mathbf{0.27^{*}}$	0.43**
Suprise-AR	0.96	0.89	0.86	0.78	0.68	0.60*	0.51*	0.38*	0.27*	$\mathbf{0.38^{**}}$
Global-AR	$\mathbf{0.91}$	0.84	0.84	$\mathbf{0.71^{*}}$	$\mathbf{0.60^{*}}$	$\mathbf{0.57^{*}}$	$\mathbf{0.44^{*}}$	0.29*	0.27*	0.41**
LASSO										
Local	$\mathbf{0.90}$	0.81	$\mathbf{0.76}$	0.72	0.64	$\mathbf{0.53^{**}}$	0.49*	0.42*	0.32*	0.44**
Uncertainty	0.98	0.81	0.81	0.72*	$\mathbf{0.58^{*}}$	0.56**	0.44*	0.32*	0.33*	0.51**
Suprise	0.92	0.82	0.83	0.74	0.66	0.54**	0.49*	0.41*	0.33*	0.41**
Global	0.92	$\mathbf{0.80}$	0.87	$\mathbf{0.70^{*}}$	0.59*	0.57**	0.44*	0.32*	0.34*	0.53*
Local-AR	0.95	0.85	0.85	0.77	0.68	0.66*	0.50*	0.41*	0.35*	$\mathbf{0.34^{**}}$
Uncertainty-AR	1.00	0.83	0.85	0.74*	0.59*	0.57**	0.43*	$\mathbf{0.28^{*}}$	0.25*	0.42**
Suprise-AR	0.96	0.84	0.84	0.75*	0.67*	0.65*	0.48*	0.39*	0.35*	0.35**
Global-AR	0.95	0.82	0.85	0.71*	0.59*	0.57*	$\mathbf{0.42^{*}}$	0.29*	$\mathbf{0.25^{*}}$	0.39**
AdaLASSO										
Local	0.91	0.86	0.85	0.75	0.67	0.63*	0.51*	0.40*	0.33*	0.38**
Uncertainty	0.87	0.82	0.83	0.71*	0.61*	0.59*	0.46*	0.33*	0.31*	0.40**
Suprise	0.91	0.86	0.85	0.77	0.68	0.62*	0.53*	0.40*	0.30*	0.35**
Global	$\mathbf{0.85}$	$\mathbf{0.81}$	$\mathbf{0.83}$	$\mathbf{0.69^{*}}$	$\mathbf{0.60^{*}}$	$\mathbf{0.58^{*}}$	0.46*	0.32*	0.29*	0.37**
Local-AR	0.93	0.87	0.87	0.77	0.68	0.65*	0.52*	0.39*	0.31*	$\mathbf{0.34^{**}_{GB}}$
Uncertainty-AR	0.89	0.83	0.85	0.72*	0.61*	0.59*	0.46*	0.31*	0.27*	0.37**
Suprise-AR	0.93	0.87	0.86	0.77	0.68	0.63*	0.52*	0.40*	0.29*	0.34**
Global-AR	0.87	0.83	0.84	0.70*	0.60*	0.58*	$\mathbf{0.45^{*}}$	$\mathbf{0.31^{*}}$	$\mathbf{0.27^{*}}$	0.39*
Bayesian LASSO										
Local	0.80	0.75	0.76	$\mathbf{0.62^{*}_{GB}}$	0.54*	0.53**	$\mathbf{0.28^{*}_{GB}}$	$\mathbf{0.14^{*}_{GB}}$	0.13*	0.47*
Uncertainty	0.81	0.76	0.77	0.64*	0.56*	0.54**	0.31*	0.16*	$\mathbf{0.12^{*}_{GB}}$	0.45*
Suprise	$\mathbf{0.79}$	$\mathbf{0.74}$	$\mathbf{0.75}$	0.63*	$\mathbf{0.54^{*}_{GB}}$	$\mathbf{0.53^{**}}$	0.30*	0.16*	0.14*	0.46*
Global	0.80	0.75	0.76	0.64*	0.56*	0.54*	0.31*	0.17*	0.13*	0.43**
Local-AR	0.88	0.82	0.82	0.70*	0.61*	0.58*	0.39*	0.24*	0.14*	0.36**
Uncertainty-AR	0.89	0.83	0.83	0.71	0.62*	0.59*	0.41*	0.26*	0.14*	$\mathbf{0.35^{**}}$
Suprise-AR	0.88	0.82	0.82	0.70*	0.61*	0.58*	0.40*	0.24*	0.14*	0.36**
Global-AR	0.88	0.82	0.82	0.71*	0.62*	0.58*	0.40*	0.25*	0.13*	0.35**
Bayesian AdaLASSO										
Local	0.79	$\mathbf{0.73_{GB}}$	$\mathbf{0.71^{*}_{GB}}$	0.66*	$\mathbf{0.58^{*}}$	0.53**	$\mathbf{0.48^{*}}$	0.41*	0.37*	0.48**
Uncertainty	0.80	0.74	0.72	0.67*	0.59*	$\mathbf{0.52^{**}_{GB}}$	0.48*	0.42*	0.35*	0.47**
Suprise	0.80	0.79	0.75	0.70*	0.65*	0.56**	0.53*	0.48*	0.37*	0.48**
Global	$\mathbf{0.76_{GB}}$	0.79	0.74	$\mathbf{0.65^{**}}$	0.62	0.53*	0.49*	0.44*	0.33*	0.45**
Local-AR	0.86	0.79	0.79	0.73*	0.65*	0.61**	0.52*	0.43*	0.34*	$\mathbf{0.35^{**}}$
Uncertainty-AR	0.83	0.76	0.75	0.70**	0.60*	0.54**	0.49*	$\mathbf{0.39^{*}}$	0.26*	0.36**
Suprise-AR	0.85	0.80	0.78	0.73*	0.66*	0.59**	0.52*	0.46*	0.31*	0.38**
Global-AR	0.81	0.79	0.77	0.68**	0.62*	0.54*	0.49*	0.40*	$\mathbf{0.26^{*}}$	0.41**

Entries in this table are MSFEs. Models that yield the smallest MSFE are denoted in bold, for each estimation method and forecast horizon; and models that are denoted in bold with a "GB" subscript denote models that are "globally" MSFE-"best", across all models and estimation methods, for a given forecast horizon. Entries in the first row of the table are point MSFEs based our benchmark AR(SIC) model, while the rest of the entries in the table are relative MSFEs (i.e., relative to the AR(SIC) benchmark model). Thus, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the AR(SIC) benchmark, for a particular forecast horizon. Quarterly forecast horizons are denoted by h=-1,0,1, or 2; and monthly forecasts within each of these quarters are denoted by month 1, 2, or 3. Entries superscripted with asterisks (** = 5% level; * = 10% level) are significantly superior than the AR(SIC) benchmark model, based on application of the Diebold-Mariano (1995) predictive accuracy test. All models are listed in the first column of the table, and Local, Uncertainty, Surprise, and Global correspond to Specifications 1-4 from Section 3.3, respectively; while the models appended with "-AR" are the same as Specifications 1-4, but with additional lagged dependent variables added as regressors. For complete details, refer to Section 3.

Table 2: MSFEs based on the use of different dimension reduction and shrinkage methods with added global diffusion indexes

Panel B: Indonesia

All Sample	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
AR	1.07	1.07	1.01	1.05	1.05	0.97	0.80	0.80	0.73	0.73
Local	**0.83**	**0.83**$_{\mathbf{GB}}$	**0.92**	**0.72***	**0.75***	**0.82***	0.76*	0.79	0.88	1.16
Uncertainty	1.35	1.56	1.33	1.25	1.39	1.32	1.21	1.30	1.31	1.40
Suprise	1.13	1.18	1.28	0.98	1.01	1.11	0.94	0.93	1.02	1.07
Global	1.13	1.19	1.24	1.09	1.13	1.23	1.11	1.13	1.23	1.32
Local-AR	0.86	0.86	0.97	0.76*	0.76*	0.85	**0.75***	**0.71***	**0.84**	**0.94**
Uncertainty-AR	1.38	1.55	1.33	1.24	1.33	1.27	1.12	1.17	1.16	1.25
Suprise-AR	1.26	1.21	1.30	1.10	1.00	1.11	1.01	0.89	0.97	1.01
Global-AR	1.28	1.21	1.26	1.21	1.13	1.23	1.17	1.09	1.18	1.30
LASSO										
Local	0.95	0.90	0.93	0.87*	0.87	**0.82***	0.89*	0.86	0.88	1.03
Uncertainty	1.60	1.63	1.29	1.43	1.45	1.30	1.36	1.38	1.31	1.45
Suprise	1.26	1.17	1.23	1.15	1.08	1.06	1.13	1.08	0.99	1.11
Global	1.33	1.23	1.19	1.28	1.19	1.17	1.30	1.25	1.18	1.36
Local-AR	**0.90**	**0.87**	**0.93**	**0.81***	**0.83***	0.83	**0.81***	**0.79***	**0.86**	**0.98**
Uncertainty-AR	1.63	1.70	1.12	1.41	1.44	1.15	1.26	1.27	1.12	1.34
Suprise-AR	1.31	1.22	1.20	1.16	1.09	1.06	1.11	1.00	0.98	1.07
Global-AR	1.36	1.25	1.09	1.29	1.21	1.13	1.29	1.21	1.16	1.38
AdaLASSO										
Local	0.89	0.89	0.92	0.77	0.74	0.76*	0.73*	0.65*	0.63*	0.96
Uncertainty	0.90	1.01	0.96	0.83	0.91	0.85*	0.91	0.92	0.83*	1.09
Suprise	0.93	1.01	1.00	0.83	0.86	0.84*	0.79	0.74*	0.68*	0.96
Global	0.90	0.94	0.89	0.82	0.85	0.79*	0.88	0.85	0.73*	1.05
Local-AR	0.95	0.97	0.97	0.79	0.80	0.75	**0.65***	**0.61***	**0.55***	1.00
Uncertainty-AR	**0.82**$_{\mathbf{GB}}$	**0.89**	**0.84**$_{\mathbf{GB}}$	**0.67***$_{\mathbf{GB}}$	**0.68***$_{\mathbf{GB}}$	**0.71***	0.72*	0.72	0.67*	1.11
Suprise-AR	1.04	1.04	1.04	0.86	0.85	0.81	0.71*	0.70*	0.63*	**0.95**
Global-AR	0.88	0.91	0.85	0.71*	0.70*	0.73*	0.74*	0.76	0.70*	1.08
Bayesian LASSO										
Local	1.32	1.22	1.24	0.92	0.78	0.68*	0.55*	0.56*	0.39*	0.79
Uncertainty	1.25	1.20	1.21	0.85	0.76	0.69*	0.48*	0.57*	0.41*	0.86
Suprise	1.40	1.31	1.30	0.99	0.86	0.78	0.54*	0.54*	0.37*	0.73
Global	1.36	1.28	1.28	0.94	0.83	0.80	0.46*	0.51*	0.39*	0.78
Local-AR	1.21	1.13	1.06	0.85	**0.77**	**0.67***$_{\mathbf{GB}}$	0.43*	0.38*	**0.29***$_{\mathbf{GB}}$	0.49
Uncertainty-AR	1.23	1.16	1.17	**0.82**	0.77	0.75	**0.35***$_{\mathbf{GB}}$	**0.36***$_{\mathbf{GB}}$	0.32*	0.56
Suprise-AR	1.16	1.09	1.12	0.88	0.82	0.77*	0.53*	0.46*	0.42*	**0.43**$_{\mathbf{GB}}$
Global-AR	1.21	1.16	1.20	0.89	0.84	0.82	0.50*	0.46*	0.44*	0.50
Bayesian AdaLASSO										
Local	**0.95**	**0.94**	1.03	0.83*	**0.80**	**0.87**	0.81*	0.73*	0.82	0.99
Uncertainty	1.04	0.97	1.13	1.05	0.97	1.06	1.20	1.16	1.17	1.43
Suprise	1.15	1.11	1.21	1.02	0.97	1.04	0.99	0.88	0.92	1.08
Global	1.28	0.99	1.12	1.19	0.95	1.04	1.24	1.10	1.09	1.33
Local-AR	1.00	1.00	1.10	**0.83**	0.83	0.92	**0.71***	**0.63***	**0.75**	**0.88**
Uncertainty-AR	1.09	0.98	**0.99**	1.03	0.88	0.90	1.09	1.02	0.97	1.36
Suprise-AR	1.22	1.14	1.18	1.04	0.96	1.00	0.91	0.77*	0.83	1.00
Global-AR	1.42	1.16	1.08	1.26	1.01	0.96	1.24	1.09	0.97	1.36

See notes to Table 1.

Table 3: MSFEs based on the use of different dimension reduction and shrinkage methods with added global diffusion indexes

Panel C: Mexico

All Sample	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
AR	4.38	4.38	3.98	3.72	3.72	3.26	2.73	2.73	2.25	2.25
Local	**0.63**	**0.53**	0.52	**0.45***	0.38**	**0.44****	0.35**	0.33**	**0.60***	**0.66**
Uncertainty	0.70	0.63	0.54	0.50*	0.45*	0.48**	0.37**	0.36**	0.62*	0.72
Suprise	0.65	0.53	0.57	0.48*	0.39**	0.52**	0.36**	0.33**	0.68	0.78
Global	0.70	0.61	0.57	0.50*	0.43*	0.52**	0.37**	0.34**	0.68	0.79
Local-AR	0.72	0.59	0.55	0.49*	0.40**	0.45**	0.34**	0.32**	0.62*	0.70
Uncertainty-AR	0.75	0.65	0.55	0.51*	0.45*	0.48**	0.36**	0.35**	0.63*	0.74
Suprise-AR	0.67	0.53	**0.51**	0.47*	**0.37****	0.47**	**0.33****	**0.30****	0.65	0.79
Global-AR	0.70	0.58	0.52	0.49*	0.40*	0.49**	0.35**	0.32**	0.65	0.79
LASSO										
Local	**0.68**	0.58	0.53	0.47*	0.39**	0.46**	0.32**	0.28**	0.60*	**0.71**
Uncertainty	0.73	0.69	0.55	0.48*	0.43**	0.48**	0.31**	0.29**	0.61*	0.77
Suprise	0.69	**0.55**	0.53	**0.45***	**0.37****	0.48**	0.30**	0.26**	0.64	0.77
Global	0.71	0.65	0.56	0.46*	0.37**	0.48**	0.29**	0.26**	0.64	0.80
Local-AR	0.78	0.64	0.55	0.52*	0.42*	0.46**	0.31**	0.27**	**0.60***	0.74
Uncertainty-AR	0.81	0.73	0.57	0.52*	0.45*	0.50**	0.31**	0.28**	0.60*	0.79
Suprise-AR	0.77	0.61	**0.52**	0.50*	0.39*	**0.46****	0.30**	0.25**	0.61*	0.79
Global-AR	0.78	0.70	0.56	0.49*	0.39*	0.48**	**0.29****	**0.25****	0.62*	0.81
AdaLASSO										
Local	**0.53$_{GB}$**	**0.48$_{GB}$**	**0.48*$_{GB}$**	**0.41*$_{GB}$**	**0.40***	**0.42**$_{GB}$**	0.34**	0.33**	0.52**	**0.64*$_{GB}$**
Uncertainty	0.63	0.56	0.61	0.45*	0.44*	0.53**	0.34**	0.32**	0.57*	0.79
Suprise	0.55	0.52	0.52	0.42*	0.42*	0.49**	0.34**	0.34**	0.62*	0.78
Global	0.61	0.54	0.62	0.45*	0.42*	0.56**	0.33**	0.31**	0.64*	0.87
Local-AR	0.64	0.56	0.54	0.46*	0.41*	0.44**	0.31**	**0.29****	**0.52***	0.67
Uncertainty-AR	0.71	0.64	0.67	0.49*	0.47*	0.58**	0.32**	0.32**	0.56*	0.79
Suprise-AR	0.63	0.57	0.52	0.44*	0.43*	0.46**	0.31**	0.32**	0.58*	0.81
Global-AR	0.67	0.59	0.64	0.46*	0.43*	0.56**	**0.31****	0.31**	0.60*	0.87
Bayesian LASSO										
Local	0.91	**0.74**	**0.82**	0.47*	**0.41***	**0.57***	**0.19**$_{GB}$**	0.17**	0.18**	0.78
Uncertainty	**0.90**	0.80	0.83	**0.47***	0.43*	0.58*	0.20**	0.21**	0.18**	0.78
Suprise	0.91	0.75	0.83	0.47*	0.41*	0.58*	0.19**	**0.16**$_{GB}$**	**0.18**$_{GB}$**	0.77
Global	0.90	0.80	0.84	0.47*	0.43*	0.59*	0.21**	0.22**	0.18**	0.77
Local-AR	1.18	0.87	0.99	0.66	0.52*	0.72	0.23**	0.26**	0.31**	0.70
Uncertainty-AR	1.25	0.97	1.03	0.71	0.56*	0.75	0.24**	0.20**	0.33**	0.71
Suprise-AR	1.17	0.88	0.99	0.65	0.52*	0.72	0.23**	0.25**	0.32**	**0.70**
Global-AR	1.23	0.96	1.04	0.70	0.55*	0.76	0.24**	0.22**	0.34**	0.70
Bayesian AdaLASSO										
Local	**0.61**	0.53	**0.48**	0.45*	0.40*	**0.43****	0.35**	0.33**	**0.58***	**0.69**
Uncertainty	0.66	0.56	0.50	0.47*	0.41*	0.47**	0.35**	0.34**	0.61*	0.78
Suprise	0.62	**0.51**	0.48	**0.42***	0.36**	0.44**	0.32**	0.31**	0.62*	0.74
Global	0.65	0.52	0.51	0.44*	**0.36**$_{GB}$**	0.47**	0.33**	0.31**	0.63*	0.80
Local-AR	0.73	0.62	0.53	0.52*	0.44*	0.46**	0.35**	0.32**	0.59*	0.74
Uncertainty-AR	0.76	0.62	0.54	0.52*	0.44*	0.49**	0.35**	0.33**	0.60*	0.80
Suprise-AR	0.74	0.60	0.52	0.49*	0.41*	0.46**	**0.33****	0.31**	0.62*	0.78
Global-AR	0.75	0.60	0.54	0.49*	0.38*	0.49**	0.33**	**0.30****	0.62*	0.81

See notes to Table 1.

Table 4: MSFEs based on the use of different dimension reduction and shrinkage methods with added global diffusion indexes

Panel D: South Africa

All Sample	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
AR	2.55	2.55	2.38	2.10	2.10	1.90	1.44	1.44	1.30	1.30
Local	0.94	0.91	1.10	0.93	0.77	0.90	0.85	0.77	1.01	1.04
Uncertainty	1.04	0.94	**0.94**	0.86	0.74	**0.74***	0.76*	0.78	0.84	0.88
Suprise	0.91	0.82	1.18	0.91	0.76	0.97	0.85	0.73*	0.99	1.03
Global	**0.78**	**0.76**	0.99	**0.79***	**0.71***	0.80	**0.72***	**0.72****	**0.80**	**0.80**
Local-AR	1.28	1.13	1.27	1.04	1.00	1.04	0.89	0.88	1.09	1.14
Uncertainty-AR	1.07	1.14	1.12	0.95	0.98	1.05	0.78*	0.89	1.08	0.98
Suprise-AR	1.25	1.06	1.47	1.01	0.94	1.21	0.88	0.82	1.09	1.12
Global-AR	1.09	1.04	1.05	0.88	0.94	0.93	0.73**	0.88	0.99	0.91
LASSO										
Local	0.82	0.85	1.10	0.81**	0.72**	1.04	0.70**	0.67**	0.86	0.77
Uncertainty	0.92	0.85	1.02	0.82**	0.69**	**0.95**	0.69**	0.65**	**0.80**	0.96
Suprise	**0.75**	**0.80**	1.18	0.79**	**0.68****	1.18	0.68**	0.65	0.93	0.77
Global	0.92	0.87	1.06	0.89	0.75**	1.06	0.80	0.73**	0.82	1.01
Local-AR	0.87	0.86	1.18	0.83**	0.72**	1.16	0.71**	**0.64****	0.90	0.68
Uncertainty-AR	0.85	0.80	1.07	0.82*	0.68*	1.01	0.72**	0.67**	0.83	0.75
Suprise-AR	0.77	0.87	1.28	**0.76****	0.72**	1.35	**0.65****	0.66**	0.99	**0.67***$_{GB}$
Global-AR	0.90	0.85	1.18	0.84	0.72**	1.18	0.81	0.67**	0.88	0.88
AdaLASSO										
Local	0.99	0.99	1.09	0.87*	0.89*	1.09	0.86*	0.89	1.50	0.87
Uncertainty	**0.90**	**0.92**	**0.83**	**0.79***	**0.82***	**0.70***	**0.78****	0.86*	**0.71***	0.84
Suprise	0.95	0.98	0.93	0.85*	0.89	0.78*	0.85*	**0.84****	0.82	0.85
Global	0.91	0.97	0.99	0.80*	0.89	1.03	0.80*	0.89	1.47	0.86
Local-AR	1.20	1.08	1.07	0.99	1.02	0.95	0.88**	1.00	0.94	0.80
Uncertainty-AR	1.10	0.98	0.98	0.90	0.92	0.85	0.82**	0.90	0.94	**0.70**
Suprise-AR	1.29	1.24	1.12	1.15	1.18	1.21	1.09	1.24	1.88	0.91
Global-AR	1.03	1.02	0.95	0.91	1.03	0.77	0.81**	0.94	0.73*	0.70
Bayesian LASSO										
Local	0.97	0.71	0.79	0.95	0.68**	0.79*	0.81**	0.89*	1.05	1.16
Uncertainty	0.87	0.78	0.79	0.85*	0.71**	0.82*	0.83**	0.92*	1.09	1.17
Suprise	0.97	**0.69***$_{GB}$	0.76	0.89	0.66**	0.77*	0.79**	0.85*	1.01	1.16
Global	0.82	0.75	0.77	0.79*	0.69**	0.77*	0.83*	0.92*	1.05	1.18
Local-AR	0.80	0.74	0.68	0.61**	0.58**	0.53**	0.52**	0.57**	0.70**	0.91
Uncertainty-AR	0.79	0.75	0.68	0.62**	0.57**	0.53**	0.53**	0.61**	0.73**	0.94
Suprise-AR	0.74	0.72	**0.68***$_{GB}$	**0.58****$_{GB}$	0.56**	**0.52****$_{GB}$	**0.50****$_{GB}$	**0.56****$_{GB}$	**0.67****	**0.88**
Global-AR	**0.74**$_{GB}$	0.75	0.69*	0.60**	**0.55****$_{GB}$	0.53**	0.51**	0.61**	0.70**	0.92
Bayesian AdaLASSO										
Local	**0.92**	0.81	0.91	0.79*	0.65**	0.81	0.73*	0.81	0.77*	0.85
Uncertainty	1.11	0.97	**0.85**	0.98	0.82	**0.77**	0.91	1.00	**0.64***$_{GB}$	0.92
Suprise	0.94	**0.75**	1.04	**0.79***	**0.55****	0.97	**0.71***	**0.77***	0.80	**0.82**
Global	1.12	0.95	1.01	0.96	0.81	0.97	0.95	0.83	0.74*	1.12
Local-AR	1.12	1.04	1.15	0.95	0.93	1.04	0.78*	1.05	0.86	0.93
Uncertainty-AR	1.29	1.17	1.04	1.18	1.06	1.01	1.03	1.25	0.87	1.10
Suprise-AR	1.13	1.00	1.33	0.93	0.88	1.29	0.73*	1.09	0.98	0.87
Global-AR	1.10	1.20	1.16	0.98	1.09	1.16	0.94	0.95	0.94	1.08

See notes to Table 1.

Table 5: MSFEs based on the use of different dimension reduction and shrinkage methods with added global diffusion indexes

Panel E: Turkey

All Sample	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
AR	7.21	7.21	6.58	6.63	6.63	5.94	5.48	5.48	4.69	4.69
Local	0.68	0.65	0.72	0.62**	0.56**	0.60	0.56	0.55	0.66**	0.67
Uncertainty	0.69	0.69	0.75	**0.60**	0.55	0.58	0.56	0.55	0.66**	0.72
Suprise	**0.68**$_{GB}$	**0.64**$_{GB}$	**0.69**	0.60**	**0.54****	0.56*	0.53	0.53	0.64**	0.74
Global	0.68	0.67	0.73	0.60**	0.55*	0.57	0.55**	0.55	0.64**	0.71
Local-AR	0.71	0.68	0.73	0.62	0.58	0.58	0.51	0.50	0.52	0.58*
Uncertainty-AR	0.71	0.71	0.75	0.60	0.56	0.56*	0.51*	0.50	0.52	0.56*
Suprise-AR	0.73	0.69	0.73	0.62**	0.58**	0.56*	**0.50***	0.49	0.48	0.54*
Global-AR	0.72	0.71	0.74	0.62*	0.59*	**0.55***	0.51*	**0.50**	**0.48**	**0.51***
LASSO										
Local	0.73	0.66	0.70	0.64*	0.57**	0.58	0.52*	0.51	0.58*	0.61*
Uncertainty	0.71	0.70	0.73	0.61	0.57	0.58*	0.54	0.53	0.58**	0.66
Suprise	0.73	**0.65**	**0.68***$_{GB}$	0.63**	0.56**	0.56	0.50*	0.51	0.57	0.71
Global	**0.70**	0.67	0.71	**0.59***	**0.56***	**0.55***	0.53	0.55	0.57*	0.65
Local-AR	0.79	0.72	0.73	0.66**	0.61**	0.59	0.49*	0.48	0.47	0.56*
Uncertainty-AR	0.75	0.72	0.75	0.63*	0.59	0.57*	0.49*	**0.48**	0.48	0.54*
Suprise-AR	0.78	0.71	0.73	0.65*	0.60**	0.58	**0.48****	0.49	**0.45**	0.54*
Global-AR	0.74	0.70	0.74	0.62*	0.59	0.56*	0.50	0.50	0.47	**0.51***
AdaLASSO										
Local	0.74	0.70	0.81	0.67	0.62	0.70	0.60	0.58	0.70**	0.72
Uncertainty	0.75	0.79	0.82	0.64	0.62	0.64	0.63	0.61	0.69**	0.76
Suprise	**0.71**	**0.68**	**0.75**	0.64	0.60	0.64	0.56	0.56	0.67**	0.78
Global	0.72	0.76	0.79	0.60	0.60	0.61	0.62	0.62	0.68**	0.74
Local-AR	0.75	0.75	0.80	0.66	0.64	0.66	0.54*	0.52	0.51	0.56*
Uncertainty-AR	0.76	0.77	0.79	0.62	0.61	0.61	0.55	0.52	0.54	0.58*
Suprise-AR	0.76	0.75	0.79	0.66	0.63	0.64	**0.53***	**0.52**	**0.48***	0.53*
Global-AR	0.73	0.75	0.77	**0.60***	**0.59***	**0.58***	0.55	0.54	0.51*	**0.53***
Bayesian LASSO										
Local	0.76	0.73	0.78	0.62*	0.58	0.63	0.40**	0.39*	0.40	**0.46**$_{GB}$
Uncertainty	0.74	0.72	0.78	0.58*	0.52	0.59	0.37**	0.36*	0.37*	0.61*
Suprise	0.75	0.72	**0.76**	0.61*	0.58	0.61	0.39**	0.38**	0.38*	0.65*
Global	**0.74**	**0.72**	0.78	**0.57***	**0.52**	**0.59**	**0.36****$_{GB}$	0.35*	0.36*	0.62*
Local-AR	0.94	0.82	0.84	0.69	0.61	0.62	0.38**	0.36*	0.32**	0.55*
Uncertainty-AR	0.93	0.82	0.83	0.67	0.59	0.61	0.37**	0.35*	0.30**	0.54*
Suprise-AR	0.96	0.83	0.83	0.69	0.62	0.62	0.38**	0.36*	0.31**	0.55*
Global-AR	0.94	0.82	0.83	0.67	0.59	0.60	0.36**	**0.35***$_{GB}$	**0.30****$_{GB}$	0.53*
Bayesian AdaLASSO										
Local	0.76	0.67	0.72	0.62*	0.55*	0.58	0.46**	0.45	0.50	**0.53***
Uncertainty	0.73	0.70	0.74	0.54	0.50	0.54**	0.42**	0.43	0.48	0.65
Suprise	0.76	**0.66**	**0.69**	0.62*	0.54*	0.56	0.44**	0.44	0.49	0.72
Global	**0.72**	0.69	0.71	**0.54***$_{GB}$	**0.50***$_{GB}$	0.52**	0.42**	0.44	0.48	0.65
Local-AR	0.85	0.71	0.73	0.64	0.56*	0.57*	0.42**	0.42*	0.43	0.61
Uncertainty-AR	0.81	0.72	0.75	0.58	0.52	0.54**	0.39**	**0.39***	0.42*	0.58*
Suprise-AR	0.84	0.69	0.72	0.63	0.55*	0.55*	0.41**	0.41*	0.42*	0.61*
Global-AR	0.78	0.70	0.72	0.57	0.51	**0.52****$_{GB}$	**0.39****	0.40	**0.41***	0.56*

See notes to Table 1.

Appendix A: Supplementary Tables

Table A1: The number of times the each specification types ranked MSFE-best model across all dimension reduction methods

	Brazil	Indonesia	Mexico	S.Africa	Turkey
AR	0	3	0	1	0
Local	10	11	25	1	2
Uncertainty	3	0	2	15	1
Suprise	5	0	7	11	12
Global	12	0	1	8	13
Local-AR	3	24	3	1	0
Uncertainty-AR	5	10	0	1	2
Suprise-AR	1	2	8	10	6
Global-AR	11	0	4	2	14

Table A2: Summary of the “globally-best” model across all dimension reduction methods and specification types

	Forecast (h=2)			Forecast (h=1)			Nowcast (h=0)			Backcast (h=-1)
	1	2	3	1	2	3	1	2	3	1
Brazil	BaLASSO-4	BaLASSO-1	BaLASSO-1	BLASSO-1	BLASSO-2	BaLASSO-2	BLASSO-1	BLASSO-1	BLASSO-2	AdaLASSO-5
Indonesia	AdaLASSO-6	ALL-1	AdaLASSO-6	AdaLASSO-6	AdaLASSO-6	BLASSO-5	BLASSO-6	BLASSO-6	BLASSO-5	BLASSO-7
Mexico	AdaLASSO-1	AdaLASSO-1	AdaLASSO-1	AdaLASSO-1	BaLASSO-4	AdaLASSO-1	BLASSO-1	BLASSO-3	BLASSO-3	AdaLASSO-1
S.Africa	BLASSO-8	BLASSO-3	BLASSO-7	BLASSO-7	BLASSO-8	BLASSO-7	BLASSO-7	BLASSO-7	BaLASSO-2	LASSO-7
Turkey	ALL-3	ALL-3	LASSO-3	BaLASSO-4	BaLASSO-4	BaLASSO-8	BLASSO-4	BLASSO-8	BLASSO-8	BLASSO-1

See notes to Table 3. The following abbreviations; Local = ”1”, Uncertainty = ”2”, Surprise = ”3”, Global = ”4”, Local-AR = ”5”, Uncertainty-AR = ‘”6”, Surprise-AR = “7”, and Global-AR = ”8”. For example, BLASSO-4 means that the Global factor model given as Specification 4 in Section 3.3 yields the lowest MSFE across all different models and different targeted predictor selection methods for a given country, as listed in column 1 of the table.

Appendix B: Data

Table B1: Dataset-Brazil

Number	Ticker	Description
1	2236689 Index	IMF Brazil Unemployment Rate
2	BZJCYTOT Index	Brazil Government Registered Job Creation Total NSA YTD
3	BZMW Index	Brazil Minimum Wage
4	BZGDWGSL Index	Brazil Wages and Salaries
5	BRMWRL Index	Brazil Real Minimum Wage
6	BZCCEXUN Index	Brazil CNI Consumer Confidence Expectations on Unemployment
7	BZCCEXIN Index	Brazil CNI Consumer Confidence Income Expectations
8	BZUETAYL Index	BR Unemployment Rate - Taylor Rule
9	BZREOFFR Index	Brazil Sao Paulo Secovi Real Estate Units Offered
10	BZRESTRT Index	Brazil Sao Paulo Secovi Real Estate Units Started
11	BZREPERD Index	Secovi Brazil Real Estate Units Average Sale Time Period
12	BZRESOLD Index	Brazil Sao Paulo Secovi Real Estate Units Sold

Continued on next page

Table B1 – *Continued from previous page*

Number	Ticker	Description
13	IBREINCM Index	FGV Brazil IGP-M Construction Prices INCC-M
14	USDBRL Curncy	USDBRL Spot Exchange Rate - Price of 1 USD in BRL
15	EURBRL Curncy	EURBRL Spot Exchange Rate - Price of 1 EUR in BRL
16	JPYBRL Curncy	JPYBRL Spot Exchange Rate - Price of 1 JPY in BRL
17	USDBRLV1M Index	USDBRL 1 Month ATM Implied Volatility
18	USDBRL25R3M Index	USDBRL 3 Month 25 Delta Risk Reversal
19	BISBBRR Index	Brazil Real Effective Exchange Rate Broad
20	IBOV Index	Ibovespa Brasil Sao Paulo Stock Exchange Index
21	WCAUBRAZ Index	Bloomberg Brazil Exchange Market Capitalization USD
22	IFNCBV Index	Brazil Financial Index
23	BZLIQDTY Index	Bovespa Volume Brazil Settlement
24	IBOVIEE Index	Sao Paulo Stock Exchange Electrical Energy Index
25	CBRZ1U5 Curncy	Federative Republic of Brazil
26	BZSTSETA Index	Brazil Selic Target Rate
27	BZTJLP Index	Brazil BNDES Long Term Interest Rate TJLP
28	BZAD1Y Index	Anbima Brazil Govt Bond Fixed Rate 1 Year
29	BZAD2Y Index	Anbima Brazil Govt Bond Fixed Rate 2 Years
30	GEBR5Y Index	Brazil Government Generic Bond 5 Year
31	GEBR10Y Index	Brazil Government Generic Bond 10 Year
32	GEBU10Y Index	Brazil Government Generic Bond 10 Year USD
33	BZLNTOTA Index	Brazil Financial System Loans
34	BZLNPTOT Index	Brazil Financial Private System Loans
35	BZMBMB Index	Brazil Monetary Base
36	BZMS1 Index	Brazil Money Supply M1 Brazil M1
37	BZMS2 Index	Brazil Money Supply M2 Brazil M2
38	BZMS3 Index	Brazil Money Supply M3 Brazil M3
39	BZMS4 Index	Brazil Money Supply M4 Brazil M4
40	BRCDDEFT Index	Brazil Personal Loans More Than 90 Days Late
41	BZIDINTL Index	Brazil International Daily Reserves
42	BRCCVEHB Index	Brazil Consumer Credit Operations for Vehicle Acquisition
43	BZPIIPCA Index	Brazil CPI IPCA Dec 1993=100
44	BZCILIVE Index	Brazil FIPE CPI Sao Paulo Living
45	BZCIFOOD Index	Brazil FIPE CPI Sao Paulo Food Main
46	BZCIPERS Index	Brazil FIPE CPI Sao Paulo Personal
47	BZCITRAN Index	Brazil CIPE CPI Sao Paulo Transportation
48	IPEAEXIN Index	Brazil IPEA Export Price Index
49	IPEAIMIN Index	Brazil IPEA Import Price Index
50	IBREIPAM Index	FGV Brazil IGP-M Wholesale Prices IPA-M
51	IBREIPA1 Index	FGV Brazil Wholesale Prices IPA-10
52	BZICINDX Index	CNI Brazil Industrial Confidence General
53	BZCCI Index	CNI Brazil Consumer Confidence

Continued on next page

Table B1 – *Continued from previous page*

Number	Ticker	Description
54	OLEDBRAZ Index	OECD Brazil Composite Leading Ind. Total Trend Restored Stck
55	OEBRI003 Index	OECD Brazil Cons. Opin. Confidence Composite & OECD Indicators SA amp adj
56	MPMIBRMA Index	Markit Brazil Manufacturing PMI SA
57	BZTBBALM Index	Brazil Trade Balance FOB Balance NSA
58	BZTBEXPM Index	Brazil Trade Balance FOB Exports
59	BZTBIMPM Index	Brazil Trade Balance FOB Imports NSA
60	BZTWBALW Index	Brazil Trade Balance Weekly Balance
61	BZDPGOD Index	Brazil General Government Net Debt
62	BZDPNDTL Index	Brazil Public Net Debt
63	BZPBPRDM Index	Brazil Public Primary Budget Result
64	BZCACURR Index	Brazil Current Account Monthly
65	BZEDTLEX Index	Brazil External Debt Brazil External Gross Debt
66	BZCA%GDP Index	Brazil Current Account % of GDP Last 12 Months Accumulated
67	BZFDTMON Index	Brazil Foreign Direct Investment Net
68	BZDPNDT% Index	Brazil Public Net Debt % of GDP
69	BSRFTOFD Index	Brazil Total Federal Revenue
70	BZBGEXPN Index	Brazil Central Government Total Expenditures
71	BZPBNODM Index	Brazil Public Nominal Budget Result
72	BZBGPRIM Index	Brazil Central Government Primary Budget Surplus/Deficit
73	BZBGNOMI Index	Brazil Central Government Nominal Budget Surplus/Deficit
74	BZIPTLSA Index	Brazil Real Industrial Production SA 2012=100
75	BZIXEXTR Index	Brazil Industrial Production Activity Extractive Industry2012
76	BZASSUBT Index	Brazil Auto Sales Subtotal
77	BZCNCNIS Index	CNI Brazil Manufacture Industry Capacity Utilization SA
78	BZCNSALS Index	CNI Brazil Manufacture Industry Real Sales SA 2006=100
79	BZCNEMPS Index	CNI Brazil Manufacture Industry Employment SA 2006=100
80	BZCNHOUS Index	CNI Brazil Manufacture Industry Working Hours SA 2006=100
81	BZVPTLVH Index	Anfavea Brazil Vehicle Production
82	BZVLTLVH Index	Anfavea Brazil Vehicle Sales Licensed
83	BZVXEXTL Index	Anfavea Brazil Vehicle Exports
84	BZVLTOTL Index	Anfavea Brazil Vehicle Sales Licensed Cars
85	BZRTRTSA Index	Brazil Retail Sales Volume SA
86	BZRTCOSA Index	Brazil Retail Sales Volume Construction Materials Index SA
87	BZRTFDSA Index	Brazil Retail Sales Volume Supermarket Food Beverages & Tobacco SA
88	BZRTFURN Index	Brazil Retail Sales Volume Furniture & Domestic Appliance
89	OEBRV008 Index	OECD Brazil Prod. Manufacturing Total Manufacturing SA 2010=100
90	BZEASA Index	Economic Activity GDP SA IBC-BR
91	BZGDCAPX Index	Brazil GDP Qtrly Gross Formation of Fixed Capital SA 1995=100
92	BZGDFAMX Index	Brazil GDP Qtrly Family Consumption SA 1995=100
93	BZGDAGRX Index	Brazil GDP Qtrly Agriculture SA 1995=100
94	BZGDIDTX Index	Brazil GDP Qtrly Industry SA 1990=100

Continued on next page

Table B1 – *Continued from previous page*

Number	Ticker	Description
95	BZGDTRNX Index	Brazil GDP Qtrly Transformation Industry SA 1995=100
96	BZGDSERX Index	Brazil GDP Qtrly Services SA 1995=100
97	EHGDBR Index	Brazil Real GDP (Annual YoY %)

Table B2: Dataset-Indonesia

Number	Ticker	Description
1	IDEMUNE% Index	Indonesia Unemployment Rate
2	IDEMEMPL Index	Indonesia Number of People Emp
3	CPNFIDCU Index	BIS Indonesia Credit to Non Fi
4	EHPIID Index	Indonesia Consumer Price Index
5	IDTIBINC Index	Indonesia Business Tendency In
6	IDTIBPRD Index	Indonesia Business Tendency In
7	IDTIBTOT Index	Indonesia Business Tendency In
8	IDTINCGR Index	Indonesia Consumer Tendency In
9	IDTIIRCG Index	Indonesia Consumer Tendency In
10	IDTIHINC Index	Indonesia Consumer Tendency In
11	IDCABAL Index	Indonesia Balance of Payments
12	IDCAPORT Index	Indonesia BOP Financial Accoun
13	IDPUMANU Index	Indonesia Production Utilizati
14	IDPUTOTL Index	Indonesia Production Utilizati
15	IDCGRFY Index	Indonesia GDP Current Prices E
16	IDCGREXY Index	Indonesia GDP Current Prices E
17	IDCGRIMY Index	Indonesia GDP Current Prices E
18	IDCGRGY Index	Indonesia GDP Current Prices E
19	IDCGRHY Index	Indonesia GDP Current Prices P
20	IDWGCDN Index	Indonesia Wage for Constructio
21	IDWGSMN Index	Indonesia Wage for Household S
22	IDELHOUS Index	Indonesia Property Loans House
23	IDANITEM Index	ANZ Roy Morgan Indonesia Consu
24	USDIDR Index	USD-IDR X-RATE
25	JPYIDR Index	JPY-IDR X-RATE
26	CADIDR Curncy	CAD-IDR X-RATE
27	USDIDRV1M Index	USD-IDR OPT VOL 1M
28	USDIDR25R3M Index	USD-IDR RR 25D 3M
29	BISBIDR Index	Indonesia Real Effective Excha
30	WCAUINDO Index	Bloomberg Indonesia Exchange M
31	MXID Index	MSCI INDONESIA
32	JCI Index	JAKARTA COMPOSITE INDEX
33	IDBIRATE Index	Bank Indonesia Reference Inter
34	INDON CDS USD SR 5Y D14 Corp	INDON CDS USD SR 5Y D14

Continued on next page

Table B2 – *Continued from previous page*

Number	Ticker	Description
35	BIASINVP Index	BI Indonesian Bank Val
36	IDBRLDR Index	Indonesia Bank Ratio - Loan to
37	IDBRCAR Index	Indonesia Bank Ratio - Capital
38	IDBRNIM Index	Indonesia Bank Ratio - Net Int
39	IDBRROA Index	Indonesia Bank Ratio Return on
40	GTIDR1Y Govt	INDONESIA GOVERNMENT
41	GTIDR5Y Govt	INDONESIA GOVERNMENT
42	GTIDR10Y Govt	INDONESIA GOVERNMENT
43	GTUSDID5Y Govt	REPUBLIC OF INDONESIA
44	IDGBFRGN Index	Indonesia Govt Bond Outstandin
45	ELI GIND Index	J.P. Morgan EMBIG Indonesia So
46	IDBLHOUS Index	Indonesia Outstanding Loans by
47	IDBLOTHR Index	Indonesia Outstanding Loans by
48	IDBLSHOP Index	Indonesia Outstanding Loans by
49	IDWCTOTL Index	Indonesia Working Capital Loan
50	IDWCLIO Index	ID Total Working Capital Loans
51	IDWCCONS Index	Indonesia Working Capital Loan
52	IDWCMANU Index	Indonesia Working Capital Loan
53	IDBRNPLG Index	Indonesia Bank Ratio - Non Per
54	IDBDTD Index	Indonesia All Commercial Banks
55	IDBDALLR Index	Indonesia All Commercial Banks
56	IDBDALLF Index	Indonesia All Commercial Banks
57	IDM2YOY Index	Indonesia Money Supply M2 YoY
58	IDM1YOY Index	Indonesia Money Supply M1 YoY
59	IDRMR Index	Indonesia Reserve Base Money
60	IDPGDEBT Index	Indonesia Government Portfolio
61	IDNRIRR Index	Indonesia Net Foreign Assets I
62	IDGFA Index	Indonesia Net International Re
63	IDGFFORC Index	Indonesia International Reserv
64	IDCPIY Index	Indonesia CPI YoY
65	IDCCI Index	Bank Indonesia Consumer Confid
66	MPMIIDMA Index	Nikkei Indonesia Manufacturing
67	IDANCCT Index	ANZ Roy Morgan Indonesia Consu
68	IDANFL1Y Index	ANZ Roy Morgan Indonesia Consu
69	IDANFN1Y Index	ANZ Roy Morgan Indonesia Consu
70	IDEXPY Index	Indonesia Exports YoY
71	IDBALTOL Index	Indonesia Trade Balance
72	IDEXPEGY Index	Indonesia Export Oil & Gas YoY
73	IDIMPTLY Index	Indonesia Import Total YoY
74	IDIMPEGY Index	Indonesia Import Oil & Gas YoY
75	IDEDTOTL Index	Indonesia External Debt Total

Continued on next page

Table B2 – *Continued from previous page*

Number	Ticker	Description
76	IDEDGI Index	Indonesia External Debt Govern
77	IDMPIYOY Index	Indonesia Industrial/Manufactu
78	ASEAINDO Index	Automotive Production by Indon
79	ASEAINDS Index	Automotive Sales for Indonesia
80	IDVHCLOC Index	Gaikindo Indonesia Motor Vehic
81	IDVHMTLC Index	Asosiasi Industri Sepedamotor
82	IDRSTOTY Index	Indonesia Retail Sales Survey
83	IDCETOTL Index	Indonesia Cement Consumption
84	IDTOTOT Index	Indonesia Tourist Arrivals
85	IDHTTOTL Index	Indonesia Hotel Occupancy Rate
86	OLE3INDO Index	OECD Indonesia Composite Leadi
87	EHGDID Index	Indonesia Real GDP (Annual YoY

Table B3: Dataset-Mexico

Number	Ticker	Description
1	MXR4TTSA Index	Mexico Real GDP by Industry Total SA
2	MXR4CNSA Index	Mexico Real GDP by Industry Construction SA
3	MXR4MFSA Index	Mexico Real GDP by Industry Manufacturing SA
4	MXR4RESA Index	Mexico Real GDP by Industry Wholesale and Retail Trade SA
5	MXGNTTAL Index	Mexico Nominal GDP Total SA
6	MXCACUAC Index	Mexico Nominal Current Account Balance
7	MXSDPRYO Index	Mexico Supply & Demand Private Consumption YoY
8	MXSDPUYO Index	Mexico Supply & Demand Public Consumption YoY
9	MXSDGCFY Index	Mexico Supply & Demand Total SA Annual Change 2008 Pesos
10	MEXHMEXY Index	Mexico House Price Index YoY
11	MXUEUNSA Index	Mexico Unemployment Rate SA for Workers 15 and Older ENOE
12	MXWICONS Index	Mexico Formal Job Temporary & Permanent Workers Construction
13	MXWIRETL Index	Mexico Formal Job Temporary & Permanent Workers Retail
14	MXWITRCO Index	Mexico Formal Job Temporary & Permanent Workers Transportation & Communication
15	MXWICOSV Index	Mexico Formal Job Temporary & Permanent Workers Commercial Services
16	MXWIMANU Index	Mexico Formal Job Temporary & Permanent Workers Manufacturing
17	MXWITOTL Index	Mexico Formal Job Temporary & Permanent Workers Total
18	MXUETEPT Index	Mexico Employment Rate
19	MXMIMITO Index	Mexico Wages by Manufacturing Industry Total
20	IMEFMNOR Index	Mexico Manufacturing Index New Orders SA
21	IMEFNMNO Index	Mexico Non Manufacturing Index New Orders SA
22	MXBLMORT Index	Mexico Bank Lending Mortgages
23	MXCSBUIL Index	Mexico Construction Spending Buildings
24	USDMXN Index	USDMXN Spot Exchange Rate - Price of 1 USD in MXN
25	JPYMXN Index	JPYMXN Spot Exchange Rate - Price of 1 JPY in MXN

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Table B3 – *Continued from previous page*

Number	Ticker	Description
26	CADMXN Curncy	CADMXN Spot Exchange Rate - Price of 1 CAD in MXN
27	USDMXNV1M Index	USDMXN 1 Month ATM Implied Volatility
28	USDMXN25R3M Index	USDMXN 3 Month 25 Delta Risk Reversal
29	BISBMXR Index	Mexico Real Effective Exchange Rate Broad
30	WCAUMEX Index	Bloomberg Mexico Exchange Market Capitalization USD
31	MEXBOL Index	Mexican Stock Exchange Mexican Bolsa IPC Index
32	MXONBR Index	Bank of Mexico Official Overnight Rate
33	MEX CDS USD SR 5Y D14 Corp	United Mexican States
34	MXFRCINR Index	BOM Government Funding Rate Closing Interest Rate
35	MPTBF CMPN Curncy	MXN T-BILL 6 MO
36	MPTB1 CMPN Curncy	MXN T-BILL 1 YR
37	GMXN02YR Index	Mexico Generic 2 Year
38	GMXN05YR Index	Mexico Generic 5 Year
39	MXLCLFCB Index	Mexico Loans from Commercial Banks
40	MXLCMOLO Index	Mexico Mortgage Loans
41	MXLCCOLO Index	Mexico Consumption Loans
42	MXBDNPLR Index	Mexico Non-Performing Loans as % of Total Loans
43	MXLCEXSE Index	Mexico External Sector
44	MXBLCNST Index	Mexico Bank Lending Construction
45	MXBLMAIN Index	Mexico Bank Lending Manufacturing Industry
46	MXBLFFAF Index	Mexico Bank Lending Farming Forestry and Fishing
47	MXBLSAOA Index	Mexico Bank Lending Services and Other Activities
48	MXDFCONS Index	Mexico Private Sector Direct Financing Total
49	MXBLPERF Index	Mexico Bank Lending Performing Loans
50	MXBLNONB Index	Mexico Bank Lending Performing Loans for Non Bank Financial
51	MXMB Index	Mexico Monetary Base Money Base
52	MXMSM1 Index	Mexico Money Supply M1-M4 M1 Total
53	MXMSM2 Index	Mexico Money Supply M1-M4 M2 Total
54	MXMSM3 Index	Mexico Money Supply M1-M4 M3 Total
55	MXMSM4 Index	Mexico Money Supply M1-M4 M4 Total
56	MXDEINT Index	Mexico Federal Government Net Domestic Debt in Millions of Mexican Pesos
57	MXDEEXT Index	Mexico Public Sector Net External Debt in Millions of U.S. Dollars
58	MXERBUDD Index	Mexico Public Rev & Expend Budgetary Deficit YTD
59	MXIRINUS Index	Mexico International Reserves in USD
60	MXDBPDDV Index	Mexico Development Banks Total Public Demand Deposits Volume
61	MXDBPTDV Index	Mexico Development Banks Total Public Time Deposits Volume
62	2735E55 Index	IMF Mexico Financial Corp Deposits
63	MXPII Index	Mexico Producer Price Index
64	MFGSMANU Index	Mexico Fin Gds & Srvs Secondary Sector Manufacturing 2012
65	MFGSCONS Index	Mexico Fin Gds & Srvs Secondary Sector Construction 2012
66	MXPIIXO Index	Mexico Producer Price Index Ex Oil

Continued on next page

Table B3 – *Continued from previous page*

Number	Ticker	Description
67	MFGSMINE Index	Mexico Fin Gds & Srvs Primary Sector Mining 2012
68	MFGSELGA Index	Mexico Fin Gds & Srvs Tertiary Water Electricity and Gas 2012
69	MPPRIMPT Index	Mexico International Trade Import Price NSA 1980=100
70	MPPREXPT Index	Mexico International Trade Export Price NSA 1980=100
71	MXCPI Index	Mexico CPI
72	MXCCCORE Index	Mexico Core CPI
73	MXCNFDAT Index	Mexico CPI Index 2010=100 Food Drinks and Tobacco
74	MXCNNFGD Index	Mexico CPI Index 2010=100 Non Food Goods
75	MXCNSERV Index	Mexico CPI Index 2010=100 Services
76	MXCNAGRI Index	Mexico CPI Index 2010=100 Agriculture
77	MXCNERAG Index	Mexico CPI Index 2010=100 Energy Rates Auth by Govt
78	MXCIHOUS Index	Mexico CPI by Expenditure Housing
79	IMEFMAIN Index	Mexico Manufacturing Index SA
80	IMEFNMIN Index	Mexico Non Manufacturing Index SA
81	IMEFMPRO Index	Mexico Manufacturing Index Production SA
82	SCMXPROI Index	Mexico Producer Confidence Indicator SA
83	MXMAAITR Index	Mexico Manufacturing Aggregate Trend Indicator
84	MXMAEXPT Index	Mexico Manufacturing Aggregate Trend Indicator Exports
85	MXMAMNOR Index	Mexico Manufacturing Aggregate Orders Indicator Manufacturing Orders SA
86	CSMXCONU Index	MX Consumer Confidence Index SA
87	CSMXPOSU Index	Mexico Compared Economic Situation with a Year Ago at Present SA
88	MXCLYLEA Index	Mexico Leading Indicator YoY
89	MXCLSALE Index	Mexico Seasonally Adjusted Leading Indicator
90	MXCLSACO Index	Mexico Seasonally Adjusted Coincident Indicator
91	MXTBBEXP Index	Mexico Trade Balance Exports Monthly Total USD Million
92	MXOTAMER Index	Petroleos Mexicanos (Pemex) Crude Oil Mexico Trade Data/Americas
93	MXOTEURO Index	Petroleos Mexicanos (Pemex) Crude Oil Mexico Trade Data/Europe
94	MXEXPETR Index	Mexico Nominal Current Account Balance
95	MXEXNONP Index	Mexico Exports by Sector Non Petroleum Mexico Exports Monthly Total USD Million
96	MXRETOT$ Index	Mexican Remittances Money Sent from Workers Outside Mexico
97	IGAEINDX Index	Mexico Indicator of Economic Activity Index SA
98	IGAEPADI Index	Mexico Economic Activity Primary Activities Series Index SA
99	MINVCNST Index	Mexico Capital Investment Construction
100	MXPSTOTL Index	Mexico Industrial Production Total Seasonally Adjusted
101	MXPSOGSA Index	Mexico Industrial Production Oil and Gas Extraction Seasonally Adjusted
102	MXPSELEC Index	Mexico Industrial Production Utilities Seasonally Adjusted
103	MXPSCONS Index	Mexico Industrial Production Construction Seasonally Adjusted
104	MXPSMANF Index	Mexico Industrial Production Manufacturing Seasonally Adjusted
105	MXSATOTL Index	Mexico Antad Same-Store Sales Overall YoY%
106	MXSLMOGA Index	Mexico Gasoline Sales Monthly
107	MXSLDIES Index	Mexico Diesel Sales Monthly

Continued on next page

Table B3 – *Continued from previous page*

Number	Ticker	Description
108	MXMNMCEQ Index	Mexico Capacity Utilization Manufacture of Machinery and Equipment
109	MXMNPECO Index	Mexico Capacity Utilization Manufacture of Petroleum Products and Coal
110	MXVPTOTL Index	Mexico Vehicle Production Total Production
111	MXWRTWHO Index	Mexico Wholesale/Retail Sale Totl Whole
112	MXVHTOTL Index	Mexican Vehicle Sales Auto+truck NSA
113	MXVETOTL Index	Mexican Vehicle Exports Total
114	MDPCSAIN Index	Mexico Total Season Adjusted Index Base 2008
115	MINVTOSA Index	Mexico Gross Fixed Inv Total Seasonally Adjusted
116	EHGDMX Index	Mexico Real GDP (Annual YoY %)

Table B4: Dataset-South Africa

Number	Ticker	Description
1	SAUEQEMP Index	South Africa Labour- Employed
2	SAUEQABS Index	South Africa Labour - Labor Absorption Rate
3	SAUEQPRT Index	South Africa Labour - Labor Force Participation Rate
4	SAUEQNLF Index	South Africa Labour - Not in the Labor Force
5	EHUPZA Index	South Africa Unemployment Rate (%)
6	SACWC Index	South Africa Consumer Confidence
7	SACWE Index	South Africa Consumer Confidence Economic Position in Next 12m
8	SACWF Index	South Africa Consumer Confidence Financial Position During Next 12m.
9	SACTLVL Index	South Africa Current Account SA
10	SACTMEX Index	South Africa Current Account SA - Merchandise Exports Free on Board
11	SACTGEX Index	South Africa Current Account SA - Net Gold Exports
12	SACTLMI Index	South Africa Current Account SA - Less Merchandise Imports
13	SACTCTR Index	South Africa Current Account SA - Current Transfers Net Receipts
14	SACUI Index	South Africa Utilization of Production Capacity
15	SABTHDIQ Index	South Africa Household Debt to Disposable Income of Households
16	SAGNDISA Index	South Africa Nominal Household Disposable Income SA
17	SADXFCFR Index	South Africa Real GDP Gross Fixed Capital Formation SA
18	SASGAGR Index	South Africa Agriculture SA Constant Prices
19	SASGMINE Index	South Africa Mining SA Constant Prices
20	SASGMANU Index	South Africa Manufacturing SA Constant Prices
21	SASGELEC Index	South Africa Electricity SA Constant Prices
22	SASGCON Index	South Africa Construction sa constant 2000 prices
23	SASGWRH Index	South Africa Wholesale Retail Hotels SA Constant Prices
24	SADXRGSA Index	South Africa Real GDP Expenditure on GDP
25	SATCTREM Index	Trade Activity Index Employment
26	SAPME Index	South Africa Barclays PMI Employment SA
27	SATCTRBL Index	Trade Activity Index Backlog on Orders
28	SATCTEBL Index	Trade Expectations Index Backlog on Orders

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Table B4 – *Continued from previous page*

Number	Ticker	Description
29	SATCTRNO Index	Trade Activity Index New Orders
30	SATCTENO Index	Trade Expectations Index New Orders
31	SACSPSTO Index	SA Recorded Building Plans Total SA
32	SACSPSRB Index	SA Recorded Building Plans Residentual Buildings SA
33	SACSPSNR Index	SA Recorded Building Plans Non-Residentual Buildings SA
34	SACSPSAA Index	SA Recorded Building Plans Additions and Alterations SA
35	SACSCSTO Index	SA Completed Buildings Recorded Total SA
36	SACSCSRB Index	SA Completed Buildings Recorded Residentual Buildings SA
37	SACSCSNR Index	SA Completed Buildings Recorded Non-Residentual Buildings SA
38	SACSCSAA Index	SA Completed Buildings Recorded Additions and Alterations SA
39	ZAR Curncy	USDZAR Spot Exchange Rate - Price of 1 USD in ZAR
40	EURZAR Curncy	EURZAR Spot Exchange Rate - Price of 1 EUR in ZAR
41	GBPZAR Curncy	GBPZAR Spot Exchange Rate - Price of 1 GBP in ZAR
42	JPYZAR Curncy	JPYZAR Spot Exchange Rate - Price of 1 JPY in ZAR
43	TRYZAR Curncy	TRYZAR Spot Exchange Rate - Price of 1 TRY in ZAR
44	USDZARV1M Index	USDZAR 1 Month ATM Implied Volatility
45	USDZAR25R3M Index	USDZAR 3 Month 25 Delta Risk Reversal
46	BISBZAR Index	South Africa Real Effective Exchange Rate Broad
47	TOP40 Index	FTSE/JSE Africa Top40 Tradeable Index
48	JFINX Index	FTSE/JSE Africa Financials Index
49	JBIND Index	FTSE/JSE Africa Basic Materials Index
50	JGIND Index	FTSE/JSE Africa Industrials Index
51	JGOLD Index	FTSE/JSE Africa Gold Mining Index
52	WCAUSAF Index	Bloomberg South Africa Exchange Market Capitalization USD
53	JALSH Index	FTSE/JSE Africa All Share Index
54	REPSOU CDS USD SR 5Y D14 Corp	Republic of South Africa
55	SARPRT Index	South Africa Repo Avg Rate
56	GSAB2YR Index	South Africa Govt Bonds 2 Year Note Generic Bid Yield
57	GSAB3YR Index	South Africa Govt Bonds 3 Year Note Generic Bid Yield
58	GSAB5YR Index	South Africa Govt Bonds 5 Year Note Generic Bid Yield
59	GSAB10YR Index	South Africa Govt Bonds 10 Year Note Generic Bid Yield
60	SALQCMPN Index	South Africa Liquidations Cos
61	SACEI Index	South Africa Private Credit Extension
62	SACEINV Index	South Africa Private Credit Extension Investments
63	SACEMORT Index	South Africa Private Credit Extension Mortgage Advances
64	SACELEAS Index	South Africa Private Credit Extension Leasing Finance
65	SACELOAN Index	South Africa Private Credit Extension Total Loans and Advances
66	SACESALE Index	South Africa Private Credit Extension Installment Sales Credit
67	SACEHOUS Index	South Africa Private Credit Extension Of Which To Households
68	SAMYSAM3 Index	South Africa Money Supply M3 Seasonally Adjusted
69	SAMYM1 Index	South Africa Money Supply M1

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Table B4 – *Continued from previous page*

Number	Ticker	Description
70	SAMYM2 Index	South Africa Money Supply M2
71	SAMYM0 Index	South Africa Money Supply M0
72	199.055 Index	IMF South Africa Foreign Exchange Reserves in Millions of USD
73	SANOGOL$ Index	South Africa Gold Reserves
74	SANOGR$ Index	South Africa Gross Reserves
75	1995E55 Index	IMF South Africa Deposits in Rand
76	SACPI Index	South Africa CPI 2012=100
77	SABCI Index	SACCI South Africa Business Confidence
78	SAPMI Index	South Africa Barclays SA
79	SAPMIPP Index	South Africa Barclays PMI Prices NSA
80	SCP8COUN Index	South Africa CPI For Total Country NSA
81	SCP8EPNY Index	South Africa Ex Food NAB Petrol & Energy YoY
82	SCP8EENR Index	South Africa Ex Energy
83	MPMIZAWA Index	Standard Bank South Africa PMI SA
84	SACBLI Index	Composite Business Cycle Indicator - Leading Indicator
85	SACBLG Index	Composite Business Cycle Indicator - Lagging Indicator
86	SACBCI Index	Composite Business Cycle Indicator - Coincident Indicator
87	SANOFP$ Index	South Africa Net Open Foreign Currency Position
88	SABBBAL Index	South Africa Budget Summary National Budget Balance
89	SATBAL Index	South Africa Trade Balance Incl Oil Arms & Bullion
90	SATBEX Index	South Africa Trade Balance Exports Incl Oil Arms & Bullion
91	SATBEOTH Index	South Africa Trade Export Other Gd
92	SATBIM Index	South Africa Trade Balance Imports Incl Oil Arms & Bullion
93	SABBEXP Index	South Africa Budget Summary National Expenditures
94	SABBREV Index	South Africa Budget Summary National Revenue
95	NAAMTTMS Index	NAAMSA South Africa Total Market Sales Level
96	SARSTCSA Index	South Africa Retail Sales Total Sales Constant Prices SA 2012=100
97	SASRGEN Index	South Africa Retail Trade Sales Constant 2012 Prices General
98	SATWCOS Index	South Africa Wholesale Trade Constant 2000 Prices SA
99	SFMPPET Index	South Africa Manufacturing Production SA 2005=100 Petroleum Chemical Prod
100	SFPMI Index	South Africa Manufacturing Production SA 2010=100
101	SFMPFB Index	South Africa Manufacturing Production SA 2005=100 Food & Beverages
102	SFMPTCF Index	South Africa Manufacturing Production SA 2005=100 Textile Leather Footwear
103	SFMPMVP Index	South Africa Manufacturing Production SA 2005=100 Parts & Other Transport Equip
104	SAMSTGSA Index	South Africa Mining Sales Total Including Gold SA
105	SAMPGDSY Index	South Africa Mining Production Volume Gold SA YoY
106	SAMPTTSY Index	South Africa Mining Production Volume Total Inc Gold SA YoY
107	SAPW09Y Index	South Africa Electricity Production Index Year on Year %
108	SAPW08Y Index	South Africa Electricity Consumption Year on Year %
109	EHGDZA Index	South Africa Real GDP (Annual YoY %)

Table B5: Dataset-Turkey

Number	Ticker	Description
1	TULSUR Index	Turkey Labor Statistics Unemployment Rate SA
2	TULSER Index	Turkey Labor Statistics Employment Rate SA
3	TULSCO Index	Turkey Labor Statistics Employment in Construction SA
4	TULSSER Index	Turkey Labor Statistics Employment in Services SA
5	TULSIN Index	Turkey Labor Statistics Employment in Industry SA
6	TULSAGRI Index	Turkey Labor Statistics Employment in Agriculture SA
7	TULSLPAR Index	Turkey Labor Statistics Labor Participation Rate SA
8	TULSNO Index	Turkey Labor Statistics Non Agricultural Unemployment Rate SA
9	TULSYOU Index	Turkey Labor Statistics Youth Unemployment Rate SA
10	TUPYUK1 Index	Turkey Non-Residents Holdings of Equity Stock
11	TUPYUK2 Index	Turkey Non-Residents Holdings Government Domestic Debt Securities (GDSS) Stock
12	USDTRY Index	USDTRY Spot Exchange Rate - Price of 1 USD in TRY
13	EURTRY Index	EURTRY Spot Exchange Rate - Price of 1 EUR in TRY
14	JPYTRY Curncy	JPYTRY Spot Exchange Rate - Price of 100 JPY in TRY
15	USDTRYV1M Index	USDTRY 1 Month ATM Implied Volatility
16	USDTRY25R3M Index	USDTRY 3 Month 25 Delta Risk Reversal
17	CPIXBREX Index	Turkey Real Effective Exchange Rate (2003=100) CPI
18	XU100 Index	Borsa Istanbul 100 Index
19	XBANK Index	Borsa Istanbul Banks Sector Index
20	XUSIN Index	Borsa Istanbul Industrials Sector Index
21	WCAUTURK Index	Bloomberg Turkey Exchange Market Capitalization USD
22	CTURK1U5 Curncy	Republic of Turkey
23	TUBRONRA Index	Turkey Overnight Lending Rate Announcement
24	TUBROBRA Index	Turkey Overnight Borrowing Rate Announcement
25	IECM2Y Index	Turkish Government Bond 2Y Compound Yield
26	TUBOL54 Index	Turkey Banks Balance Sheet Deposits - Residents in Dollars ($)
27	WAIRCASH Index	Weighted Average Interest Rates for Turkish Banks Loans - Cash
28	WAIRVEHI Index	Weighted Average Interest Rates for Banks Loans - Vehicles
29	WAIRHOUS Index	Weighted Average Interest Rates for Banks Loans - Housing
30	WAIRCOMM Index	Weighted Average Interest Rates for Banks Loans - Commercial
31	GTRU2YR Index	USD Turkey Govt Bond Generic Bid Yield 2 Year
32	GTRU5YR Index	USD Turkey Govt Bond Generic Bid Yield 5 Year
33	GTRU10YR Index	USD Turkey Govt Bond Generic Bid Yield 10 Year
34	TBRDELT Index	Export Loans - Total
35	TBRDWCLT Index	Working Capital Loans - Total
36	TBRDTLTL Index	Total Loans
37	TUCRTOTL Index	Turkey Consumer Loans Total
38	DPMLAUTO Index	Deposit Money Banks Loans Private Sector - Automobile
39	DPMLINCC Index	Deposit Money Banks Loans Private Sector - Individual Credit Cards
40	DPMLHOUS Index	Deposit Money Banks Loans Private Sector - Housing

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Table B5 – *Continued from previous page*

Number	Ticker	Description
41	DPMLCOOT Index	Deposit Money Banks Loans Private Sector - Consumer & Other
42	TUNMM1 Index	Turkey Money Supply M1
43	TUNMM2 Index	Turkey New Money Supply M2
44	TUNMM3 Index	Turkey New Money Supply M3
45	TUNMTDTR Index	Turkey Money Supply Time Deposits TRY
46	TUNMSDFX Index	Turkey Money Supply Sight Deposits FX
47	TUNMSDTR Index	Turkey Money Supply Sight Deposits TRY
48	TUNMTDFX Index	Turkish Money Supply Time Deposits FX
49	TBRDLOAN Index	Turkey SME Loans Total
50	TURWL Index	Turkey Gross Foreign Exchange Reserves (Weekly)
51	TUDPPI Index	Turkey Domestic PPI
52	TUDPC Index	Turkey Domestic PPI Manufacturing
53	TUDPB Index	Turkey Domestic PPI Mining & Quarrying
54	TUDP6 Index	Turkey Domestic PPI Crude Petroleum & Natural Gas
55	TUDP10 Index	Turkey Domestic PPI Food Products YoY
56	TUDP29 Index	Turkey Domestic PPI Motor Vehicles Trailers & Semi-Trailers
57	TUDP25 Index	Turkey Domestic PPI Fabricated Metal Products Except Machinery & Equipment
58	TUCPI Index	Turkey CPI
59	TUCPF Index	Turkey CPI Food & Non Alcoholic Beverages
60	TUCPH Index	Turkey CPI Housing Water Electricity Gas & Other Fuels
61	TUCPHO Index	Turkey CPI Hotels Cafes & Restaurants
62	TUCPFH Index	Turkey CPI Furnishings Household Equipment & Routine House Maintenance
63	TUCPR Index	Turkey CPI Recreation & Culture
64	TUCXSG Index	Turkey CPI Ex Seasonal Goods
65	TUCXEF Index	Turkey CPI Ex Energy Food Non Alcoholic Bev Alcoholic Bev Tobacco & Gold
66	TUCOGY2S Index	Turkey Real Sector Confidence Index Volume of Orders (Current Situation) SA
67	TUCOGY3S Index	Turkey Real Sector Confidence Stocks of Finished Goods (Current Situation) SA
68	TUCOGY7S Index	Turkey Real Sector Confidence Index Export Orders (Next 3 Months) SA
69	TUCOREAL Index	Turkey Conf IndxReal Sect
70	TUCDCONF Index	Consumer Confidence
71	TUCOGY1S Index	TU Real Sector Confidence SA
72	TUCOGY9S Index	TU Business Situation SA
73	MPMITRMA Index	Markit Turkey Manufacturing PMI
74	TUCALVLP Index	Turkey Balance of Payments Portfolio Investment 12M YoY Level Change USD
75	TUCADIT Index	Turkey Balance of Payments Direct Investment in Turkey
76	TUDDTOTL Index	Turkey Domestic Debt Position Total
77	TUBTREV Index	Turkey Budget Deficit Revenue
78	TUTBEX Index	Turkey Trade Exports WDA
79	TUTBIM Index	Turkey Trade Imports WDA
80	ECOCTRN Index	Turkey Current Account Balance (Billion USD) NSA
81	TUKVDB17 Index	Turkey Short Term External Debt Stock

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Table B5 – *Continued from previous page*

Number	Ticker	Description
82	TUCSET Index	Turkey Motor Vehicle Industry Export Total
83	TUCSEP Index	Turkey Motor Vehicle Industry Export Passenger Cars
84	E50DGTR Index	EU Ind Prod Durable Consumer Goods Turkey SWDA
85	E50IGTR Index	EU Ind Prod Intermediate Goods Turkey SWDA
86	E50KGTR Index	EU Ind Prod Capital Goods Turkey SWDA
87	TUIOMT Index	Turkey Industrial Production Manufacturing 2010=100
88	TUINTURN Index	Turkey Industry Turnover 2010=100
89	TUIOSA Index	Turkey Industrial Production SWDA 2010=100
90	TUIOST Index	Turkey Industrial Production Mining 2010=100
91	TUIOET Index	Turkey Industrial Production Electricity 2010=100
92	TYCOLEVS Index	Turkey Capacity Utilization SA
93	TUCSPT Index	Turkey Motor Vehicle Industry Production Total
94	TUCSMT Index	Turkey Motor Vehicle Industry Sales Total
95	TUCSMP Index	Turkey Motor Vehicle Industry Sales Passenger Cars
96	TUTOARTO Index	Turkey Tourism Arriving Visitors Total
97	EHBBTR Index	Turkey Budget Balance (% GDP)
98	EHCATR Index	Turkey Current Account Balance (% GDP)
99	TUQRRESY Index	Turkey GDP at Constant Prices Final Consumption Expenditure of Residents YoY
100	TUQRGFY Index	Turkey Real GDP Imports of Goods and Services WDA YoY
101	TUQRIMY Index	Turkey GDP Transportation & Storage Constant Prices SWDA
102	TUGPIGDY Index	Turkey Real GDP (Annual YoY %)

Table B6: Uncertainty indices

Number	Ticker	Description
1	EPUCCUSM Index	US Economic Policy Uncertainty Composite Index
2	EPUCTRAD Index	US Categorical Economic Policy Uncertainty Trade Policy
3	EPUCCEUM Index	European Economic Policy Uncertainty Composite Index
4	EPUCNUSM Index	US Economic Policy Uncertainty Index
5	EPUCUK Index	United Kingdom Economic Policy Uncertainty Index
6	EPUCMONE Index	US Categorical Economic Policy Uncertainty Monetary Policy
7	EPUCIT Index	Italy Economic Policy Uncertainty Index
8	CONSHOMS Index	UMich Buying Conditions for Houses: Uncertain
9	EPUCJP Index	Japan Economic Policy Uncertainty
10	EPUCBRAZ Index	Brazil Economic Policy Uncertainty
11	EPUCAUST Index	Australia Economic Policy Uncertainty
12	EPUCDE Index	Germany Economic Policy Uncertainty
13	EPUCFR Index	France Economic Policy Uncertainty
14	SBOIUNCR Index	NFIB Small Business Uncertainty
15	EPUCFINR Index	US Categorical Economic Policy Uncertainty Financial Regulation
16	EPUCNINM Index	India Economic Policy Uncertainty Index

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Table B6 – *Continued from previous page*

Number	Ticker	Description
17	EPUCTAX Index	US Categorical Economic Policy Uncertainty Taxes
18	EPUCGOVT Index	US Categorical Economic Policy Uncertainty Government Spending
19	EPUCSP Index	Spain Economic Policy Uncertainty Index
20	EPUCCTGR Index	US Categorical Economic Policy Uncertainty
21	EPUCNATL Index	US Categorical Economic Policy Uncertainty National Security
22	EPUCFISC Index	US Categorical Economic Policy Uncertainty Fiscal Policy
23	EPUCCAND Index	Canada Economic Policy Uncertainty Index
24	EPUCSWED Index	Sweden Economic Policy Uncertainty
25	FEPUUSE Index	USA Migration Economic Policy Uncertainty Index
26	FEPUGEE Index	Germany Migration Economic Policy Uncertainty Index
27	EPUCSKOR Index	South Korea Economic Policy Uncertainty
28	EPUCENTI Index	US Categorical Economic Policy Uncertainty Entitlement Programs
29	EPUCREGU Index	US Categorical Economic Policy Uncertainty Regulation
30	EPUCRU Index	Russia Economic Policy Uncertainty
31	EPUCNL Index	Netherlands Economic Policy Uncertainty
32	CONSDURS Index	UMich Buying Conditions for Large Household Durables: Uncertain
33	EPUCCHIL Index	Chile Economic Policy Uncertainty
34	EPUCIREL Index	Ireland Economic Policy Uncertainty
35	FEPUFRE Index	France Migration Economic Policy Uncertainty Index
36	FEPUGBE Index	UK Migration Economic Policy Uncertainty Index
37	http://www.policyuncertainty.com/	Japan Categorical Fiscal Policy Uncertainty Index
38	http://www.policyuncertainty.com/	Japan Categorical Monetary Policy Uncertainty Index
39	http://www.policyuncertainty.com/	Japan Categorical Trade Policy Uncertainty Index
40	http://www.policyuncertainty.com/	Japan Categorical Exchange Rate Policy Uncertainty Index
41	http://www.policyuncertainty.com/	US Equity Market Uncertainty Index
42	http://www.policyuncertainty.com/	Mexico Economic Policy Uncertainty
43	http://www.policyuncertainty.com/	Hong Kong Economic Policy Uncertainty
44	http://www.policyuncertainty.com/	China Economic Policy Uncertainty
45	http://www.policyuncertainty.com/	Singapore Economic Policy Uncertainty

Table B7: Surprise indices

Number	Ticker	Description
1	GSERMEM Index	Goldman Sachs MAP Economic Surprise Index - EM
2	CESICNY Index	Citi Economic Surprise Index - China
3	GSERMUS Index	Goldman Sachs MAP Economic Surprise Index - US
4	GSERMWD Index	Goldman Sachs MAP Economic Surprise Index - Global
5	CESIG10 Index	Citi Economic Surprise Index - Major Economies
6	CESIJPY Index	Citi Economic Surprise - Japan
7	CESIUSD Index	Citi Economic Surprise - United States
8	CESIEUR Index	Citi Economic Surprise Index - Eurozone

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Table B7 – *Continued from previous page*

Number	Ticker	Description
9	CESIEM Index	Citi Economic Surprise Index - Emerging Markets
10	ECSURPUS Index	Bloomberg ECO US Surprise Index
11	CESIGBP Index	Citi Economic Surprise - United Kingdom
12	CESIGL Index	Citi Economic Surprise Index - Global
13	CESICAD Index	Citi Economic Surprise - Canada
14	CESIAUD Index	Citi Economic Surprise Index - Australia
15	CSIIUSD Index	Citi Inflation Surprise Index - United States
16	CSIIGL Index	Citi Inflation Surprise Index - Global
17	ECSURPEA Index	Bloomberg ECO Euro Area Surprise Index
18	CESIAPAC Index	Citi Economic Surprise Index - Asia Pacific
19	CESINZD Index	Citi Economic Surprise Index-New Zealand
20	CESISEK Index	Citi Economic Surprise Index - Sweden
21	CSIIEUR Index	Citi Inflation Surprise Index - Eurozone
22	ECSUHOUS Index	Bloomberg ECO US Housing and Real Estate Market Surprise Index
23	CSIIEM Index	Citi Inflation Surprise Index - Emerging Markets
24	CESICHF Index	Citi Economic Surprise Index - Switzerland
25	CESILTAM Index	Citi Economic Surprise Index - Latin America
26	CESIEMXP Index	Citi Economic Surprise Index - Emerging Markets Exports
27	CESIG10F Index	Citi Economic Surprise Index - Major Economies Fixed Weight
28	ECSUSUUS Index	Bloomberg ECO US Surveys & Business Cycle Indicators Surprise Index
29	CSIIG10 Index	Citi Inflation Surprise Index - Major Economies
30	CSIIJPY Index	Citi Inflation Surprise Index - Japan
31	ECSURPGB Index	Bloomberg ECO UK Surprise Index
32	CSIICNY Index	Citi Inflation Surprise Index - China
33	GSERMEA Index	Goldman Sachs MAP Economic Surprise Index - Euro Area
34	CESIBRIC Index	Citi Economic Surprise Index - BRIC
35	CSIIGBP Index	Citi Inflation Surprise Index - United Kingdom
36	ECSUINUS Index	Bloomberg ECO US Industrial Sector Surprise Index
37	CSIIDE Index	Citi Inflation Surprise Index - Germany
38	ITMRBI Index	Brazil Itau Economics Surprise Index
39	CESIEMFW Index	Citi Economic Surprise Index - Emerging Markets Fixed Weight
40	CESICMEA Index	Citi Economic Surprise Index - CEEMEA
41	CSIIAUD Index	Citi Inflation Surprise Index - Australia
42	CSIILTAM Index	Citi Inflation Surprise Index - Latin America
43	CSIIAPAC Index	Citi Inflation Surprise Index - Asia Pacific
44	GSERMCA Index	Goldman Sachs MAP Economic Surprise Index - Canada
45	WSUREURP Index	Westpac Positive Surprise Euro
46	ITMRMI Index	Mexico Economic Itau Surprise Index
47	GSERMDM Index	Goldman Sachs MAP Economic Surprise Index - DM
48	CSIICAD Index	Citi Inflation Surprise Index - Canada
49	WSUREURS Index	Westpac Size of Surprise Euro

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Table B7 – *Continued from previous page*

Number	**Ticker**	**Description**
50	CSIIFR Index	Citi Inflation Surprise Index - France
51	CSIISEK Index	Citi Inflation Surprise Index - Sweden
52	GSERMCE Index	Goldman Sachs MAP Economic Surprise Index - CEEMEA
53	GSERMJP Index	Goldman Sachs MAP Economic Surprise Index - Japan
54	ITMRLAI Index	Latin America Itau Surprise Index
55	WSURCADP Index	Westpac Positive Surprise Canada
56	WSURDMRP Index	Westpac Positive Surprise Developed Markets
57	CSIINOK Index	Citi Inflation Surprise Index - Norway
58	GSERMUK Index	Goldman Sachs MAP Economic Surprise Index - UK
59	GSERMLA Index	Goldman Sachs MAP Economic Surprise Index - LatAm
60	CSIIBRIC Index	Citi Inflation Surprise Index - BRIC
61	CSIICMEA Index	Citi Inflation Surprise Index - CEEMEA
62	GSERMAJ Index	Goldman Sachs MAP Economic Surprise Index - AeJ
63	SCGRMYES Index	Standard Chartered Economic Surprise Index - Malaysia
64	WSURCHFS Index	Westpac Size of Surprise Switzerland
65	WSURJPYP Index	Westpac Positive Surprise Japan
66	WSURNOKP Index	Westpac Positive Surprise Norway
67	WSURSEKP Index	Westpac Positive Surprise Sweden
68	WSURUSAS Index	Westpac Size of Surprise US
69	CSIIES Index	Citi Inflation Surprise Index - Spain
70	CSIINZD Index	Citi Inflation Surprise Index - New Zealand
71	WSURCHFP Index	Westpac Positive Surprise Switzerland
72	WSURNZDP Index	Westpac Positive Surprise New Zealand
73	WSURAUDS Index	Westpac Size of Surprise Australia
74	WSURUKP Index	Westpac Positive Surprise UK