On Foreign Drivers of EMEs Fluctuations

Gent Bajraj, Jorge Lorca and Juan M. Wlasiuk

Central Bank of Chile

July 2022

Abstract

We pose a series of contemporary interactions between a set of previously documented common factors driving emerging market economies (EMEs) business cycles in an otherwise standard dynamic factor model. By means of those constraints we estimate a set of three common factors with a structural interpretation tightly linked to specific empirical counterparts, namely a financial factor, a commodity price factor, and a growth factor. Our results point toward quantitatively relevant effects induced by shocks to the global factors that we identify: while shocks to our financial and commodity factors explain independently about 7 and 21% of GDP fluctuations, respectively, they unload rather differently on long term yields and exchange rates: the financial factor explains about half of exchange rate dynamics and more than a fifth of long rates, where our commodity factor ends up playing a much lesser role.

JEL classification: C32, C38, F44

Keywords: emerging economies, common factors, state space models.

We specially thank Miguel Fuentes, Andrés Fernández, Benjamín García and Guillermo Carlomagno for their valuable insights. Nashla Manzur and José Tomás Vergara provided excellent research assistance in early stages of the project. Opinions and conclusions expressed in this paper are those of the authors alone and do not necessarily represent the views of the Central Bank of Chile. All results have been reviewed to ensure no confidential data are disclosed.

1 Introduction

A steadily growing number of research papers in international finance focusing on emerging market economies (EMEs) continue to document the existence of global economic factors playing a key role in the economic performance of this set of countries. Such factors as changes in global financial conditions in main financial centers, encompassing variations in sovereign spreads, and commodity price cycles, just to name a few, have all been pointed out as relevant drivers of aggregate fluctuations in EMEs.[1] From a technical point of view, this set of papers rely above all on the statistical machinery of dynamic factor modeling, which by and large uncovers a set of time series responsible for the bulk of fluctuations in a panel dataset for some specific phenomena at stake, say spreads or commodity prices for instance. So in general, the great contribution of this literature and its statistical approach—coupled with some formal criteria for singling out the *most relevant* factors—is to empirically identify relevant economic factors in specific settings, such as risky asset prices (Miranda-Agrippino & Rey, 2020), spreads (Aguiar *et al.*, 2016), or commodity prices (Fernández *et al.*, 2018; Delle Chiaie *et al.*, 2022) all of them on their own data-specific realm.

So the fact that mainly because of the methodological approach, these studies have analyzed relevant factors driving EMEs cycles individually—that is, using either financial, real or commodity data on their own—leaves potential interactions and joint explanatory power between an encompassing, broader set of different kinds of factors in an entirely absent role. The problem, of course, is that such single-setting factor modeling cannot tackle relevant questions such as to what extent do changes in commodity prices merely reflect variations in global financial conditions? Or is it global demand, or simply commodity prices what really matters for emerging economies? The correct identification of the specific external conditions underlying local performance, as well as a proper understanding of their interactions and impact on the local conditions is key, not only from an academic standpoint, but also from a policy perspective, especially for small, commodity-exporting economies.

In this paper, we explore the hypothesis that EMEs business cycles are to a large extent determined by the jointly combined dynamics of a set of common external drivers. We develop this hypothesis building from the same methodological approach of the aforementioned papers, that is, by estimating a dynamic factor model, but we depart in a stark direction: starting from previous research we pose a candidate set relevant factors affect-

[1] See Longstaff *et al.* (2011), Aguiar *et al.* (2016), Fernández *et al.* (2018), Bai *et al.* (2019), Miranda-Agrippino & Rey (2020), among others.

ing different aspects of EMEs cycles and then we ex ante impose a series of constraints on the contemporary dynamics of such relevant factors.

Our approach, which tightly links a newly identified set of estimated factors to specific empirical counterparts, paves the way for endowing our estimated factors with a structural flavor. In technical words, we estimate a constrained state-space model by maximum likelihood putting together a wide range of macroeconomic variables for twelve emerging economies, where we extract the common factors with the Kalman smoother. We thereby assess the empirical validity of the resulting factors in a variety of ways.

Our results point toward the coexistence of three relevant empirical factors for the joint dynamics of EMEs cycles, with each of those factors associated with global financial conditions, commodity price cycles, and commodity-exporting EMEs growth, respectively. From a quantitative vantage point, a shock to financial conditions in our estimated state-space model explains roughly 7% of GDP fluctuations, while a shock to commodity prices commodities and growth factors explain 21 and 4%, respectively. We also perform a series side checks by plugging our very same estimated factors as exogenous shocks in a factor-augmented setting where we get consistent results. So in general, even when accounting for the presence of financial cycles, we uncover a preponderant role for the fluctuations of commodity prices in the performance of EMEs.

Our contribution lies in the way we approach the estimation of global factors, as we write down a comprehensive model that includes not only specific sets of data for EMEs (e.g. spreads only), but instead we compile a full array of macro variables including prices, activity, financial variables, and commodity prices in a multi-country setup. This action allows us to *simultaneously* estimate a set of global factors driving our dataset, which is a step forward with respect to the separate identifications in previous literature. The relevance of our modeling choice lies in the potential interactions among such factors that our approach permits. An important example in order is the popular "financialization" hypothesis of commodity prices, that is, the empirical coupling of commodity price fluctuations possibly given by the increasing role of institutional investor in these markets after 2005 (Tang & Xiong, 2010). Our methodological approach, which estimates factors simultaneously, does not rule out ex ante dynamics and therefore allows for the correct identification and precise assessment of their role in explaining EMEs business cycles. In sum, unlike the typical empirical approach that estimates factors with unconstrained models and consequently links them to real or financial data based on ex post correlations, our approach provides local uniqueness and structural interpretation by making use of educated constraints on the factors' loading matrices. We envision this step a way to allow ourselves to *name* ex ante the factors—that is, identify the empirical realm of the factors at hand—and verify ex post their potential explanatory power on the observable variables using a variety of empirical time series methods.

The motivation for a comprehensive model with multiple dynamic factors stems from the fact that—as the previous literature has documented—the cyclical behavior of the main macroeconomic and financial variables in EMEs exhibit strong similarities. Such comovement is not limited to the price of exported commodities (Fernández *et al.*, 2018) or financial variables (Miranda-Agrippino & Rey, 2020), but is also extended to the main activity and price indicators, as well as sovereign debt spreads (Longstaff *et al.*, 2011, Aguiar *et al.*, 2016). As will become clear in Section 3, these common movements are noticeable in the data we use to estimate our model.

Even though we are rather precise regarding our choice for the preferred empirical model that fits our data, we take a long digression explaining how we pick such a preferred formulation. We first discuss previous research pointing towards different common factors driving EMEs cycles, and then describe the battery of empirical tools that we use. First, regarding the optimal number of factors we dwell on statistical tests under the principal components approach and, second, we assess the marginal contribution of additional factors for the explanatory power of the unconstrained model. We also check parameter stability. Second, we evaluate the empirical fit of our model in several ways: we analyze the historical shock decomposition of factors, the forecast-error variance decomposition of the factors and variables, and impulse response functions within the model; then, we evaluate the fit with respect to known empirical correlations, and finally make use of a factor-augmented VAR to assess the effects of shocks to our estimated factors on variables outside the model.

As stated above, our paper embeds itself in the heated, long-standing debate about the different drivers of economic activity in emerging market economies—see section 2—and to the best of our knowledge, we depart from traditional approaches. As stated by Stock & Watson (2016), the main thrust of factor models lies on prediction accuracy, not directly on identifying the nature of the factors pinned down by such methodology, so here we go beyond traditional approximate factor models—for which many statistical tests for the optimal number of factors inducing data are readily available[2]—and set the spotlight on the structural interpretation of these common empirical forces.

Even though a combination of factor modeling and structural analysis is certainly present in the literature—see for instance Aguiar *et al.* (2016)—such analysis is carried out

[2]See, among others, Bai & Ng (2002, 2007); Amengual & Watson (2007) and Ahn & Horenstein (2013).

in a two-step fashion: once statistically relevant factors are identified, which is customarily done by principal components, then they are gauged through the lens of appropriately chosen *drivers*, either directly—for instance, factors become dependent variables in linear regressions—or take part as observable shocks in factor-augmented vector autoregressions.

Since we are interested, however, in both figuring out both the structural factors inducing EMEs cycles and the interdependence between them, we need to impose some structure on the behavior of factors in the estimation stage. Hence, we dodge least square methods for factor estimation and instead use state-space models with parameter constraints. By imposing such latter constraints on the loadings of the observation equations, we endow estimated factors with an ex ante interpretation: by limiting the effects of certain factors on, say, commodity prices or financial variables, we are able to associate them with certain subsets of observables, a step which has only been taken in ex post analysis by previous literature in international macroeconomics.

The rest of the paper is organized as follows: after reviewing recent essays on the determinants of EMEs cycles in Section 2, we lay out in Section 3 our data and empirical model approach: we carefully analyze the number of statistically relevant factors in addition to the state-space formulation we use and run formal stability tests. In Section 4 we work with our chosen baseline specification: we analyze the estimated factors, their interaction and the explanatory power of their shocks within the framework of the state-space model. Additionally, we perform a thorough investigation regarding the drivers of our estimated common factors, where we run several exercises: cross-correlations, regressions, and a factor-augmented vector autoregression where our estimated factors take part as observable shocks. We then perform some robustness exercises in Section 5 to figure out the consistency of the macroeconomic responses we obtain from factor shocks of the previous section. Lastly, in Section 6 we provide some final remarks.

2 Related Literature

This paper relates to several strands of literature on international economics, with a focus on the drivers of business cycles for emerging market economies. We first certainly touch on the global financial cycle hypothesis pushed forward most recently by Miranda-Agrippino & Rey (2020), who analyze a comprehensive risky assets dataset for the identification of a ubiquitous financial force. Even though the global financial hypothesis founds some dissent (Cerutti *et al.*, 2019), we use similar statistical machinery to the one used in these papers, but we go beyond by discussing the primary nature of estimated common factors, for instance, financial cycles versus commodity cycles. Another relevant strand of papers are those related to common factors in commodity prices such as Fernández *et al.* (2018) and Delle Chiaie *et al.* (2022), where both papers identify one global factor that drives commodity prices, and where the former elaborates on the way in which it affects other observed macroeconomic variables in EMEs. We take a different stand here, by assuming the existence of multiple global factors whose interactions are, ultimately, responsible for the common behavior of a wide set of observed variables. We use, therefore, an ample spectrum of observable macroeconomic variables in order to ensure the factors' proper identification and estimation. We also touch upon the previous work by Aguiar *et al.* (2016) and Longstaff *et al.* (2011) who use data on sovereign debt spreads to identify global factors on their respective environments.

As we deal with a set of common factors in possibly driving different kinds of EMEs data, we cannot avoid discussing the effects of commodity prices onto our estimated factors in the light of the financialization of commodity prices hypothesis (e.g. Cheng & Xiong, 2014 and Basak & Pavlova, 2016). Here we compare some of our exercises involving impulse-response functions with previous studies on the sources of EME fluctuations, specially interest rates vs. commodity prices (Neumeyer & Perri, 2005; Uribe & Yue, 2006; Aguiar & Gopinath, 2007; Maćkowiak, 2007; Chang & Fernández, 2013; Fernández *et al.*, 2017, and Schmitt-Grohé & Uribe, 2018). We partially relate to research on the varied factors leading economic activity in EMEs, such as global risk and dollar fluctuations (e.g. Hofmann & Park, 2020).

As mentioned in the introduction, one of the motivations for this paper was trying to figure out the dynamic, structural relationship between the usual suspects regarding fluctuations of EMEs cycles: financial cycles and commodity prices, and here we found insights in the papers by Aguiar *et al.* (2016) and Ludvigson & Ng (2009). In these papers, the authors effectively incorporate unobserved factors driving different sets of data, which they subsequently analyze in order to find out primitive sources of such factor behavior. Our departure from this work lies in the combined step in which we pursue the same idea: we embed constraints in a state-space model so as to try to get ex ante meaning for identified common factors in our dataset. As we try to make sense of the unobservable factors that we uncover from the state-space formulation that we lay out, we build from the original factor-augmented VAR setting of Bernanke *et al.* (2005) as we gauge the dynamic responses of shocks to precisely these factors onto the observable variables for a set of EMEs, even though our use of this factor augmented VAR setting has a lesser role in our computations and diagnostics checks.

Finally, as we reviewed the working paper version of this work, it came along to us the unpublished paper by Bork *et al.* (2009), where they also try to extract statistical factors with some economic interpretation in a large panel of U.S. macroeconomic series. While we pursue the same idea of giving content to common factors, both the methodological steps to estimate them and the empirical application are markedly different, as we use an iterative process directly based on the Kalman filter using a variety of sign constraints, while they focus on specific sectoral factors for the U.S. using binary constraints.

3 Empirical Model

The intent of figuring out common, latent components affecting different macroeconomic aspects of a broad range of emerging market business cycles comprises a relevant feature for the research agenda in international finance, which is particularly propped up by dynamic factor modeling. One particular trait in this line of research—of course consistent with the underlying methodological approach—is the ex ante confinement of the data under scrutiny to conform a tight, particular angle of these economies, namely focusing only spreads, or only asset or commodity prices for instance. Consider two recent, prominent examples in this set of papers: Miranda-Agrippino & Rey (2020) and Delle Chiaie *et al.* (2022). In order to introduce our point, we plot in Figure 1 both of the common factors identified in those papers, where we also attach a simple first dynamic factor estimated by principal components for the corresponding data that we compile.

Our data is a customary unbalanced quarterly panel ranging from 2003Q2 to 2018Q4 for twelve commodity-exporting EMEs that includes measures of GDP, inflation, sovereign spreads, stocks and commodity prices (see details in Appendix A). So in Figure 1a, we plot both the common factor estimated by Miranda-Agrippino & Rey (2020)—who use several hundreds risky assets time series for many countries—and the first principal component of our data set when using only stock prices for the set of EMEs that we consider. In Figure 1b likewise, we plot the corresponding common factor of Delle Chiaie *et al.* (2022)—who focus on commodity prices—and the first common factor for our data conditioned for commodity prices only. What we get from this couple of pictures is that even for a comparative small number of observations, relative to the papers we refer to, the common forces shaping EMEs performance from different vantage points actually show up with a much lesser number sample, both time and country wise, that is, by means of a simple, unconstrained dynamic factor model, we may get a perfectly reasonable approximation to previously established common factors driving EMEs cycles, with the sample size we pose.

Moreover, as we show in Figure 1c, when we put together those unobserved factors coming from our data in comparison to the overall GDP performance—using the same previous empirical approach—they end up broadly resembling each other, so the discussion ensues: if there are roughly similar common factors appearing across different empirical vantage points when gauging at EMEs performance, which is the ultimate force driving cycles in those countries? Put in other words, how can we disentangle the actual primary source of fluctuations showing up across different estimated common factors? That's the attempt we try to answer here.

Before we dive into our empirical approach, in order to assess the relevance of disentangling the empirical relations between different estimated common factors for EMEs, we briefly touch upon the consequences of following one of those very same factors as the ultimate sounding board for EMEs performance. For this aim, in Figure fig:BS we include one by one the common factors depicted in Figure 1c as an additional variable in the VAR postulated by Bruno & Shin (2015). What we get from such exercise is a dynamic response from estimated factors to liquidity and commodity price fluctuations as originally posed by the authors. What we obtain, in sum, is that the set of impulse-response functions that come from such VAR show a remarkable contrast between the common factors that we consider: if we were for instance to consider the GDP factor as the incontestable indicator of overall performance across EMEs, we would conclude a strong negative impact of both negative shocks to liquidity and commodity prices on it, while a contrasting effect would ensue if we summarize EMEs cycles by means of stocks and commodity prices. This is just an example that props up the relevance of carefully laying out the set of these macro drivers actually driving EMEs cycles, and that is the primary reason to establish some ex ante arbitrary connections, and then assess whether such empirical model match evidence on EMEs cycles.

3.1 State-Space Formulation

Let $Y_t = ((Y_{it})_{i=1}^N, \text{CMDTY}_t')'$ denote our vector of observable time series, where $Y_{it} = (\text{GDP}_{it}, \text{CPI}_{it}, \text{EMBI}_{it}, \text{Stock}_{it})$ represents the specific variables described above for each EME $i = 1, \ldots, N$ in period $t = 1, \ldots, T$. The vector CMDTY_t has the stacked observations for the M commodity prices included. We model the dynamics of the $(4N + M) \times 1$ vector Y_t as

$$Y_t = \Lambda F_t + u_t, \qquad t = 1, \ldots, T. \tag{1}$$

where F_t is the $q \times 1$ vector of (unobserved) factors and Λ is the $(4N + M) \times q$ matrix of factor loadings.[3]

The factors are meant to capture the common sources of variation in the observed macroeconomic variables across countries. These could be changes in global financial conditions (e.g. changes in global risk appetite, or in US monetary policy) which are likely to affect a wide array of variables, shocks that affect commodity prices (e.g. changes in China's investment or growth perspectives), or other changes in global conditions that typically affect EMEs' macroeconomic performance (e.g. changes in global demand, changes in the international prices of capital goods or global inflation). The vector u_t, $u_t \sim N(0, H)$, captures variability at the country-variable level associated with idiosyncratic events or measurement error.

The vector of unobserved factors F_t is assumed to follow an autoregressive process

$$F_t = \Phi F_{t-1} + w_t, \qquad t = 1, \ldots, T, \tag{2}$$

where $w_t \sim N(0, Q)$ and $F_0 \sim N(\mu_0, \Sigma_0)$. The matrices H and Q are assumed to be diagonal, while Φ is left unconstrained. Furthermore, we fix H to be the identity matrix which amounts to fixing the scale of the factors. We estimate the model parameters by maximum likelihood and extract the factors using the Kalman smoother.

It should be noted that, without further restrictions, the state-space model defined by equations (1) and (2) does not allow for a structural interpretation of the estimated factors, so we impose a set of constraints on the loading matrix Λ (i.e. we set to 0 some of its entries), and therefore limit the effect of the estimated factors on the observable

[3] Following Aguiar *et al.* (2016), we include a set of exogenous controls for the exclusive case of spreads, so we in practice estimate

$$Y_t = \Lambda F_t + \Gamma X_t + u_t, \qquad t = 1, \ldots, T,$$

where X_t is a vector obtained by stacking $X_{it} = [\Delta\text{GDP}_{it}, \text{Debt-to-GDP}_{it}]'$ for country $i = 1, \ldots, N$ in period $t = 1, \ldots, T$. We constrain Γ so that X_{it} only affects their respective, country-specific spreads.

variables. Among the multiple constraints that could be imposed on the $(4N + M) \times q$ matrix Λ, we restrict the analysis to those alternatives that appear the most compatible with the set of factors identified by previous research, as laid out above.

3.2 Model Specification

The way in which we arrive at our preferred empirical model deserves a discussion of the number of factors considered and the specific constraints imposed. We proceed with an iterative process in which we assemble different pieces of information. First, we consider a list of empirical common drivers of EMEs cycles borrowed directly from previous research, and contrast them with the exact number of factors spitted out by statistical tests for the optimal number of factors—as if we were running a principal components approach. We make sure that the number of factors included does not change throughout the sample period by means of a stability test for our model. Once we have a properly backed idea on the number of factors, we turn into the constraints we look to impose on the state-space model. Among the multiple constraints that could be imposed on the $(4N+M)\times q$ matrix Λ, we restrict the analysis to those that (a) are consistent with our economic intuition (given, among other things, by the previous findings of the literature), and (b) provide a straightforward interpretation to the estimated factors. In this stage we can already look at the estimated factors and, therefore, we run a battery of tests to grasp the validity of results: we look at cross-correlations with international macroeconomic variables, and make usage of a factor-augmented model. Apart from the empirical model that we pick, we include a set of robustness exercises in order to figure out alternative scenarios for our modeling choices.

3.2.1 Number of Factors

How many factors should we consider for the state-space model we have in mind? From a theoretical viewpoint, this question has been tackled by several papers, with cornerstone contributions given by Bai & Ng (2002, 2007); Amengual & Watson (2007) and Ahn & Horenstein (2013). The common thread across papers is the specification of either a dynamic or static approximate factor model that is consequently estimated by principal components. With such estimation results at hand, these papers formulate some penalty criteria that ultimately provides the true asymptotic number of factors. Now, in our case however, since we are posing a state-space model with constraints on the loading matrix estimated by maximum likelihood, we cannot directly apply the results of the aforementioned tests into our specific formulation, although we can still use such statistical machinery if we momentarily fit that very same dynamic factor approach to our data. By doing so, we allow ourselves to take the tests for the optimal number of factors as a statistical guide for the specification that we actually pursue later on. In all, in this subsection we merely take a digression from the state-space model that we previously laid out by running a battery of tests that permits us to peek into the number of factors that we should consider from the vantage point of a constraint-free, least-squares estimation procedure.

With the panel data set for emerging countries described in the previous section at hand, our aim is to disentangle the time series of common factors uniformly affecting EMEs cycles versus those idiosyncratic components that unlock specific country performances. Here, of course, we completely dodge our plan to name factors ex ante. Rather, we just attempt to figure out the number of relevant, orthogonal factors inducing our data from a strictly statistical point of view. As it is customary in factor analysis—see Stock & Watson (2016)—we pre-process original data by normalizing our series into zero-mean, unit variance processes and removing outliers and trends.

Therefore, we run the following approximate dynamic factor model (Chamberlain & Rothschild, 1983)

$$Y_t = \Lambda F_t + u_t, \qquad t = 1, \ldots, T, \tag{3}$$

$$F_t = \sum_{j=1}^{p} \Phi_j F_{t-j} + w_t.$$

As in Bai & Ng (2002) and Stock & Watson (2002) we pose the model in static form and estimate factors $F_t = (F_{1t}, \ldots, F_{rt})$ through principal components. We then identify the number of static and dynamic factors through the methods of Bai & Ng (2002, 2007); Amengual & Watson (2007) and Ahn & Horenstein (2013).

Table 1 shows the number of factors arising from Equation (3) through several methods. It is well known that the maximum number of factors considered for the principal component estimation of a dynamic factor model may end up affecting the actual number identified by statistical tests. Hence, we consider several thresholds listed in the first column of the table. The main pattern that emerges is the following: from the vantage point of the relatively more short-sample focus of Ahn & Horenstein (2013), we get about two dynamic factors inducing cycles into the features of the emerging economies we consider. This result is not utterly surprising since at least two empirical factors have been pointed

Table 1: Statistical number of factors

	Statistical test		
Max. number of factors	BN	AH	AW
2	2	1	2
4	4	2	4
6	5	2	5

Notes: *Max. number of factors* corresponds to the maximal amount of factors considered in the corresponding principal components estimation. BN: Bai & Ng (2002), IC_{p2} information criterion; AH: Ahn & Horenstein (2013), eigenvalue ratio criterion; AW: Amengual & Watson (2007) estimate of dynamic factors given BN. Sample: 2003Q1–2018Q4.

out previously in some other settings, notably by Miranda-Agrippino & Rey (2020) and Fernández *et al.* (2018). From the point of view of Bai & Ng (2002) though, the number of factors varies almost pari passu with respect to the total number of factors allowed. Moreover, even though the size of our dataset is relatively small when compared to the time span or the N size of recent studies in the dynamic factor models literature (e.g. Stock & Watson, 2016), our estimated common series capture reasonably well the time path of factors arising from models of asset prices in emerging markets with much bigger sample size.[4]

To appraise the number of factors given by the principal components approach, we directly estimate our state-space model for a different number of factors without any resort to identifying constraints. This is what we show in Table 2, where we evaluate the average marginal contributions to both variance decomposition and coefficient of determination when we adhere new unconstrained factors to our model. While there is an obvious spike for one factor in both statistics, the table shows a noticeable impact of a second and a third factor: the latter has an even higher marginal contribution in terms of the R-squared than the second. In all, these results tend to prop-up our view with regards the inclusion of about three factors in our baseline scenario.

3.2.2 Stability

As it is customary in factor analysis though, a key feature to gauge for an estimated dynamic factor model is to check the stability of parameter estimates. Here we follow

[4]As Figure 10 shows—see Appendix B—the estimated factors arising from Equation (3) fairly resemble the trend of Miranda-Agrippino & Rey's (2020), where shaded areas represent U.S. recessions.

Table 2: Marginal increase in the model's explanatory power, depending on the number of factors (%, average across all observable variables)

	Number of factors in the unconstrained model			
	1	2	3	4
20-quarter FEVD	31.1	9.2	6.6	5.3
R-squared	29.5	7.7	8.3	5.4

Notes: The first row of the table reports the increase in the 20-quarter forecast error variance decomposition (average across all observable variables in the model), as additional factors are included in the unrestricted model defined by equations 1 and 2. Similarly, values in the second row correspond to the increase in the (average across observables) R-squared of OLS regressions of the observable variables on the estimated factors.

the relatively recent work by Chen *et al.* (2014) to figure out an eventual break in factor loadings. Since we explicitly bound ourselves to look for an unknown breakpoint, we ultimately resort to the results by Andrews (1993). As Figure 11 points out, Andrews's (1993) Sup-Wald test—reframed into a factor setting by Chen *et al.* (2014)—reveals no break in factor loadings: the dotted line comes from Andrews, 1993, Table 1 for a trimming parameter of 0.3. at the 10% level. This result is robust to the number of factors and smaller confidence levels when we perform robustness checks by changing the number of factors.

What we end up concluding up to this point from the mere estimation of a dynamic factor model for our dataset, with no constraints whatsoever, is that the optimal number of tests designed for the usage of principal components suggest the presence of at least two relevant factors. Specifically, as Table 1 displays—using again the better finite sample properties of Ahn & Horenstein (2013) as guidance—the unconstrained model points towards two factors driving the EME data we consider, but given the higher ceiling pointed out by the asymptotic tests, we take a prudential approach and consider therefore at least three factors in the battery of state-space models we run.

4 Baseline Specification and Estimated Factors

In order to be able to *name* the factors—that is, our attempt to endow them with a structural interpretation—we fix the values of some of the factor loadings to zero. An unavoidable couple of questions regarding our model are the following: why three factors? And how do we choose the specific constraints to impose over the factor loadings? The

Table 3: Model restrictions

Variable	Financial factor	Commodity factor	Growth factor
GDP	●	○	●
Inflation	●	○	○
Commodity prices	●	●	○
EMBI spreads	●	○	○
Stock market index	●	○	○

Notes: The table depicts the restrictions imposed on the factor loadings in the Baseline model. A filled circle indicates that the corresponding factor in the column is allowed to contemporarily impact the observable variable in the respective row. An empty circle in contrast, indicates a value of 0 for the loading of the corresponding factor on the variable of the row.

answer for both questions lies in the iterative process we followed. First, on the number of factors side, the discussion from the statistical approach to the number of factors hinted at considering about three factors. Now, we complement this answer with the findings of previous research: Indeed, the existing literature suggests that we consider at least a financial factor (Miranda-Agrippino & Rey, 2020) and a commodity factor (Fernández *et al.*, 2017), with potentially overlapping effects. When we initially estimated models with two factors—imposing a variety of constraints over the factor loadings—the factors that we got from such models were inconsistent with previous evidence in terms of both time series behavior and correlations with customary drivers such as U.S. monetary policy, risk aversion measures and commodity price indexes. Once we included a third factor, which rather followed the economic intuition of including non mining exports for a variety of countries, the resulting factors noticeably resembled the common factors of previous papers. This fact was particularly explicit when we embedded the so-called financialization hypothesis in our setting, which in practice meant that we allowed the financial factor to influence the observed path of commodities contemporaneously in our ex ante constraints. All of this eyesight focus regarding our estimated common factors was then formally probed through the statistical machinery that we next introduce in the rest of the document. Table 3 shows the specific constraints imposed on the factor loadings in our baseline specification.

4.1 Estimated Global Factors and Their Relevance

The estimated factors, along with their historical shocks decomposition are presented in the top panel of Figure 3. Since the model is estimated in log-differences, the estimated factors are interpreted in the same way. Colored bars show each shock's incidence in the dynamics of the factors. The bottom panel of the figure presents the estimated factors in levels (net of initial values) and the cumulative dynamics of the shocks' contributions.

The factors' dynamics are consistent with the US recession indicator as identified by NBER (shaded area). Both the financial and growth factors gradually increase up to the first quarter of 2008 followed by a plunge reflecting the financial crisis. The financial factor begins its recovery in the first quarter of 2009 with the growth factor following suit two quarters later and less rapidly. The commodity factor, on the other hand, experienced a dramatic increase between 2007 and 2008, and only fell in 2009.

The historical shocks decomposition in Figure 3 highlights the existing interaction among the estimated factors. Financial shocks, for example, not only affect the financial factor but also have significant effects on the growth and commodity factors. From simple inspection, commodity shocks appear to be particularly important in explaining the dynamics of all three factors, which is confirmed in Panel A of Table 4, which reports the share of each factor's variance explained by the different shocks. Commodity shocks are the most relevant driver behind the factors' dynamics, explaining between 36 and 72pp of the factors' 20-quarter ahead forecast error variance. Financial shocks are also relevant, explaining not only most of the financial factor dynamics, but also more than a quarter of the variability in the commodity factor. Growth shocks, on the other hand, contribute the least, with only mild effects on all three factors.

The strong comovement among factors is also reflected in their impulse responses to shocks. Figure 4 shows that, despite their relatively short persistence, shocks to the financial factor induce prominent positive responses in both the commodity and the growth factors. Growth shocks, on the other hand, tend to be more persistent, but they hardly affect the dynamics of the other factors. Shocks to the commodity factor also induce strong responses from its counterparts, though with negative signs.

Panel B of Table 4 allows us to appreciate the relevance of the estimated global factors for the dynamics of the different groups of variables in the model.[5] Together, shocks to the three factors account for more than 35% of the variance of GDPs of EMEs (sample median), 27% of the variance of sovereign risks (as measured by the EMBI indices), and almost two-thirds of the variance of the stock market indices. A more modest role is found when accounting for CPI dynamics, for which the factors explain 2%. Shocks to these factors also contribute to an important fraction of the movements in commodity prices,

[5] For an illustration of the fit of the model to the data, see figures 13–17.

Table 4: Share of variance explained by global factor shocks (%)

	Shocks			Total
	Financial	**Commodity**	**Growth**	
A. Factors				
Financial	62.6	36.2	1.2	100.0
Commodity	25.5	71.2	3.3	100.0
Growth	14.4	72.1	13.5	100.0
Average factors	**34.2**	**59.8**	**6.0**	**100.0**
B. Observable variables (group medians)				
GDP	6.6	25.6	3.7	35.6
Inflation	1.3	0.7	0.0	2.1
EMBI spreads	17.0	9.8	0.3	27.1
Stock market index	41.1	23.7	0.8	65.6
Commodity prices	9.7	14.6	0.6	26.5
Crude oil	34.9	22.1	1.0	58.0
Copper	40.6	23.6	0.9	65.1
Aluminum	42.5	28.3	1.4	72.3
Median all obs. variables	**9.7**	**16.7**	**0.7**	**33.2**

Notes: Percentage. Figures correspond to the share of the 20-period ahead forecast error variance that is attributable to each of the global factors shocks. In panel B, group medians are reported for each column (which implies that the sum of the columns does not necessarily add up to the total).

in particular crude oil, copper and aluminum (the top-three most exported commodities in our sample of EMEs), for which roughly two-thirds of the variance is explained.

Table 4 allows us to further appreciate the individual contribution of each one of the factors to the dynamics of the different groups of variables in the model. Financial shocks explain roughly 10% of the variance of the median observed variable and, as expected, have a particular preponderance for the dynamics of stocks, EMBI spreads, and the main commodities exported. But the most relevant shocks, on average, are those directly affecting the commodity factor: they explain a quarter of the variance of GDP for the median country, almost 10% of EMBI spreads and, as expected, an important fraction of the variability in commodity prices. Growth shocks play only a minor role for the dynamics of most observable variables in the model.

Figure 4 shows that a shock to the global financial factor induces a strong positive response of these EMEs stock market indices, a reduction of sovereign risk, and a marked increase in the prices of commodities exported by these economies. These episodes also translate into higher growth and (initially) lower inflation, which is probably a consequence of an appreciation of the local currencies. Growth shocks are mainly associated with increases in GDP growth, and very mild effects on the rest of variables. Commodity shocks, have very different effects on the dynamics of these emerging commodity-exporting economies: commodity prices increase only transitorily, while inflation increases significantly; economic activity slows down and stocks indices fall, and sovereign risk raises. As such, shocks to the commodity seem to be associated with cost-push shocks, or negative (global) supply side shocks. We explore more on this in section 5.2.

4.2 Analysis of Factors

In the current and the following subsections we chase two targets: on one hand we want to understand the relationship between the factors we got above with respect to traditional variables pointed out as drivers of EME cycles, and on the other—once we have a clearer picture of their nature—we want to figure out the quantitative properties of the factors. For the latter purpose we will insert the factors as observable shocks into a factor-augmented vector autoregression, which we do in order to assess the response of macro-financial activity in a set of emerging economies when facing shocks to our factors.

The way in which we proceed therefore is as follows: we first gaze at the cross-correlations of factors with respect to a broad set of formerly studied drivers, and then formally test two-way Granger causality to arrive at a set of exogenous drivers to be used as explanatory variables in factor regressions. The main insight of the section comes from the following exercise: since previous regressions look at the driver vs. factor relationships one at a time, we attempt to disentangle the effects of multiple drivers on factors in a multivariable setting by means of a vector autoregression. Particularly, we unravel the way in which interest rates, risk aversion and commodity prices affect our financial–commodity factors dynamically.

The first batch of drivers we considered consists of those utilized by Bruno & Shin (2015), namely the real Federal Funds Rate target rate of the U.S. Federal Reserve, the leverage of the U.S. Brokers-Dealers sector, the Cboe VIX index of implied volatility on the S&P index options and the real effective exchange rate of the U.S. dollar. We gathered additional measures of financial markets liquidity and risk aversion such as the Chicago Fed national financial conditions index (NFCI), Jurado *et al.*'s (2015) measures of macroeconomic and financial uncertainty, Etula's (2013) measure of risk aversion, and Baker *et al.*'s (2016) proxy of economic policy uncertainty. Next we built from the insights of Reinhart *et al.* (2016) and Clark *et al.* (2019), and collected a series of commodity price indexes both from the IMF, and also the S&P GSCI, data that we transformed into deviations from trend. We also considered China's GDP growth and Hamilton's (2019) index of global economic activity. In all, we take into account an initial set of 24 measures previously considered as candidate drivers of EME cycles.

Figure 5 shows a summary of the cross-correlations of several drivers with respect to the factors coming from Equations (1)–(2) for the period 2003Q1–2018Q4. The main noticeable pattern that shows up corresponds to the general intuitive sign of the correlations, even for the diverse nature and sources of information of the drivers we compare our factors with. For instance, when we contrast our financial factor with measures of risk aversion, and macroeconomic and policy uncertainty—as panel 5a shows—we observe worse financial conditions for EMEs in periods of risk-off preferences and high uncertainty, all broadly documented facts across different studies.[6] On the contrary, during periods of looser liquidity—as measured for instance by higher leverage of the U.S. Brokers-Dealers sector (cf. Bruno & Shin, 2015)—or stronger growth in China, our common financial factor goes in the same direction, which is also the case when commodity prices go up. As panel 5b shows also, there is a positive association between commodity price surges and our commodity factor. Such factor is also positively associated with the fluctuations in measures of liquidity, as in the case of the financial factor. For the case of our residual growth factor in panel 5c, there is still a somewhat positive association with commodity prices, although the effects are less clear compared to our previous factors; in contrast here, we observe a stronger positive association between our common growth factor and Chinese growth, while keeping the negative correlation with measures of economic and policy uncertainty. In sum, regardless of the miscellaneous nature of the drivers we considered, we obtained rather consistent results with respect to the effects of liquidity, uncertainty and commodity price fluctuations onto our factors.

Now, even though previous plots are informative, we look for a relatively more formal way to appraise relationship between our factors and the set of eventual drivers we posed. In Table 5 we lay out this criterion: from the set of aforementioned drivers we identify only those who satisfy weak exogeneity with respect to our estimated factors. Once we have this set, we use them as independent variables in linear regressions of our factors in order to gaze the variance explained by them. Indeed, Table 5 mainly shows a noticeable role of commodity price indexes, and measures of financial, economic and policy uncertainty

[6]For example Cetorelli & Goldberg (2012); Bruno & Shin (2015); Aizenman *et al.* (2016); Choi *et al.* (2017); Cesa-Bianchi *et al.* (2018) and Temesvary *et al.* (2018).

Table 5: Drivers of estimated factors

	Financial factor		Commodity factor		Growth factor	
	Coef.	R^2	Coef.	R^2	Coef.	R^2
Brokers-Dealers	0.04	0.02	0.13^{**}	0.12	0.53^{**}	0.20
VIX	-0.10^{**}	0.34	-0.07^{**}	0.13	-0.32^{**}	0.23
Commodity index	-0.66	0.01	1.88^{*}	0.09	2.51	0.01
Metals index	0.07	0.00	1.30^{*}	0.07	4.10^{*}	0.06
NonFuel index	-0.58	0.01	1.92	0.05	3.29	0.02
Materials index	0.05	0.00	1.59^{*}	0.08	4.92^{*}	0.07
Food index	-1.07	0.01	3.50^{*}	0.09	2.87	0.01
China	0.32^{**}	0.12	0.44^{**}	0.17	2.14^{**}	0.37
Macro uncertainty	-4.99^{**}	0.13	-4.28^{*}	0.07	-22.32^{**}	0.18
Financial uncertainty	-4.41^{**}	0.21	-2.82^{*}	0.06	-18.78^{**}	0.27
GSCI	-0.83	0.02	2.84^{**}	0.19	3.69	0.03
DJCI	-0.56	0.01	2.10^{*}	0.10	3.41	0.02
SPGSCI	0.19	0.00	1.65^{**}	0.12	4.88^{*}	0.10
SPGSCN	-0.76	0.03	0.72	0.02	-0.47	0.00
WTI	-0.24	0.00	1.66^{**}	0.13	2.46	0.03
Policy uncertainty	-0.02^{**}	0.20	-0.01	0.04	-0.06^{**}	0.22

Notes: This table reports the output of linear regressions of factors against all of those drivers previously identified as strongly exogenous from Granger causality exercises. Factors sample: 2003Q1—2018Q4. Brokers-Dealers: Leverage of the U.S. Brokers-Dealers sector. VIX: Cboe index of implied volatility on the S&P index options. Commodity index: IMF's Global Price Index of All Commodities (same source for subindexes Metals, nonFuels, Materials and Food). China: China GDP growth. Macro and Financial uncertainty: indexes from Jurado *et al.* (2015). GSCI: Goldman Sachs Commodities Index. DJCI: Dow Jones Commodity Index. SPGSCI: S&P GSCI copper Index. SPGSCN: S&P GSCI corn Index. WTI: West Texas Intermediate crude oil. Policy Uncertainty: index from Baker *et al.* (2016). *,** mean significant at 5% and 1%, respectively.

on our estimated factors. The VIX, for instance—as well as the rest of uncertainty measures—shows a negative, statistically significant association with respect all of our estimated factors. On the contrary, China's GDP growth is strongly associated with positive variations in our factors, which is specially relevant for the growth factor we identify.

4.3 Factor-augmented VAR

Now we dwell into the main exercise on the ex post analysis of factors, which consists of performing an empirical evaluation of the effects of shocks to our estimated factors onto the macroeconomic data of emerging economies. The specific toolkit that we deploy corresponds to the original concept of Bernanke *et al.*'s (2005) factor-augmented VAR model, in which we introduce one standard deviation shocks of the common factors we identified in order to observe the responses of a set of macroeconomic variables in emerging countries.

The rationale for this exercise lies in the kind of information we may obtain with a factor-augmented VAR model. Since we already gave structure to the contemporary relation between our estimated factors in the state-space model and derived variance explained of observable variables—see Table 4—we now want to evaluate the way in which these very same factors are able to fit EMEs data, but when they are individually posed as observable shocks for these countries.[7]

The dataset we put together for our factor-augmented VAR estimation involves real, seasonally adjusted gross domestic product (GDP), nominal exchange rates (FX), consumer price indexes (CPI), monetary aggregates (M1), 10-year yields (10Y), and Uribe & Yue's (2006) measure of real gross country interest rates (r), for the following EMEs: Brazil, Chile, Colombia, Hungary, Mexico, Poland, Russia, South Africa, Thailand and Turkey. The period of analysis starts from 2010Q1 up to 2018Q4 in order to to avoid the great recession.

Now following Bernanke *et al.*'s (2005) setting, and using both the dataset of macroeconomic variables for EME described above and our identified factors, we estimate

$$X_t = \Lambda^o Y_t + \Lambda^u G_t + u_t, \tag{4}$$

$$\begin{pmatrix} Y_t \\ G_t \end{pmatrix} = \Phi(L) \begin{pmatrix} Y_{t-1} \\ G_{t-1} \end{pmatrix} + B e_t, \quad \mathbb{E}(e_t e_t') = I_q, \tag{5}$$

where $X_t = ((\text{GDP}_{it}, \text{FX}_{it}, \text{CPI}_{it}, \text{M1}_{it}, 10\text{Y}_{it}, r_{it})_{i=1,\dots,N})$, Y_t corresponds to the estimated factors from equations (1) and (2), G_t are the unobserved factors, $\Phi(L)$ is a finite lag polynomial, and B transforms the structural shocks e_t into the reduced-form factor errors.

We estimate Equations (4)–(5) through the algorithm of Abbate *et al.* (2016), and we construct the confidence intervals for impulse-response functions using Yamamoto's (2019) bootstrap Procedure A. We also compute variance decompositions for the long-term horizon of 60 quarters, and we carry out all of this procedure for each factor separately for the sample period 2010Q1–2018Q4.

[7] This approach allows a clearer comparison with previous literature on the effects of foreign shocks into EMEs performance, where prominent papers include Neumeyer & Perri (2005); Uribe & Yue (2006); Aguiar & Gopinath (2007); Maćkowiak (2007); Chang & Fernández (2013); Fernández *et al.* (2017), and Schmitt-Grohé & Uribe (2018).

Figure 6 shows the estimation output of the factor-augmented VAR model in the case of shocks to the financial factor. Panel 6a shows the response of GDPs across our EMEs sample, and what we find is a positive, statistically significant reaction of GDP—measured as normalized deviations from trend—after a one standard deviation shock to the financial factor in 70% of cases, broadly associated with commodity-exporting countries. Panel 6b reveals some corresponding drops of long-term yields after looser financial conditions induced by the shock to our financial factor, which are also consistent with the nominal appreciations shown in Panel 6c. The general picture that emerges is rather intuitive: a positive shock to the financial factor mostly induces a compression of yields and nominal appreciations, which somewhat translate into above-trend economic activity. The long-term variance of GDP explained by the financial factor is roughly 22% as Figure 6d shows, which is consistent with similar estimates on the impact of foreign drivers for EMEs (cf. Akinci, 2013).

The landscape is rather different for the case of shocks to the commodity factor, as Figure 7 shows. Here a shock to this factor induces relatively less statistically significant effects as compared with the financial factor. Even though there are some currency appreciations on impact, the previous effect on yields in the case of the financial factor is no longer present as well. So while the commodity factor displays a much lesser role on financial variables, it still has some pulling on economic activity by explaining around 18% of GDP variance, even though this magnitude is influenced by a couple of outliers.

What we get in sum from this exercise is a rather consistent picture of the quantitative implications of our estimated factors on the economic activity of EMEs. While there are some empirical puzzling features—such as the impulse-response functions for GDP in the case of the commodity factor—there are plenty of magnitudes consistent with previous evidence when looking from different vantage points: starting from mere correlations, regressions and finally gauging the effects of factor shocks through a FAVAR.

5 Robustness

To better understand the implications of the specific constraints on the factor loadings we impose, we compare the factors extracted from the baseline model to those of two other variants of the model.

Table 6: Restrictions on the model without commodity financialization

Variable	Financial factor	Commodity factor	Growth factor
GDP	•	◦	•
Inflation	•	◦	◦
Commodity prices	◦	•	◦
EMBI spreads	•	◦	◦
Stock market index	•	◦	◦

Notes: The table depicts the restrictions imposed on the factor loadings in the model without commodity financialization. For details, see notes in table 3.

5.1 Model without Financialization Channel

In the first exercise we analyze the extent to which the estimation of the financial and commodity factors is affected by the fact that in our baseline specification we allow the financial factor to load contemporaneously on commodity prices. Specifically, we want to verify if our financial factor captures the dynamics of the financial conditions of these economies, or if it simply captures the movement of commodity prices (something that, in principle, should not be ruled out given the relatively high number of commodity prices in our model). We check this by estimating a model that is otherwise identical to our baseline model but has the financialization channel shut down: the financial factor loading of the commodity series is set to zero (see table 6).

The estimated factors along with their historical shocks decomposition are displayed in Figure 8. In addition, each panel shows the scaled counterpart factor extracted from the baseline specification. Except for the scale, the shape of the financial factor is essentially identical to its baseline counterpart (the correlation between both estimations is 99.5%). This is highly suggestive that the estimation of the financial factor in our baseline specification is robust and is not particularly affected by the inclusion of the commodity financialization channel.[8] The financial nature of our financial factor is further confirmed by the strong resemblance between our financial factor and the global factor of Miranda-Agrippino & Rey (2020), which they extract using 858 asset price series (see figure 12 in the appendix).

On the other hand, the largest distinction when comparing these alternative and the baseline estimations appears in the commodity factor, which now further resembles the financial factor. In fact, the correlation between both factors increased from 8.1% in the

[8]As expected, even though the estimated financial factor does not change, their shock decomposition does: relative to the baseline model, financial shocks now have a much more limited role, while commodity and growth shocks become more relevant in explaining the factors' dynamics.

baseline model, to more than 97% in this alternative specification. These changes in the commodity factor are expected given that now it alone must explain all the variation across the commodity prices, when there are common elements in the dynamics of both commodity prices and the other variables used for the estimation of the financial factor. Thus, the result not only confirms that the estimation and interpretation of the commodity factor is strongly affected by the opening of the financialization channel, but is also supportive of the hypothesis that commodity prices reflect, at least in part, the dynamics of global financial conditions.

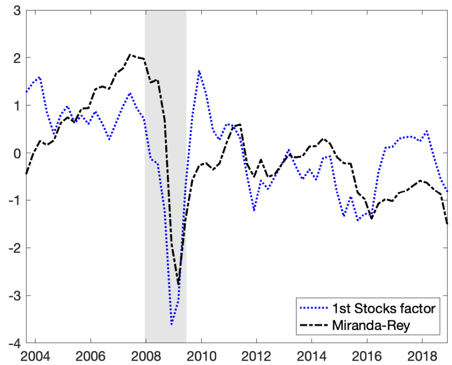
5.2 Price-factor Model

The other variant of the model we explore briefly expands on the idea suggested in section 4.1, that the commodity factor in our baseline specification might reflect movements associated with global prices or costs, and not only elements exclusively associated with commodities prices. This new specification is similar to the baseline one, but the commodity factor has been replaced with a *price* factor. More specifically, as shown in Table 7, what used to be the commodity factor now loads on inflation in addition to commodity prices.

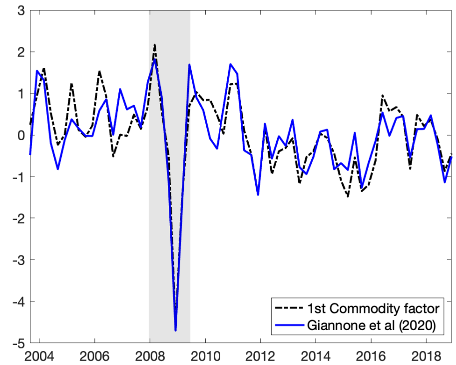
When comparing the estimated factors with their counterpart extracted from the baseline specification (not reported) we observe that, except for the scale, the shapes of the financial and growth factors remain essentially unaltered. The price factor, on the other hand, changes significantly, as it now collects information from a larger and more diverse group of variables. Interestingly, the impulse response functions of price shocks (Fig. 9) look remarkably similar to those of commodity shocks in the baseline model (Fig. 4), which supports our interpretation of both commodity shocks in the baseline model and price shocks in this alternative specification, as cost-push shocks. Table 8 allows to see that not only the share of variance explained by the factor shocks increases for the CPI series (something that is expected), but also for most of the variables, going from 33.2% in the baseline the model (table 4) to 39.1% for the median equation in the new specification. Such improvement is due in part to a higher explanatory power of the price factor (relative to the original commodity factor), but also to an improvement in the financial factor's explanatory power. These results suggest that for the EMEs considered in our analysis it is not only international commodity prices that matter, but global prices in general, more broadly defined. This result is further explored in Bajraj *et al.* (2022).

Figure 1: Comparison of Dynamic Factor Models

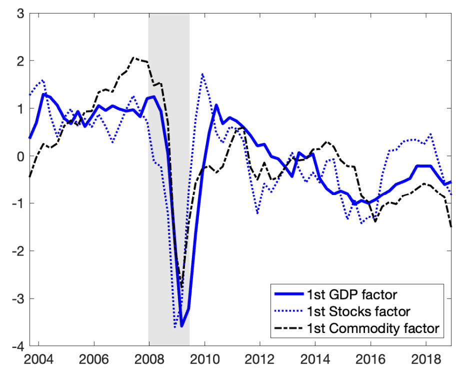
(a) Risky Assets



(b) Commodity Prices



(c) Summary of DFM Factors



Notes: The figure compares estimated factors from an unconstrained dynamic factor model in our dataset with respect to previous, relevant papers in the liteature, when we only use the corresponding data in each case. That is, our stock-based DFM first factor versus Miranda-Agrippino & Rey (2020) and our commodities-based DFM first factor versus Delle Chiaie *et al.* (2022).

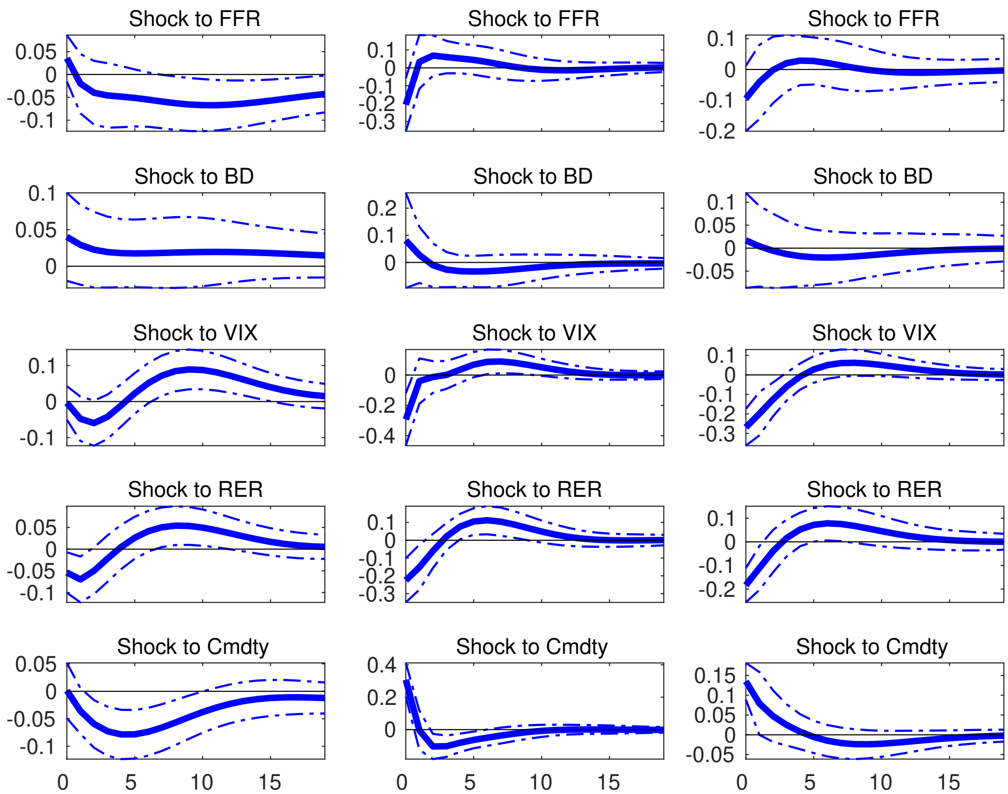
Table 7: Restrictions on the Price-factor model

Variable	Financial factor	Price factor	Growth factor
GDP	●	○	●
Inflation	●	●	○
Commodity prices	●	●	○
EMBI spreads	●	○	○
Stock market index	●	○	○

Notes: The table depicts the restrictions imposed on the factor loadings in the *Price* factor model. For details, see notes in table 3.

Figure 2: Response of Estimated Factors to Liquidity and Commodity Price Shocks

(a) **GDP Factor** (b) **Commodity Factor** (c) **Stocks Factor**



Notes: The figure shows the impulse response functions for the three common factors estimated in Fig 1(c), in the case of Bruno & Shin (2015) VAR, expanded to commodity prices. Dashed lines reflect 90% bootstrapped confidence intervals.

6 Concluding Remarks

From several research papers from the last couple of decades, we have learned a lot regarding the quantitative effects of foreign shocks on the performance of emerging market economies. By and large, the literature has already established the empirical relevance of financial market fluctuations in advanced economies for both the availability of credit and GDP repercussions in the emerging world (cf. Uribe & Yue, 2006; Bruno & Shin, 2015), as well as the bearing of commodity price cycles for the same set of countries under scrutiny here (cf. Fernández *et al.*, 2018). Now, apart from these purportedly structural inquiries, in which either financial or commodity price shocks are analyzed, there has been a recent, popular trend in which common factors affecting emerging market economies

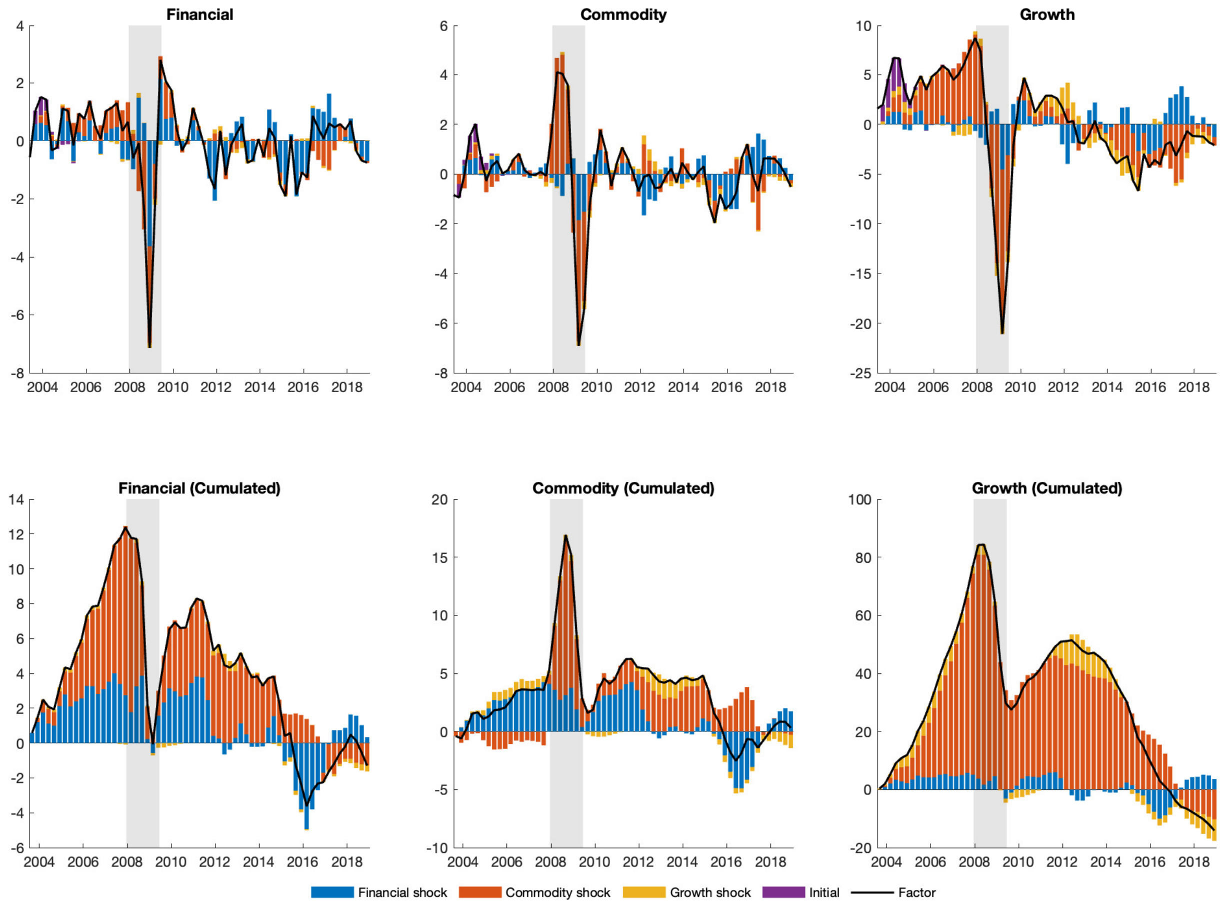


Figure 3: Historical decomposition of factors

Notes: Top panel: factors as originally estimated *in log-differences*. Bottom panel: factors *in levels* obtained by cumulating log-differences. For presentation purposes, initial values are omitted in the cumulated version. Shaded areas denote NBER US recession dates.

are directly estimated from reduced-form factor models. In these latter research efforts, the structural interpretation of the ensuing common factors identified plays a lesser role compared to the emphasis on the number of empirical factors at stake or the predictive accuracy.

In this paper we looked to hopefully combine those two ideas: we wanted to use the recent empirical machinery to identify common factors in some state-space model, but adhering at the same time a structural flavor to the time series of the factors which we attempted to single out. The rationale for this blending was our drive to unravel the intertwined effects between the structural shocks argued by different pieces of evidence, a debate that already has a dwelling on the financialization of commodities.

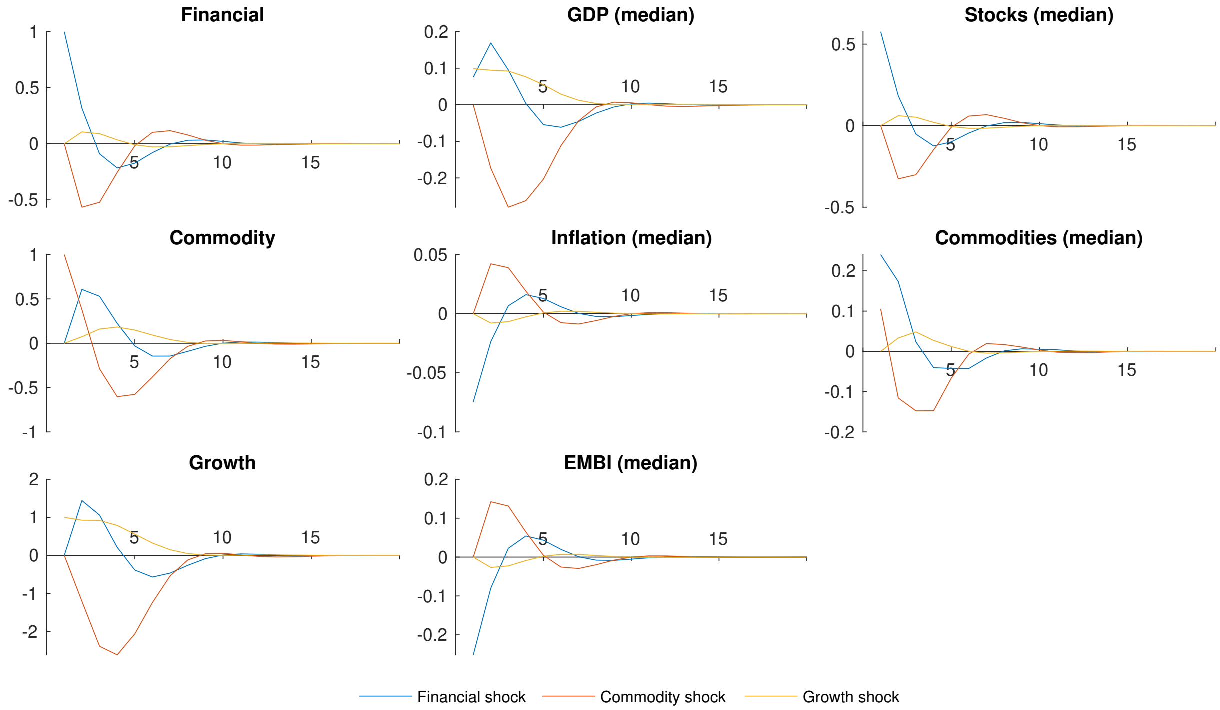


Figure 4: Impulse response functions - Baseline model
Notes: Impulse response functions of estimated factors and observable variables to the original "financial", "commodity" and "growth" shocks.

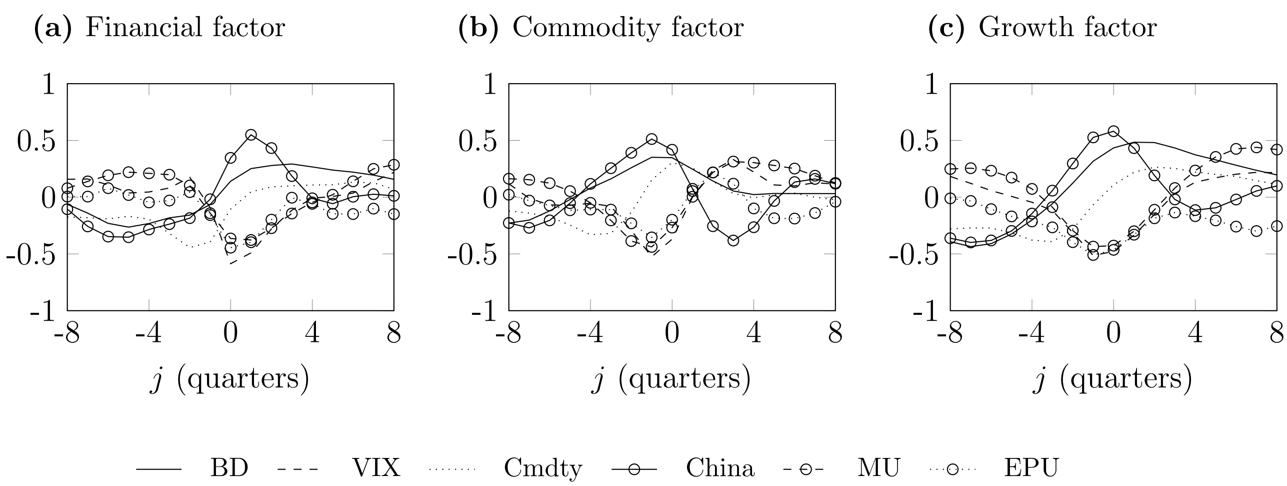


Figure 5: Cross-correlations between factors and drivers.
Notes: The figure portrays correlations between corresponding factor and depicted drivers with $(t + j)$ periods of lags/leads. BD: Leverage of the U.S. Brokers-Dealers sector. VIX: Cboe index of implied volatility on the S&P index options. Cmdty: IMF's Global Price Index of All Commodities. China: China GDP growth. MU: macroeconomic uncertainty index from Jurado *et al.* (2015). EPU: U.S. Economic Policy Uncertainty index from Baker *et al.* (2016).

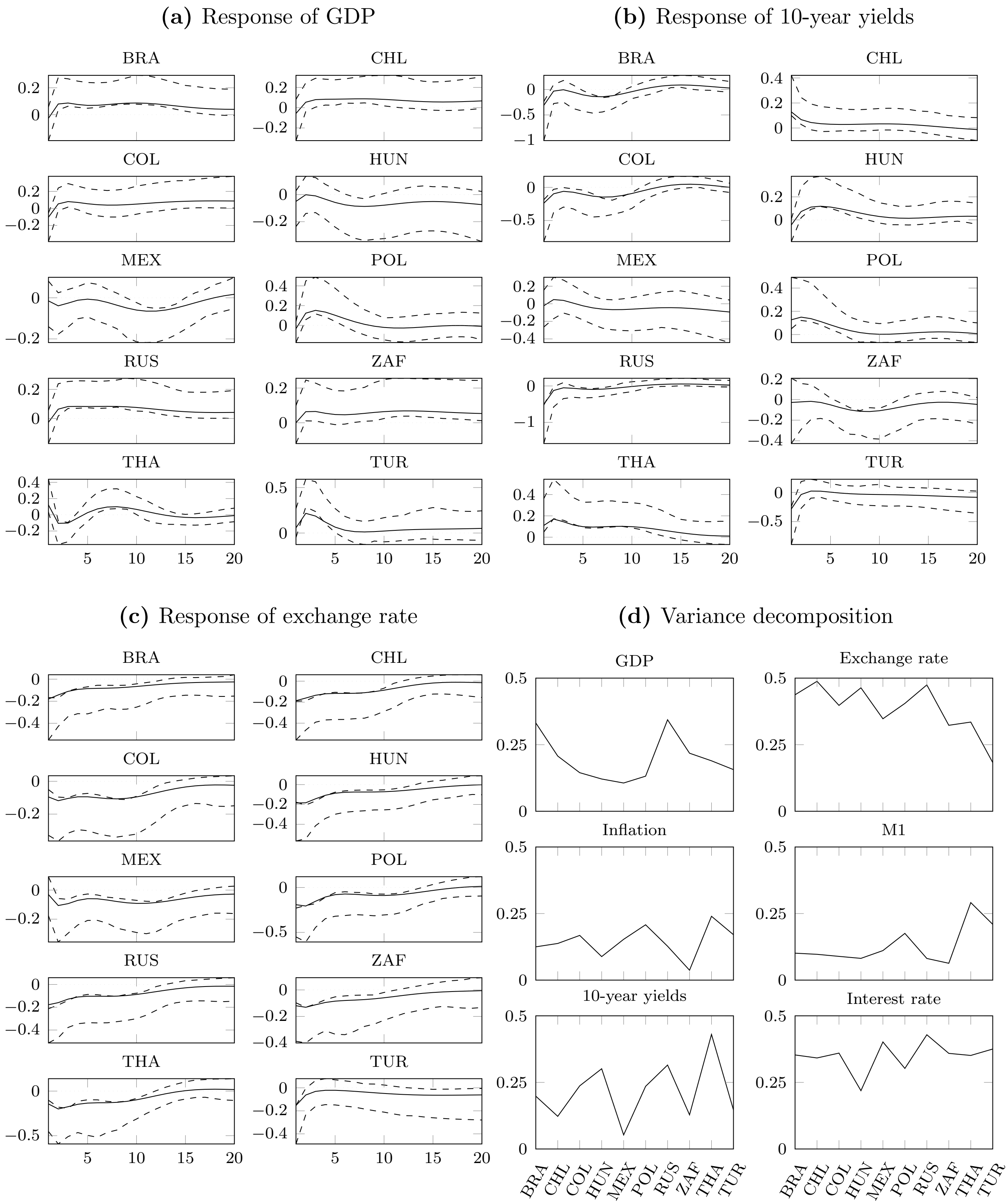


Figure 6: Factor-Augmented VAR — Shock to Financial factor

Notes: The figure shows impulse-response functions and variance decompositions from model (4)–(5). Dashed lines in figures (a)–(c) indicate 95% bootstrapped confidence intervals using Yamamoto's (2019) Procedure A.

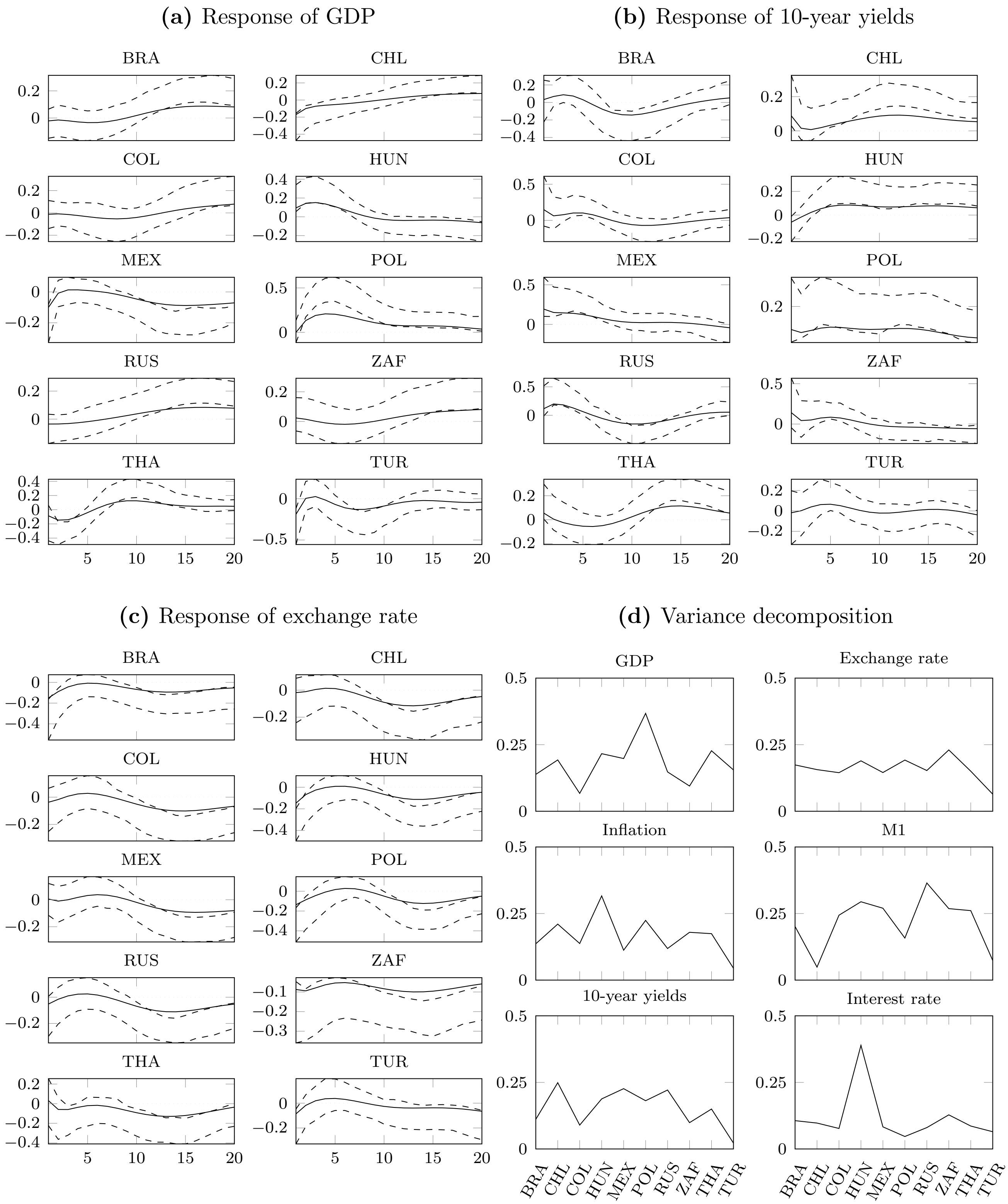


Figure 7: Factor-Augmented VAR — Shock to Commodity factor

Notes: The figure shows impulse-response functions and variance decompositions from model (4)–(5). Dashed lines in figures (a)–(c) indicate 95% bootstrapped confidence intervals using Yamamoto's (2019) Procedure A.

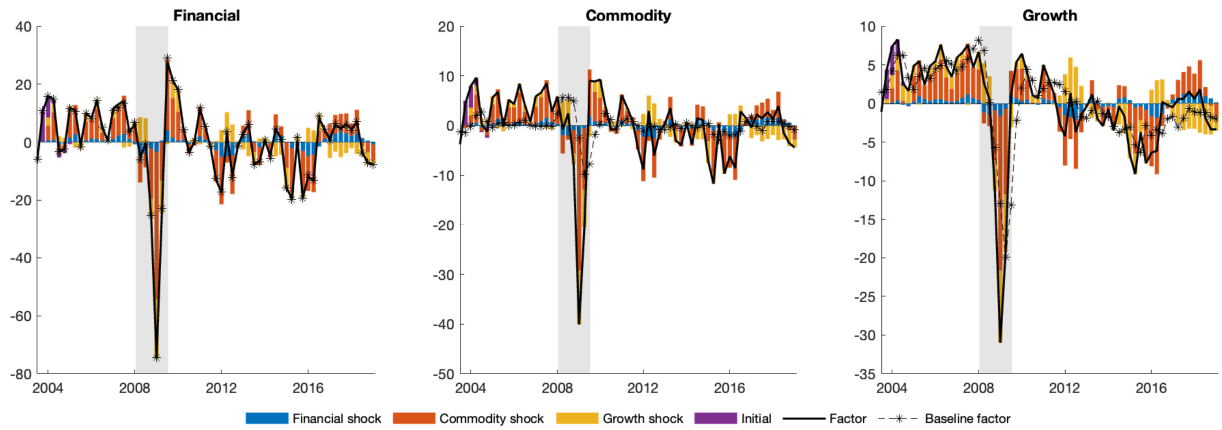


Figure 8: No commodity financialization: historical decomposition of factors
Notes: Factors as originally estimated in log-differences along with their baseline counterpart. Since the factors are identified up to scale, the baseline factors have been scaled to minimize their mean squared distance to their counterpart. Shaded areas denote NBER US recession dates.

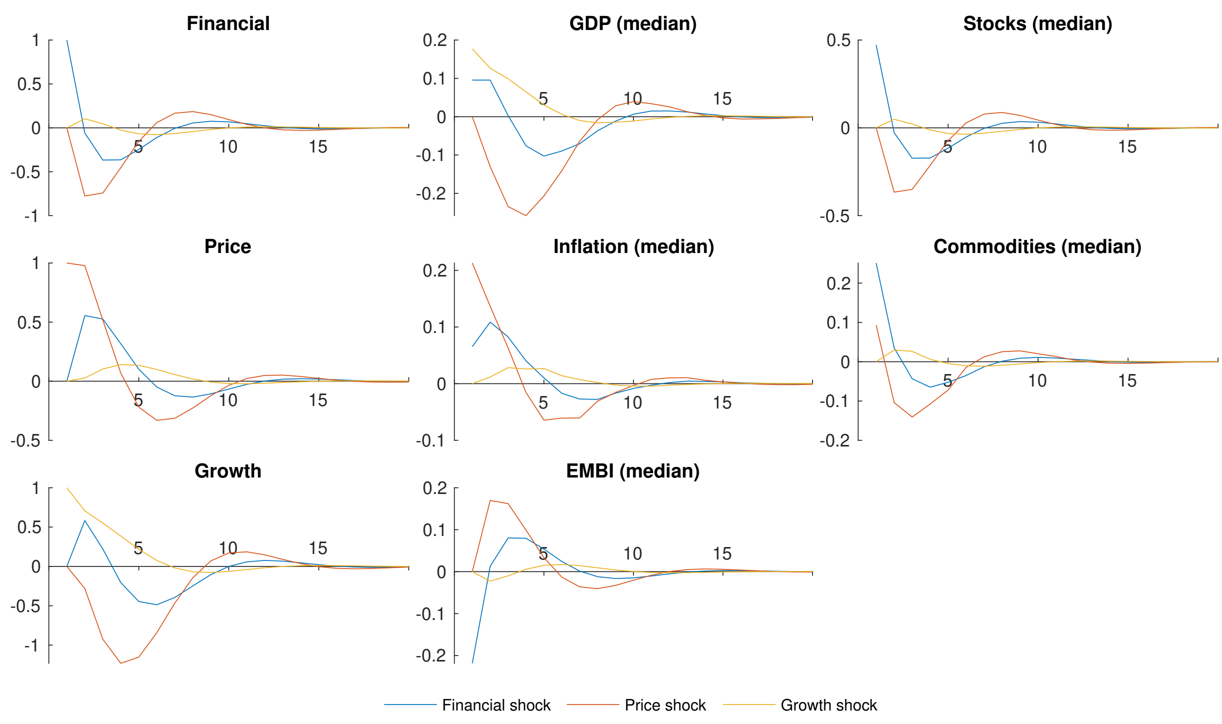


Figure 9: Impulse response functions — Price-factor model
Notes: Impulse response functions of estimated factors and observable variables to the original "financial", "growth" and "price" shocks.

Table 8: Price-factor Model
Share of variance explained by global factor shocks (%)

	Shocks			**Total**
	Financial	**Price**	**Growth**	
A. Factors				
Financial	47.3	51.6	1.1	100.0
Price	22.2	75.9	1.9	100.0
Growth	14.0	60.6	25.4	100.0
Average factors	**27.8**	**62.7**	**9.5**	**100.0**
B. Observable variables (group medians)				
GDP	5.7	22.8	6.8	35.4
CPI	6.6	12.1	0.4	19.1
EMBI spreads	14.4	15.7	0.3	30.4
Stock market index	31.5	34.4	0.7	66.6
Commodity prices	7.9	6.8	0.2	14.9
Crude oil	34.9	26.7	0.8	62.4
Copper	32.9	31.6	0.7	65.2
Aluminum	37.5	31.5	0.8	69.7
Median all obs. variables	**11.2**	**20.7**	**0.7**	**39.1**

Notes: Percentage. Figures correspond to the share of the 20-period ahead forecast error variance that is attributable to each of the global factors shocks. In panel B, group medians are reported for each column (which implies that the sum of the columns does not necessarily add up to the total).

What we got here was the outcome of a trial and error process that ended up configuring a state-space model with parameter constraints that we think conveys information regarding factors that partially resemble those of previous papers (cf. Miranda-Agrippino & Rey, 2020; Fernández *et al.*, 2018). As a punchline, our factors explain roughly the same GDP fluctuations as in the aforementioned papers of this section, with the difference that we are also able to characterize some other consistent patterns at the individual country level. Finally, the inclusion of additional data and modeling variations are eventual avenues of research to better understand common shocks in EMEs' cycles.

References

Abbate, Angela, Eickmeier, Sandra, Lemke, Wolfgang, & Marcellino, Massimiliano. 2016. The Changing International Transmission of Financial Shocks: Evidence from a Classical Time-Varying FAVAR. *Journal of Money, Credit and Banking*, **48**(4), 573–601.

Aguiar, Mark, & Gopinath, Gita. 2007. Emerging market business cycles: The cycle is the trend. *Journal of Political Economy*, **115**(1), 69–102.

Aguiar, Mark, Chatterjee, Satyajit, Cole, Harold, & Stangebye, Zachary. 2016. Quantitative models of sovereign debt crises. *Pages 1697–1755 of: Handbook of Macroeconomics*, vol. 2. Elsevier.

Ahn, Seung C., & Horenstein, Alex R. 2013. Eigenvalue Ratio Test for the Number of Factors. *Econometrica*, **81**(3), 1203–1227.

Aizenman, Joshua, Chinn, Menzie D., & Ito, Hiro. 2016. Monetary policy spillovers and the trilemma in the new normal: Periphery country sensitivity to core country conditions. *Journal of International Money and Finance*, **68**, 298–330.

Akinci, Özge. 2013. Global financial conditions, country spreads and macroeconomic fluctuations in emerging countries. *Journal of International Economics*, **91**(2), 358–371.

Amengual, Dante, & Watson, Mark W. 2007. Consistent estimation of the number of dynamic factors in a large N and T panel. *Journal of Business and Economic Statistics*, **25**(1), 91–96.

Andrews, Donald W. K. 1993. Tests for Parameter Instability and Structural Change With Unknown Change Point. *Econometrica*, **61**(4), 821–856.

Bai, Jushan, & Ng, Serena. 2002. Determining the Number of Factors in Approximate Factor Models. *Econometrica*, **70**(1), 191–221.

Bai, Jushan, & Ng, Serena. 2007. Determining the Number of Primitive Shocks in Factor Models. *Journal of Business and Economic Statistics*, **25**(1), 52–60.

Bai, Yan, Kehoe, Patrick J, & Perri, Fabrizio. 2019. World financial cycles. *In: 2019 Meeting Papers*. Society for Economic Dynamics.

Bajraj, Gent, Fernández, Andrés, Fuentes, Miguel, García, Benjamín, Lorca, Jorge, Paillacar, Manuel, & Wlasiuk, Juan M. 2022. Global Drivers and Macroeconomic Volatility in EMEs: a Dynamic Factor, General Equilibrium Perspective. *mimeo*.

Baker, Scott R., Bloom, Nicholas, & Davis, Steven J. 2016. Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, **131**(4), 1593–1636.

Basak, Suleyman, & Pavlova, Anna. 2016. A Model of Financialization of Commodities. *Journal of Finance*, **71**(4), 1511–1556.

Bernanke, Ben S., Boivin, Jean, & Eliasz, Piotr. 2005. Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *Quarterly Journal of Economics*, **120**(1), 387–422.

Bork, Lasse, Dewachter, Hans, & Houssa, Romain. 2009. *Identification of Macroeconomic Factors in Large Panels*. Unpublished manuscript.

Bruno, Valentina, & Shin, Hyun Song. 2015. Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, **71**, 119–132.

Cerutti, Eugenio, Claessens, Stijn, & Rose, Andrew K. 2019. How Important is the Global Financial Cycle? Evidence from Capital Flows. *IMF Economic Review*, **67**(1), 24–60.

Cesa-Bianchi, Ambrogio, Ferrero, Andrea, & Rebucci, Alessandro. 2018. International credit supply shocks. *Journal of International Economics*, **112**, 219–237.

Cetorelli, Nicola, & Goldberg, Linda S. 2012. Banking Globalization and Monetary Transmission. *Journal of Finance*, **67**(5), 1811–1843.

Chamberlain, Gary, & Rothschild, Michael. 1983. Arbitrage, Factor Structure, and Mean-Variance Analysis on Large Asset Markets. *Econometrica*, **51**(5), 1281–1304.

Chang, Roberto, & Fernández, Andrés. 2013. On the Sources of Aggregate Fluctuations in Emerging Economies. *International Economic Review*, **54**(4), 1265–1293.

Chen, Liang, Dolado, Juan J., & Gonzalo, Jesús. 2014. Detecting big structural breaks in large factor models. *Journal of Econometrics*, **180**(1), 30–48.

Cheng, Ing-Haw, & Xiong, Wei. 2014. Financialization of Commodity Markets. *Annual Review of Financial Economics*, **6**(1), 419–441.

Choi, Woon Gyu, Kang, Taesu, Kim, Geun Young, & Lee, Byongju. 2017. Global liquidity transmission to emerging market economies, and their policy responses. *Journal of International Economics*, **109**, 153–166.

Clark, John, Converse, Nathan, Coulibaly, Brahima, & Kamin, Steven B. 2019. Emerging market capital flows and U.S. monetary policy. *International Finance*.

Delle Chiaie, Simona, Ferrara, Laurent, & Giannone, Domenico. 2022. Common factors of commodity prices. *Journal of Applied Econometrics*, **37**(3), 461–476.

Etula, Erkko. 2013. Broker-dealer risk appetite and commodity returns. *Journal of Financial Econometrics*, **11**(3), 486–521.

Fernández, Andrés, Schmitt-Grohé, Stephanie, & Uribe, Martín. 2017. World shocks, world prices, and business cycles: An empirical investigation. *Journal of International Economics*, **108**, S2–S14.

Fernández, Andrés, González, Andrés, & Rodriguez, Diego. 2018. Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies. *Journal of International Economics*, **111**, 99–121.

Hamilton, James D. 2019. Measuring Global Economic Activity. *Journal of Applied Econometrics*.

Hofmann, Boris, & Park, Taejin. 2020. The broad dollar exchange rate as an EME risk factor. *BIS Quarterly Review*, December.

Jurado, Kyle, Ludvigson, Sydney C., & Ng, Serena. 2015. Measuring Uncertainty. *American Economic Review*, **105**(3), 1177–1216.

Longstaff, Francis A, Pan, Jun, Pedersen, Lasse H, & Singleton, Kenneth J. 2011. How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, **3**(2), 75–103.

Ludvigson, Sydney C., & Ng, Serena. 2009. Macro factors in bond risk premia. *Review of Financial Studies*, **22**(12), 5027–5067.

Maćkowiak, Bartosz. 2007. External shocks, U.S. monetary policy and macroeconomic fluctuations in emerging markets. *Journal of Monetary Economics*, **54**(8), 2512–2520.

Miranda-Agrippino, Silvia, & Rey, Hélene. 2020. US monetary policy and the global financial cycle. *The Review of Economic Studies*, **87**(6), 2754–2776.

Neumeyer, Pablo A., & Perri, Fabrizio. 2005. Business cycles in emerging economies: The role of interest rates. *Journal of Monetary Economics*, **52**(2), 345–380.

Reinhart, Carmen, Reinhart, Vincent, & Trebesch, Christoph. 2016. Global Cycles: Capital Flows, Commodities, and Sovereign Defaults, 1815-2015. *American Economic Review*, **106**(5), 574–80.

Schmitt-Grohé, Stephanie, & Uribe, Martín. 2018. HOW IMPORTANT ARE TERMS-OF-TRADE SHOCKS? *International Economic Review*, **59**(1), 85–111.

Stock, J. H., & Watson, M. W. 2016. Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. *Pages 415–525 of:* Taylor, John, & Uhlig, Harald (eds), *Handbook of Macroeconomics*, vol. 2. Elsevier.

Stock, James H., & Watson, Mark W. 2002. Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association*, **97**(460), 1167–1179.

Tang, Ke, & Xiong, Wei. 2010 (September). *Index Investment and Financialization of Commodities*. Working Paper 16385. National Bureau of Economic Research.

Temesvary, Judit, Ongena, Steven, & Owen, Ann L. 2018. A global lending channel unplugged? Does U.S. monetary policy affect cross-border and affiliate lending by global U.S. banks? *Journal of International Economics*, **112**, 50–69.

Uribe, Martín, & Yue, Vivian Z. 2006. Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, **69**(1), 6–36.

Yamamoto, Yohei. 2019. Bootstrap inference for impulse response functions in factor-augmented vector autoregressions. *Journal of Applied Econometrics*, **34**(2), 247–267.

A Data

Similar to Fernández *et al.* (2018), our sample includes mainly commodity-exporting EMEs, namely: Argentina, Brazil, Bulgaria, Chile, Colombia, Ecuador, Malaysia, Mexico, Peru, Russia, South Africa and Ukraine. For each of these countries we include a set of variables that characterize their macro-financial business cycle: real GDP,[9] CPI,[10] EMBI Spreads,[11] and a major stock market index.[12] In addition to this set of country-specific variables, we include the international prices of the top-ten commodity goods exported by this group of EMEs, namely, crude oil, copper, aluminum, natural gas, coal, iron, gold, coffee, bananas, soybean meal.[13]

To rule out the presence of integrated series, all of the time series for GDP, CPI, stock indices and commodity prices enter the model in first (log) differences. All variables correspond to quarterly averages, are centered (demeaned), and scaled by the inverse of their standard deviation. We also put together a series of potential drivers of cycles in emerging economies considered in previous research,[14] namely the U.S. Federal Funds rate, the leverage of the U.S. Brokers-Dealers sector, measures of financial and macroeconomic risk and uncertainty, and also several official price indexes of aggregate and sectoral commodity prices.[15] Finally, the last part of our data—that will be used in Section XX—is a

[9]Source: IMF, except for Peru, whose data come from the Central Reserve Bank of Peru; and for Russia and South Africa, whose data come from the OECD.

[10]Source: IMF, except for Argentina, whose data are from Bloomberg.

[11]Source: JP Morgan EMBI Global spreads, from Bloomberg. Following Aguiar *et al.* (2016), we deflate each EME's EMBI with the country's external debt (% of GDP, from the World Bank) and GDP growth.

[12]In USD, as in Miranda-Agrippino & Rey (2020). We use the following indexes from Bloomberg: Merval (ARG), IBOV (BRA), SOFIX (BGR), IPSA (CHL), COLCAP (COL), ECGUBVG (ECU), FBMKLCI (MYS), MEXBOL (MEX), SPBLPGPT (PER), RTSI$ (RUS), PSI20 (ZAF) and PFTS (UKR). USD FX are from the BIS.

[13]Commodity prices are from the IMF, expressed in USD deflated with the US CPI (from St. Louis Fed). In order to select the top-ten commodity exports of this group of EMEs, we: (1) rank the commodities exported by each country by their average exports as % of GDP in the period 2003-2018 (data from UN Comtrade); (2) for each commodity, compute the average ranking (across the 12 EMEs); and (3) select the 10 commodities with the highest average ranking. The list is similar if, instead of computing the average, we use each commodity's median ranking across EMEs.

[14]See for instance Uribe & Yue (2006); Akinci (2013); Bruno & Shin (2015); Jurado *et al.* (2015) and Baker *et al.* (2016).

[15]Most of the U.S series (Federal Funds rate, VIX, real exchange rate, financial conditions indexes) were downloaded from St. Louis Fed's FRED. The Brokers-Dealers leverage data is from the website of the Board of Governors of the Federal Reserve System. Commodity price indexes are from the IMF, except for DJ commodity index and GSCI which come from Bloomberg. Macroeconomic uncertainty (Jurado *et al.*, 2015) and economic policy uncertainty indexes (Baker *et al.*, 2016) come from their respective authors' websites.

panel that comprises real GDP, exchange rates, monetary aggregates, CPI, sovereign risk, as well as short and long interest rates for a set of emerging market economies.[16]

B Figures

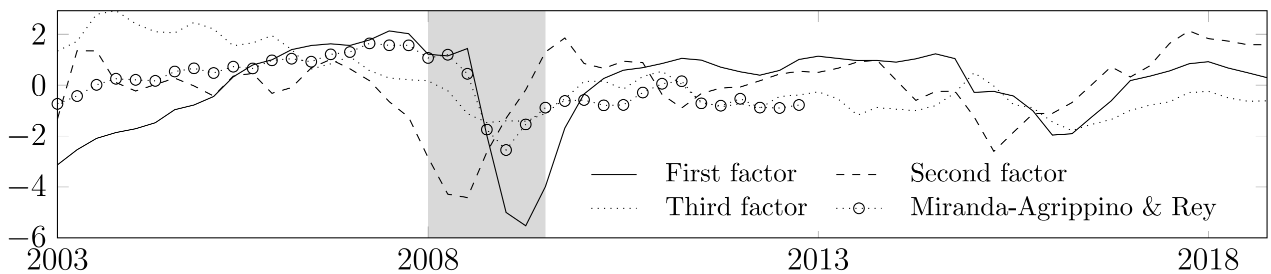


Figure 10: Factors estimated by principal components vs. Miranda-Agrippino & Rey (2020)

Notes: The figure shows the time series of factors estimated in Equation 3 versus Miranda-Agrippino & Rey's (2020) global factor in risky asset prices.

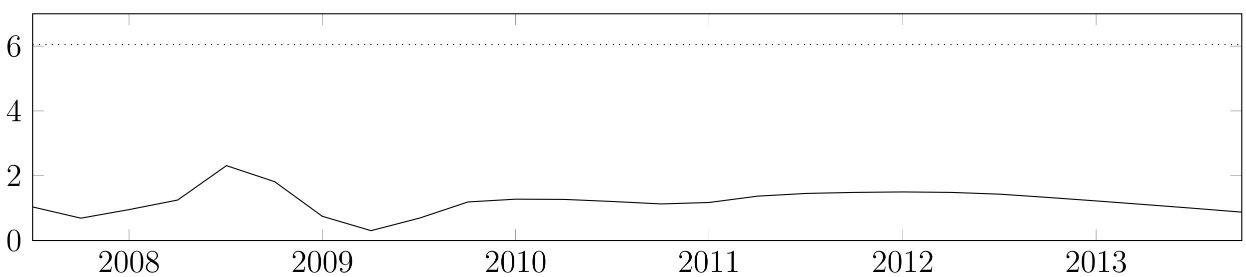


Figure 11: Stability of factor loadings

Notes: The figure shows the Sup-Wald test in Chen *et al.* (2014) applied to our dynamic factor model. The dotted line comes from Andrews (1993) for a trimming parameter of 0.3 at the 10% level. Since the solid line does not surpass the critical level, the test suggests stability in the loading matrix.

[16]GDP data for emerging countries comes from the IMF, except for Mexico, which comes from Banxico. All of the nominal exchange rate and CPI data is from the IMF International Financial Statistics database. Monetary aggregates come from IMF, OECD and Bloomberg. Ten-year interest rates and EMBI data come also from the OECD and Bloomberg. The short-term interest rate series follows Uribe & Yue (2006) procedure.

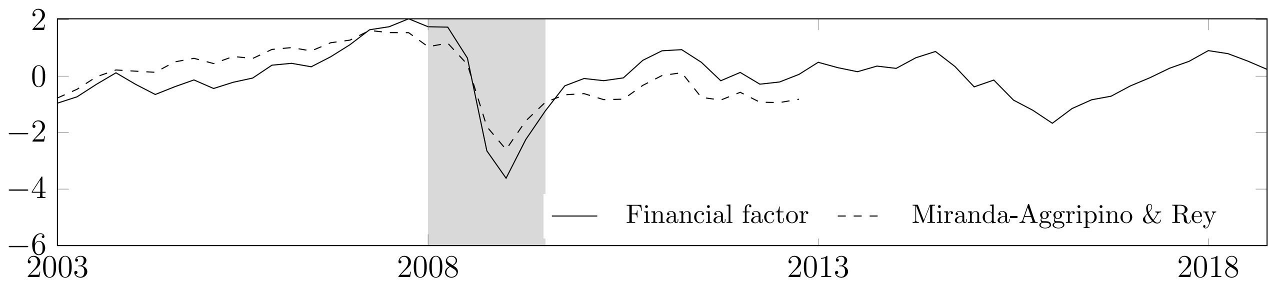


Figure 12: Cyclical component of the cumulated financial factor vs. Miranda-Agrippino & Rey (2020)

Notes: The cyclical component is obtained using a Hodrick-Prescott filter with parameter $\lambda = 1600$. Both factors have been scaled by the inverse of their standard deviation.

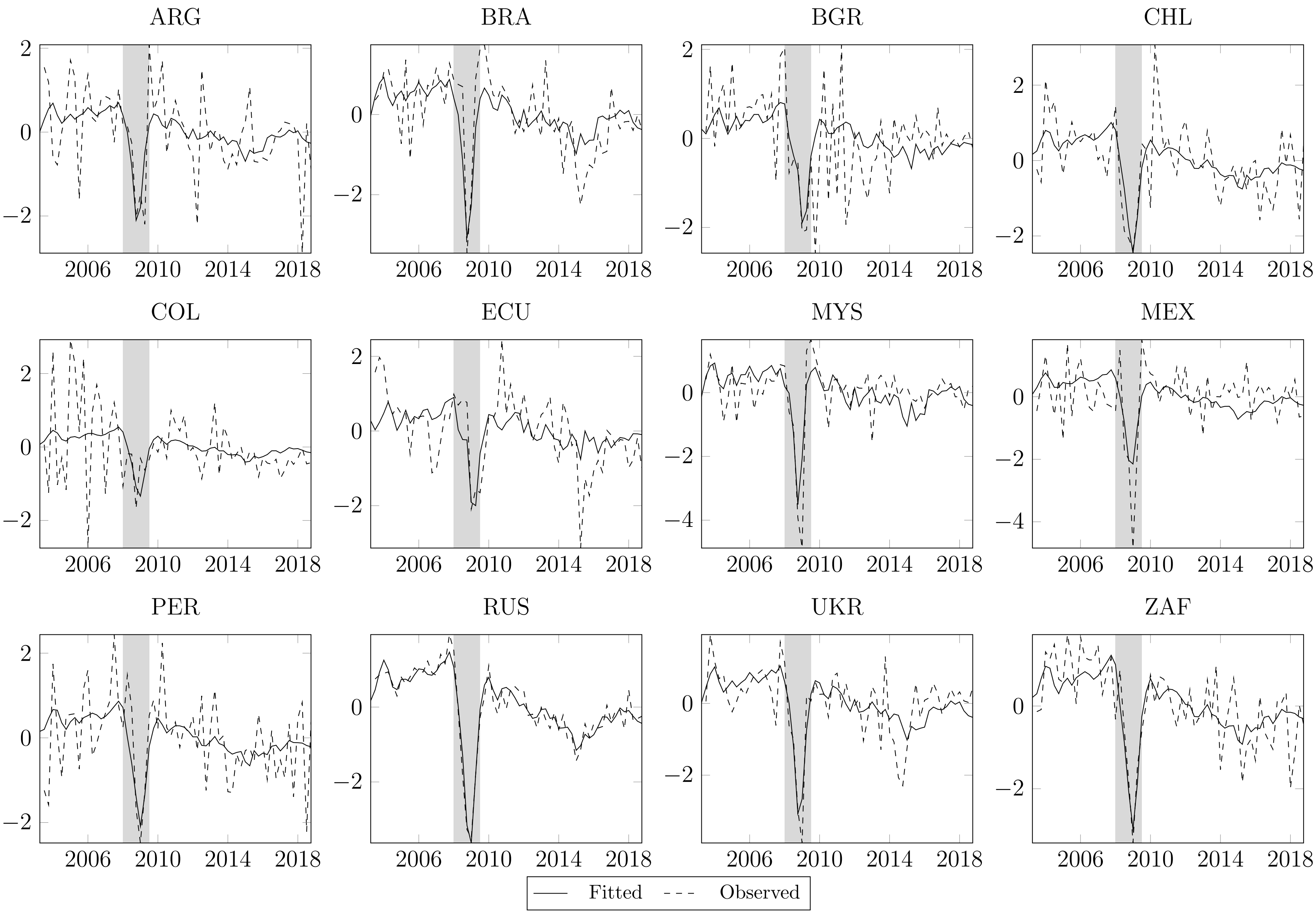


Figure 13: Comparison of fitted and observed values (GDP)

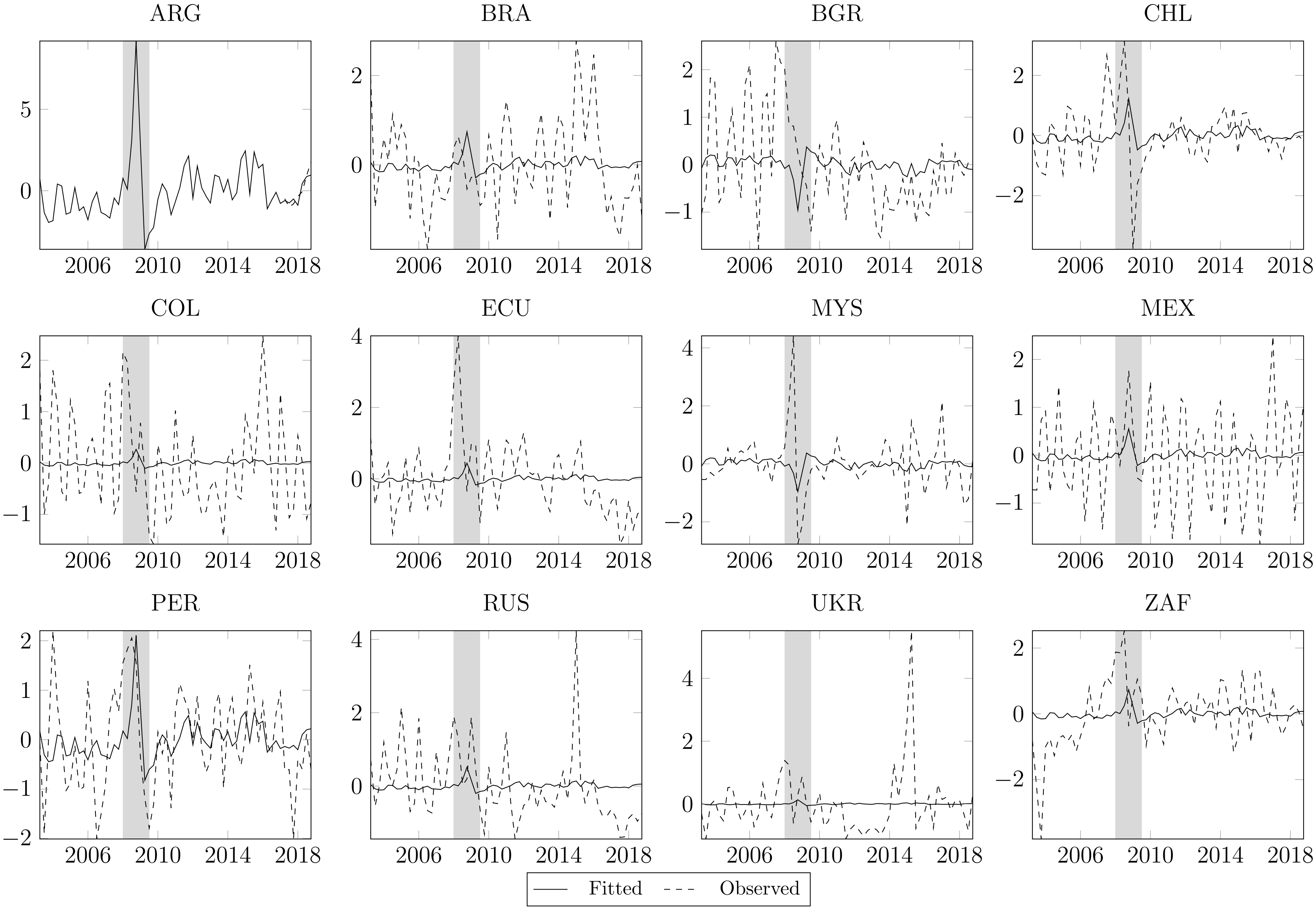


Figure 14: Comparison of fitted and observed values (Inflation)

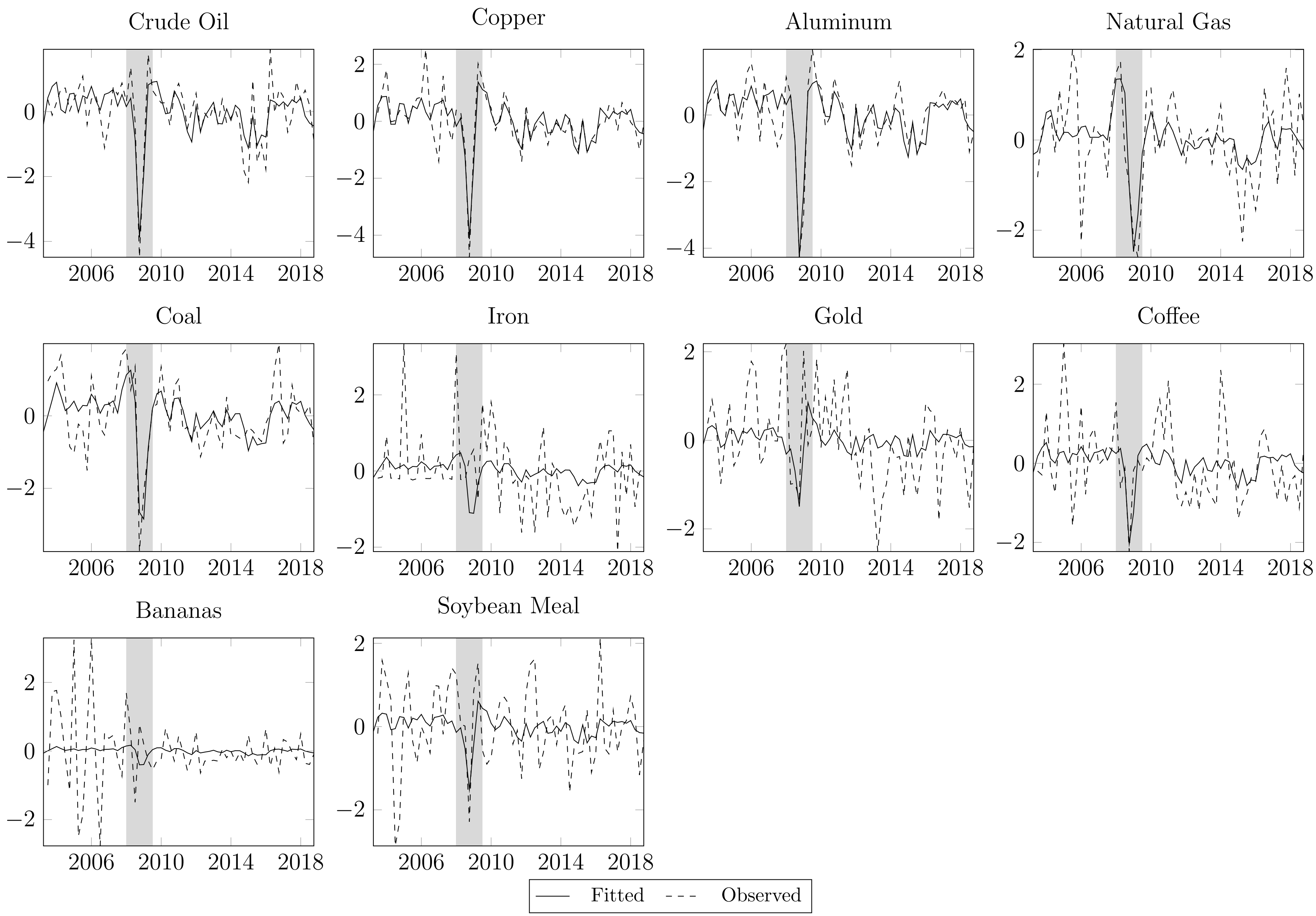


Figure 15: Comparison of fitted and observed values (Commodity Price Index)

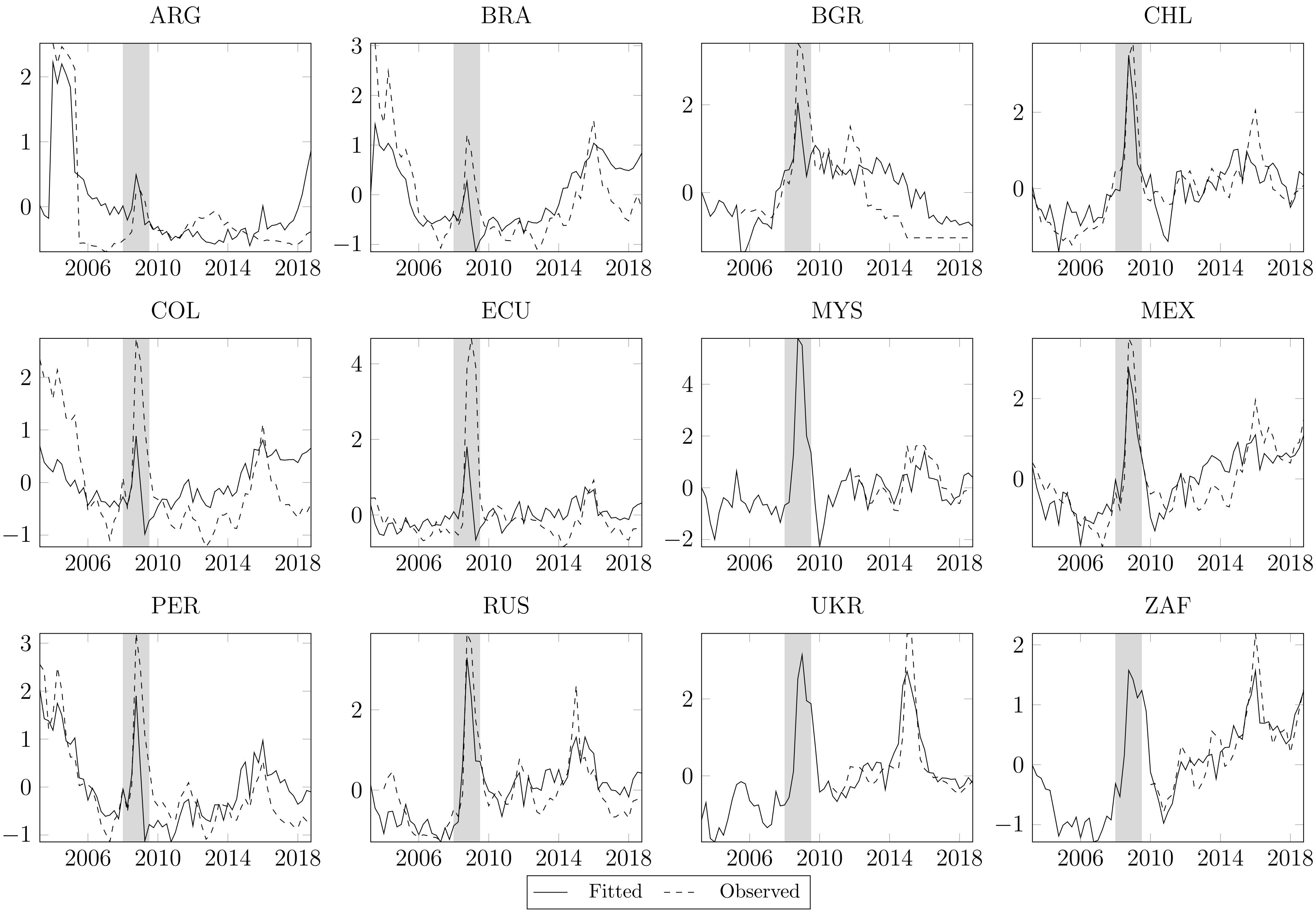


Figure 16: Comparison of fitted and observed values (EMBI Spreads)

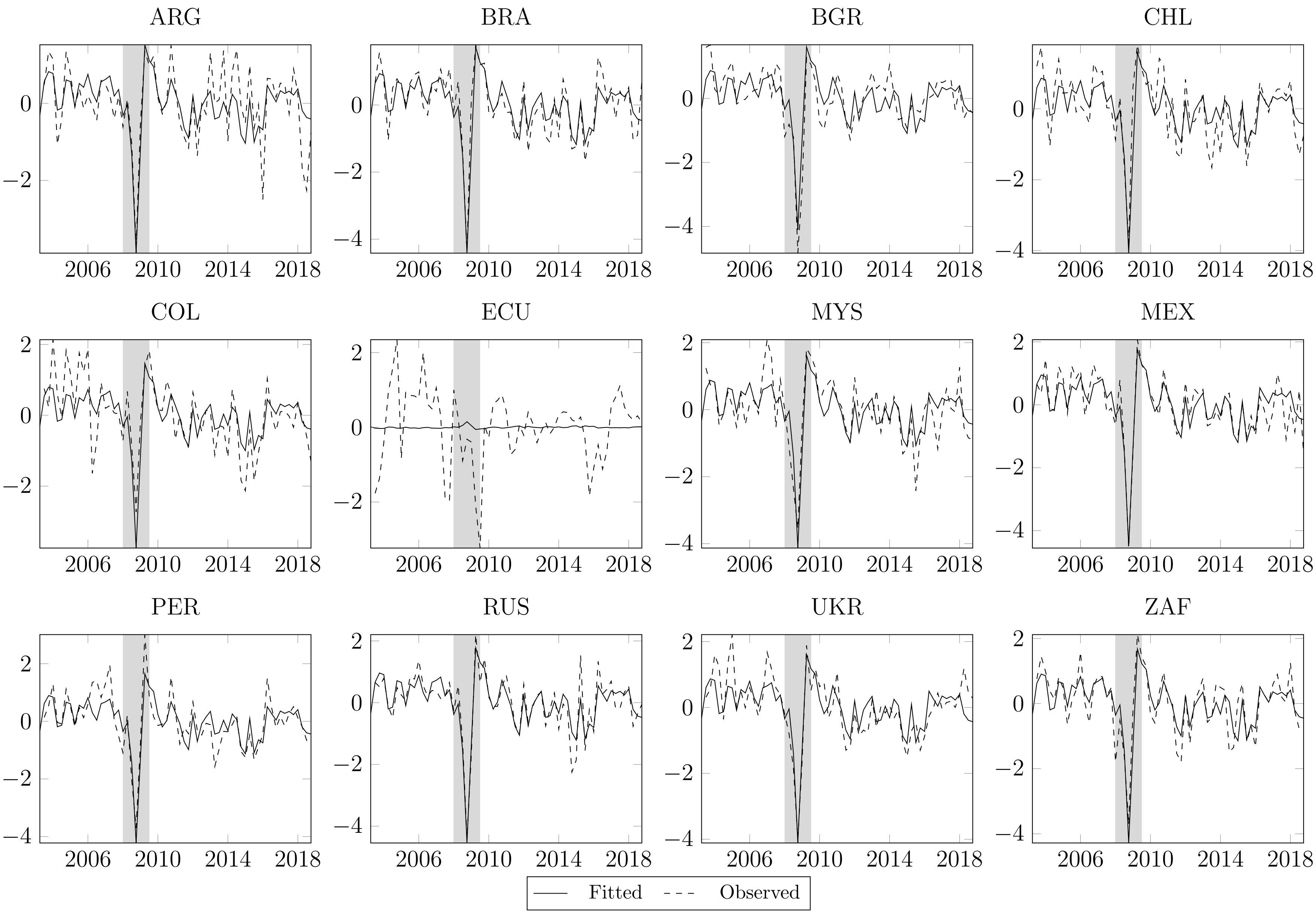


Figure 17: Comparison of fitted and observed values (Stocks)