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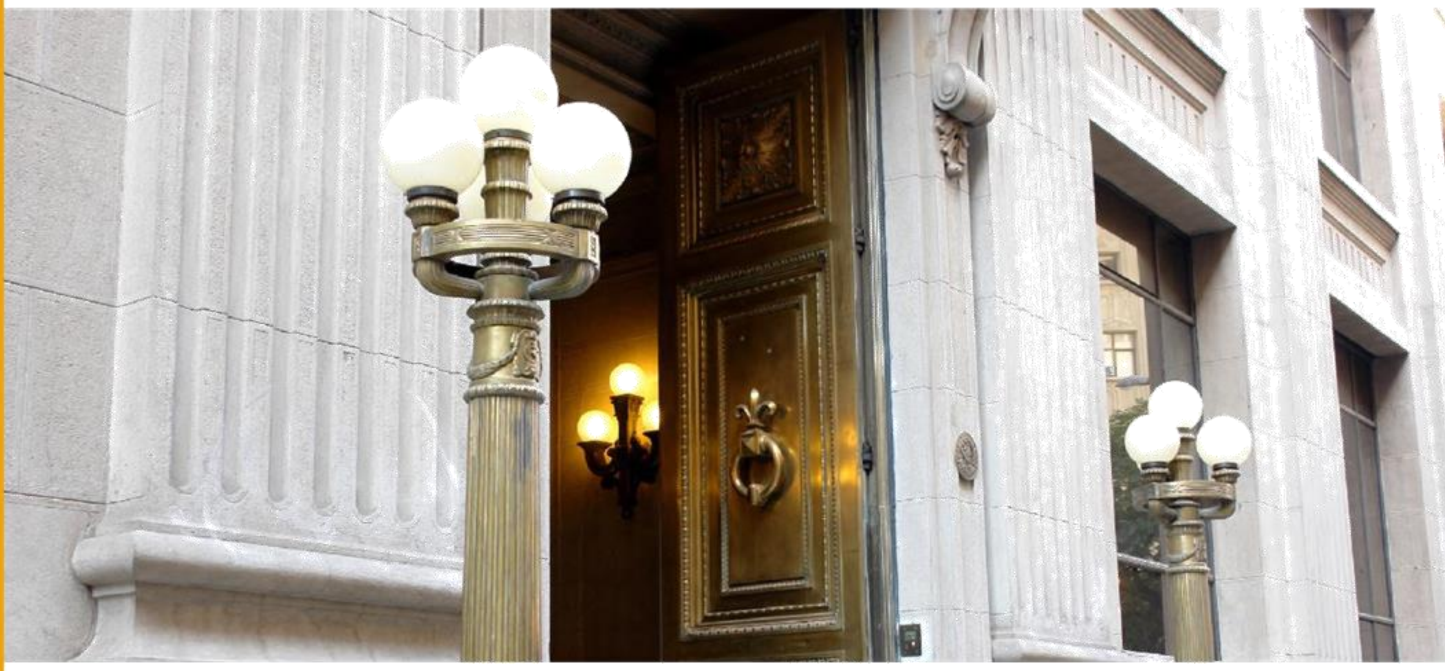

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On Foreign Drivers of EMEs Fluctuations

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Abstract

We pose a series of contemporary interactions between a set of previously documented common factors driving emerging market economies' (EMEs) business cycles in a dynamic factor model with loading restrictions. We estimate a set of three common factors with a structural interpretation tightly linked to specific empirical counterparts—a financial factor, a commodity price factor, and a growth factor—with strong interactions among them. Our results point toward quantitatively relevant effects induced by shocks to the global factors that we identify. 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.

Resumen

Planteamos una serie de interacciones contemporáneas entre un conjunto de factores comunes previamente documentados que impulsan los ciclos económicos de las economías emergentes (EMEs) en un modelo de factores dinámicos con restricciones en la matriz de cargas. Estimamos tres factores comunes con una interpretación estructural estrechamente vinculada a contrapartes empíricas específicas (un factor financiero, un factor de precios de *commodities*, y un factor de crecimiento) con fuertes interacciones entre ellos. Nuestros resultados sugieren efectos cuantitativamente relevantes inducidos por *shocks* a los factores globales que identificamos. Aun cuando se tiene en cuenta la presencia de ciclos financieros, encontramos un papel preponderante de las fluctuaciones de los precios de los *commodities* en el desempeño de las EMEs.

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1 Introduction

A steadily growing number of research papers in international finance document the existence of global economic factors that play a key role in the performance of emerging market economies (EMEs). Typically, this line of research confines the data under scrutiny to conform a particular angle of these economies—say, spreads or commodity prices—which then feeds the statistical machinery of dynamic factor modeling to uncover a set of time series responsible for the bulk of fluctuations. Its main contribution has been to uncover 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), each on their own data-specific realm.

An issue with this approach is that it leaves potential interactions and joint explanatory power between an encompassing, broader set of different factors in an entirely absent role. The single-setting factor modeling cannot tackle relevant questions such as to what extent changes in commodity prices merely reflect variations in global financial conditions, or whether is 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 to what extent are EMEs business cycles determined by the jointly combined dynamics of a set of common external drivers. We build from the same methodological approach of the aforementioned papers, that is, we estimate a dynamic factor model, but we depart in a stark direction. We compile a full array of macro variables including prices, activity, financial variables, and commodity prices in a multi-country setup. Then, starting from previous research, we pose a candidate set of relevant factors affecting different aspects of EMEs cycles and we ex ante impose a series of restrictions on the contemporary dynamics of such relevant factors. In technical words, we estimate a constrained state-space model by maximum likelihood using a wide range of macroeconomic variables for twelve emerging economies and 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 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 while allowing for interactions between them. An important example of such interactions 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 circa 2005 (Tang & Xiong, 2010).

Our results point toward the coexistence of three relevant empirical factors for the joint dynamics of EMEs cycles, with each of the factors associated to global financial conditions, commodity price cycles, and commodity-exporting EMEs growth, respectively. We find strong interactions among them. From a quantitative vantage point, shocks to the three factors account for more than 35% of the variance of GDP (sample median), 27% of the variance of sovereign risks, and almost two-thirds of the variance of the stock market indices. A shock to financial conditions in our estimated state-space model explains roughly 7% of GDP fluctuations and around 40% of the variations in the prices of oil, copper and aluminium. This highlights the interaction among the factors. Shocks to the commodity and growth factors explain 25 and 4% of GDP fluctuations, respectively. 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.

Related Literature

This paper relates to several strands of literature on international economics, with a focus on the drivers of business cycles in 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 finds 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. Other relevant 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). In the appendix, 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).

In terms of methodology, we share some similarities with 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 to try to get ex ante meaning for identified common factors in our dataset.

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, the empirical applications are markedly different.

The rest of the paper is organized as follows. In Section 2 we lay out our data and empirical model approach. We analyze the number of statistically relevant factors in addition to the state-space formulation we use and run formal stability tests. In Section 3 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. We also investigate the drivers of our estimated common factors, examining cross-correlations and regressions on previously documented drivers. We then perform some robustness exercises in Section 4 to figure out the consistency of the macroeconomic responses we obtain from factor shocks of the previous section. Lastly, in Section 5 we provide some final remarks.

2 Model

We compile an unbalanced quarterly panel dataset for the period between 2003Q1 and 2018Q4. Similar to Fernández *et al.* (2015), our sample includes twelve 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 measures of GDP, inflation, sovereign spreads and stock indices, augmented with the prices of the top ten commodities exported by the sampled countries (crude oil, copper, aluminum, natural gas, coal, iron, gold, coffee, bananas and soybean meal).[1]

Given the diverse nature of the variables in our dataset, it is instructional to take subsamples with a single variable and extract a factor from each. Figure 1a displays the factors corresponding to stock indices, commodity prices and GDP. To these we add some of the factors found in the literature, namely, the global financial cycle of Miranda-Agrippino & Rey (2020) and the commodity factors of, both, Fernández *et al.* (2015) and Delle Chiaie *et al.* (2022). As can be seen from the figure, the series show important similarities. This leads us to conjecture whether they all capture a single driving force, or instead they actually resemble different fundamentals, which in turn—through their interactions—induce similar dynamics in the observed variables. As a preliminary exercise, we took the factor extracted from stock indices, commodity prices and GDP and included each in the VAR postulated by Bruno & Shin (2015).[2] Figure 1b shows that their impulse response functions to a shock to commodity prices show quite a contrast. This suggests that despite the resemblance, these factors seem to capture different forces. We try to disentangle such forces in our model.

2.1 State-Space Formulation

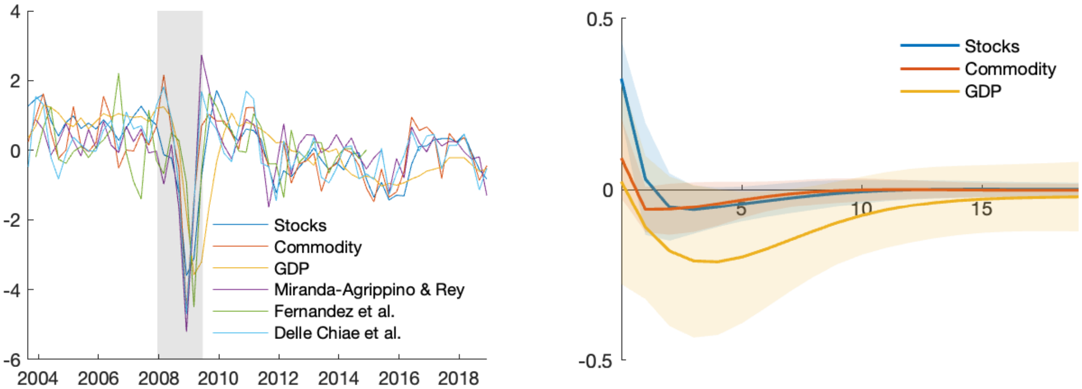
We begin by casting the model into a state-space representation. Let $Y_t = ((Y_{it})_{i=1}^N, \textsc{Commodity}_t')'$ denote our vector of observable time series, where $Y_{it} = (\text{GDP}_{it}, \text{CPI}_{it}, \text{EMBI}_{it}, \text{Stock}_{it})$ represents the specific variables described above—with GDP, CPI, stock indices and commodity prices entering the model in log differences—for each EME $i = 1, \ldots, N$ in period $t = 1, \ldots, T$. The vector $\textsc{Commodity}_t$ has the stacked observations for the M commodity prices included.[3] We model the dynamics of the $(4N + M) \times 1$ vector Y_t as

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

[1]See Appendix A for further details about the data.

[2]We describe this exercise more thoroughly in Appendix C.

[3]Here, $N = 12$ and $M = 10$.



(a) Time series of factors

(b) Factors' IRF to a shock to commodity prices in augmented Bruno & Shin (2015) VAR

Figure 1: Comparison of Factors

Notes: On the left, we show the factors extracted from stock indices, commodity prices, and GDP along with some of the factors found in the literature, namely, Miranda-Agrippino & Rey (2020), Fernández *et al.* (2015) and Delle Chiaie *et al.* (2022). All factors are scaled to have a unit variance. Moreover, to express all factors in the same units, those corresponding to Miranda-Agrippino & Rey (2020) and Fernández *et al.* (2015) are transformed taking quarterly differences. On the right, we show the impulse response functions of the factors extracted from single variable subsamples to a shock to commodity prices in augmented Bruno & Shin (2015) VAR.

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

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 which are likely to affect a wide array of variables (e.g. changes in global risk appetite, or in US monetary policy), 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.

[4]Following Aguiar *et al.* (2016), we include a set of exogenous controls for the case of spreads only, so in practice we 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 $t = 1, \ldots, T$ and Γ is constrained so that X_{it} only affects their respective, country-specific spreads.

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.

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 contemporaneous effect of the factors on the observable 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.

2.2 Model Specification

Our procedure for choosing the number of factors to include and the specific constraints to impose deserves a discussion. We proceed with an iterative process in which we assemble different pieces of information. First, we consider the number of factors spitted out by statistical tests for the optimal number of factors—as if we were following a principal component approach—and contrast them with a list of common drivers of EMEs cycles borrowed directly from previous research. 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 to the constraints we seek 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, look at cross-correlations with international macroeconomic variables to grasp the validity of results.

2.2.1 Number of Factors

How many factors should we consider for the 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). Using their results as a starting point, we estimated several variants of the model, both in terms of the number of factors and the restrictions we impose. We compared the results with previous evidence, in terms of time series behavior as well as correlations with customary drivers, to arrive at a final answer. This process is discussed further in Section 2.2.3. Here, 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.[5]

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.

Table 1 shows the number of factors arising from this approach through several methods. The actual number of factors identified by statistical tests depends on the maximum number of factors considered for the principal component estimation. Hence, we consider several thresholds listed in the first column of the table. The main pattern that emerges

[5] The common thread across this literature is the formulation of either a dynamic or static approximate factor model which is then estimated by principal components and ultimately, some penalty criteria is used to determine the true asymptotic number of factors. We are posing a state-space model with constraints on the loading matrix and estimating the parameters by maximum likelihood, so we cannot directly apply the results of the aforementioned tests into our specific formulation. We can, however, still use their statistical machinery if we momentarily dodge our plan to name the factors ex ante and 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.

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 out previously in some other settings, notably by Aguiar *et al.* (2016), Fernández *et al.* (2018) and Miranda-Agrippino & Rey (2020). 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.[6]

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 that two to three factors should be included in our baseline specification.

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.

[6] As Figure 7 shows—see Appendix B—the estimated factors arising from the principal component approach fairly resemble the trend of Miranda-Agrippino & Rey's (2020).

2.2.2 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 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 8 points out—see Appendix B—, 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.

2.2.3 Restrictions

To *name* the factors—our attempt to endow them with a structural interpretation—we fix the values of certain factor loadings to zero. How do we choose the specific constraints to impose over the factor loadings? The answer lies in the iterative process we pursued. Following the results of the statistical approach, we complemented the answer with the findings of previous research and discriminated among the different specifications based on the consistency of the results.

The existing literature suggests that we consider at least a financial factor (Miranda-Agrippino & Rey, 2020) and a commodity factor (Fernández *et al.*, 2017 and Delle Chiaie *et al.*, 2022), with potentially overlapping effects. When we initially estimated models with two factors—imposing a variety of constraints over the factor loadings—the factors 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 noticeable 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 introduce below.

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.

Table 3 shows schematically the specific constraints we impose on the factor loadings in our baseline specification. The column names list the factors we wish to identify. The constraints for each variable are encoded with black and white circles: a white circle means that we fix the corresponding loading to be zero, whereas a black circle means that the corresponding loading is unconstrained. We let the first factor impact on all the variables of the model. We call it the Financial Factor because of its resemblance to the factor obtained from using the stock indices alone.[7] The Commodity and Growth factors each affect only commodity prices and GDP, respectively. In section 4 we briefly explore two additional specifications.

3 Analysis of factors

The estimated factors, along with their historical shocks' decomposition are presented in the top panels of Figure 2. Since the model is estimated in log-differences, the factors are interpreted in the same way. Colored bars show each shock's incidence in the dynamics of the factors. The bottom panels of the figure present 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

[7] The financial nature of the factor is further confirmed by the strong resemblance between our financial factor and the global factor of Miranda-Agrippino & Rey (2020) (see Figure 9 in the appendix). See also Bajraj *et al.* (2022), which further discusses this view for a closely related model.

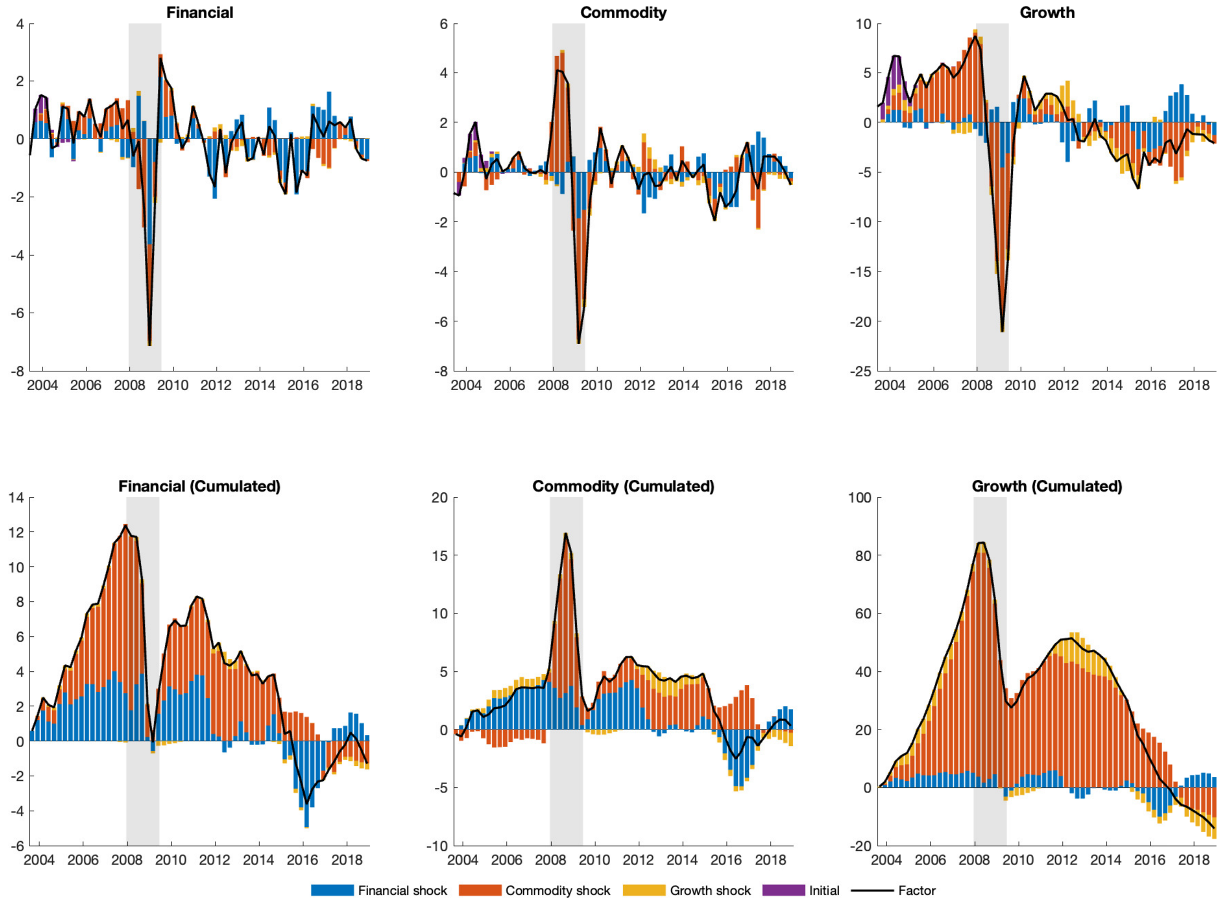


Figure 2: Historical decomposition of factors

Notes: Top panels: factors as originally estimated *in log-differences*. Bottom panels: 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.

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 2 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. This 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 72% 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

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).

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 3 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.[8] 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

[8]For an illustration of the fit of the model to the data, see figures 13–17 in Appendix E.

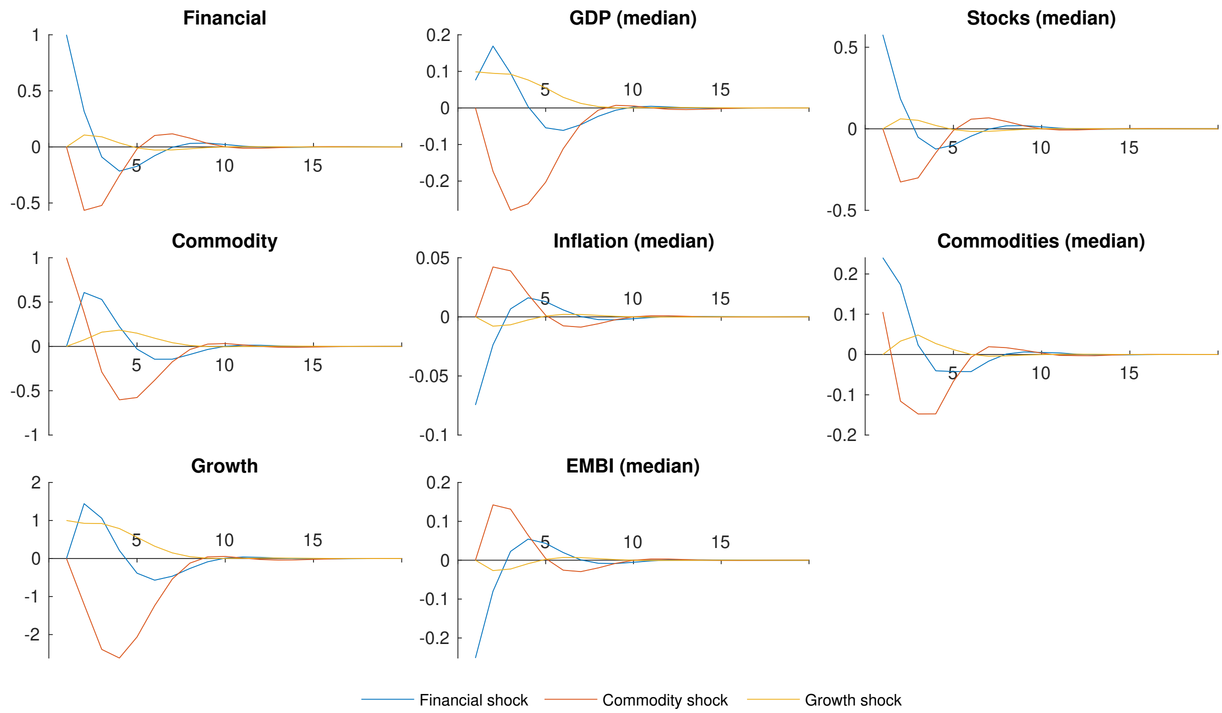


Figure 3: Impulse response functions - Baseline model

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

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, 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 3 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

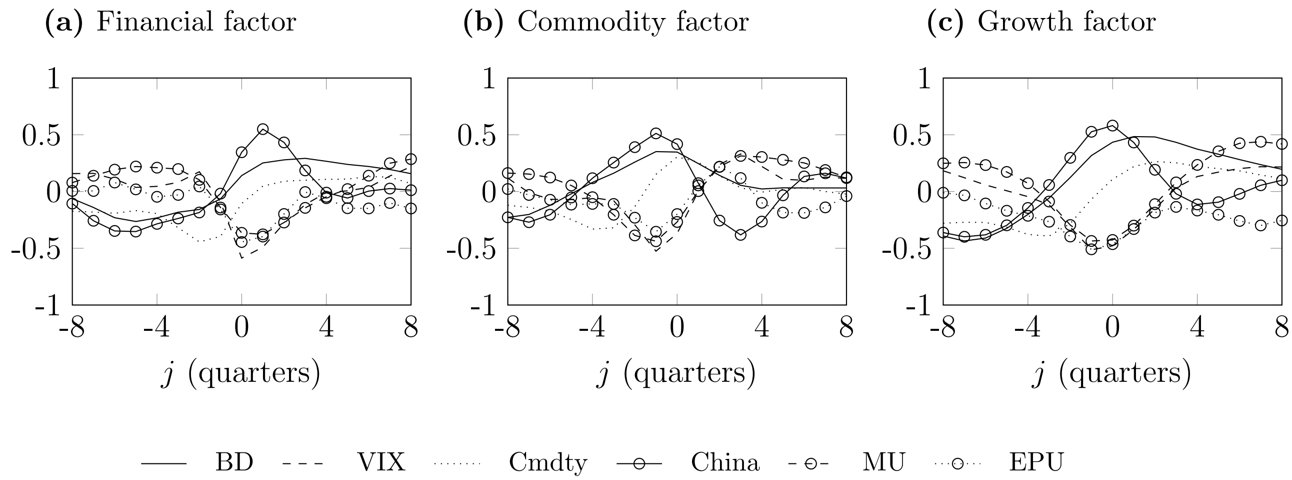


Figure 4: Cross-correlations between factors and drivers.

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).

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 increases. As such, shocks to the commodity factor seem to be associated with cost-push shocks, or negative (global) supply side shocks. We explore this idea further in Section 4.2.

3.1 Relationship to Other Variables

To better understand the relationship between the estimated factors and traditional variables pointed out as drivers of EME cycles, we conduct two exercises. First, we gaze at several cross-correlations between the factors and previously studied drivers. Next, we formally test two-way Granger causality to arrive at a set of exogenous drivers, which we then use as explanatory variables in factor regressions.[9]

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

[9] In Appendix D, we also use a factor-augmented VAR to evaluate the factors obtained.

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 4 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 4a shows—we observe worse financial conditions for EMEs in periods of risk-off preferences and high uncertainty, all broadly documented facts across different studies.[10] 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 4b 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 4c, 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.

[10]See, 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.

An alternative way to appraise the relationship between our factors and the set of eventual drivers is the following. From the set of aforementioned drivers, we identify only those that satisfy weak exogeneity with respect to our estimated factors. Each of these is then used as an independent variable 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 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.

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.

A final remark here is in order: even though we both filtered the drivers included in Table 5 to get rid of endogenous effects and merely focused on contemporary regressions, we still get a noticeable consistency of the estimated factors with respect to a rather ample, heterogeneous sample of drivers documented in previous research.

4 Robustness

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

4.1 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. 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 5. 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 the two is 99.5%). This is highly suggestive that the estimation of the financial factor in our baseline specification is

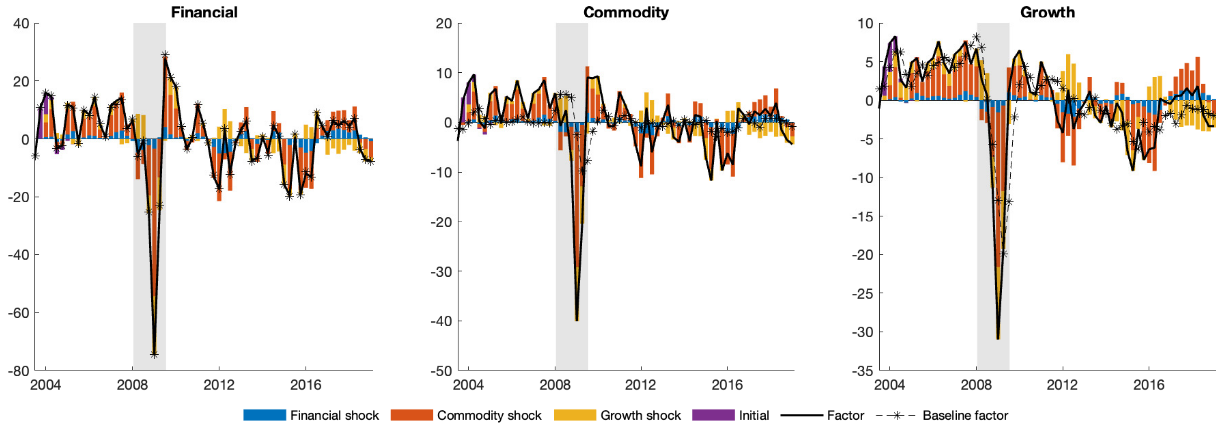


Figure 5: No commodity financialization: historical decomposition of factors
Notes: Factors as originally estimated in log-differences along with their baseline counterpart. Since the factors are identified up to scale, the baseline factors have been scaled to minimize their mean squared distance to their counterpart. Shaded areas denote NBER US recession dates.

robust and is not particularly affected by the inclusion of the commodity financialization channel.[11]

The largest distinction between this alternative and the baseline specification 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 baseline model, to more than 97% in this alternative specification. These differences are not surprising, given that now the commodity factor alone must explain all the variation across the commodity prices, whose dynamics have common elements with the other variables used in 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.

4.2 Price-factor Model

The other variant of the model we explore briefly expands on the idea suggested in Section 3, that the commodity factor in our baseline specification might reflect movements associated with global prices or costs, and not only elements associated exclusively with commodities prices. In this new specification, the commodity factor has been replaced

[11] 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.

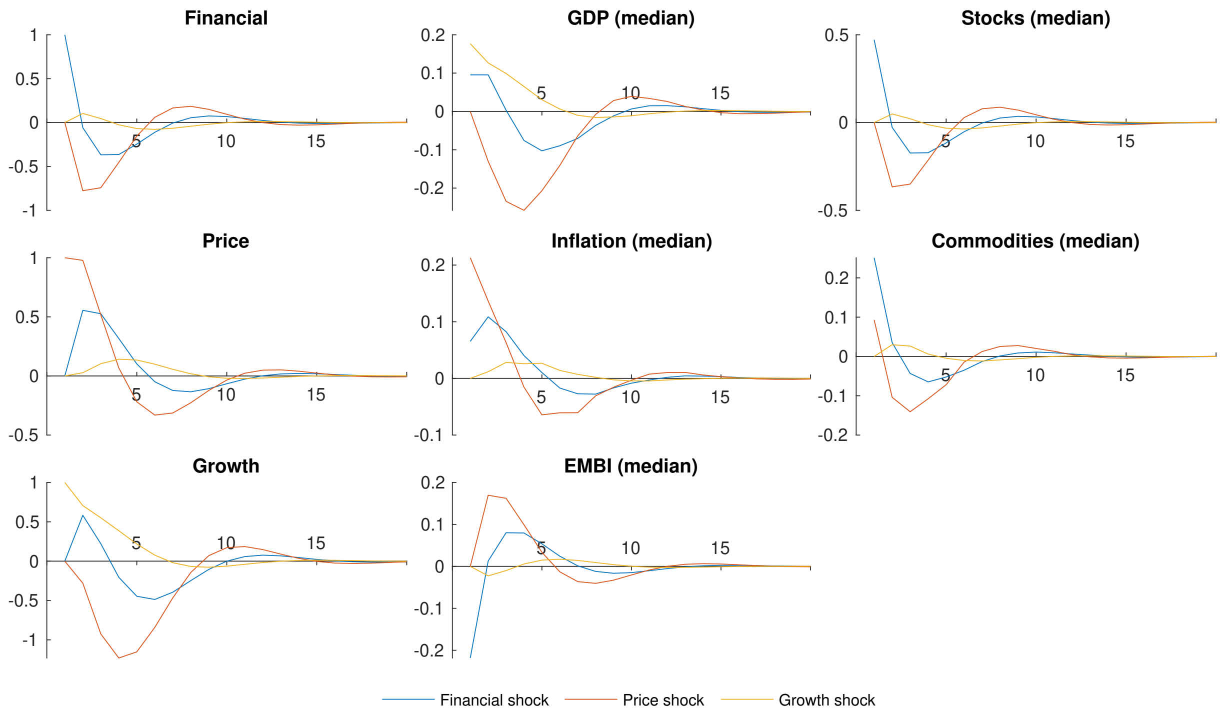


Figure 6: Impulse response functions — Price-factor model

Notes: Impulse response functions of estimated factors and observable variables to the original "financial", "growth" and "price" shocks.

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 (Figure 6) look remarkably similar to those of commodity shocks in the baseline model (Figure 3), 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 the share of variance explained by the factor shocks increases not only for the CPI series (something that is expected), but also for most of the remaining variables, going from 33.2% in the baseline model (table 4) to 39.1% for the median equation in the new specification. Such improvement is due not only 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

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.

global prices in general, more broadly defined. A variant of this result is further explored in Bajraj *et al.* (2022).

5 Concluding Remarks

From several research papers over 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 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 a group of variables while at the same time adhering a structural flavor to the time series of the factors which we attempted to single out. The rationale for this blend was to unravel the intertwined effects between the structural shocks suggested by different pieces of evidence, a debate that already has a dwelling on the financialization of commodities.

Our result is 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

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).

factors that partially resemble those of previous papers (cf. Miranda-Agrippino & Rey, 2020; Fernández *et al.*, 2018). Moreover, our factors by and large explain about the same order of magnitude of GDP fluctuations as in relevant papers for EMEs with different methodologies (Uribe & Yue, 2006; Akinci, 2013), 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.

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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,[12] CPI,[13] EMBI Spreads,[14] and a major stock market index.[15] In addition to the set of country-specific variables, we include the international prices of the top-ten commodity goods exported by the sampled group of EMEs, namely, crude oil, copper, aluminum, natural gas, coal, iron, gold, coffee, bananas, soybean meal.[16]

To rule out the presence of integrated series, all 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,[17] 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.[18] Finally, the last part of our data—that will be used in Section D—is a panel that com-

[12]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.

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

[14]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.

[15]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.

[16]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 the 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.

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

[18]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.

prises real GDP, exchange rates, monetary aggregates, CPI, sovereign risk, as well as short and long interest rates for a set of emerging market economies.[19]

[19]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.

B Auxiliary Figures

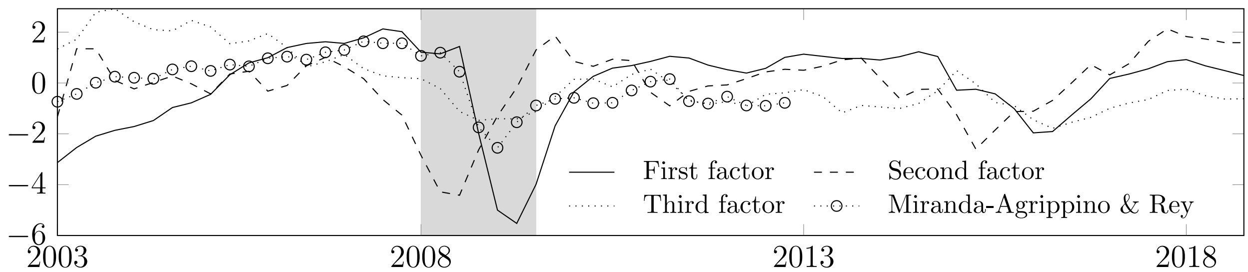

Figure 7: Comparison of the factors estimated by principal components with that of Miranda-Agrippino & Rey (2020)

Notes: The line Miranda-Agrippino & Rey is the global factor in risky asset prices of Miranda-Agrippino & Rey (2020). The remaining lines represent the factors estimated by principal components in the process of determining the number of factors in a dynamic factor model, as discussed in Section 2.2.1.

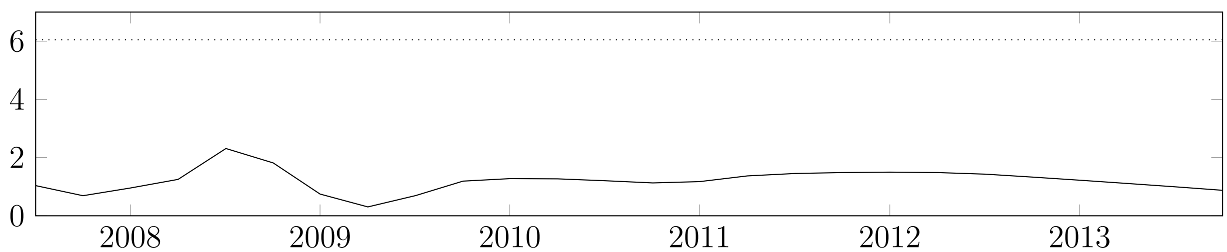

Figure 8: Stability of factor loadings

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.

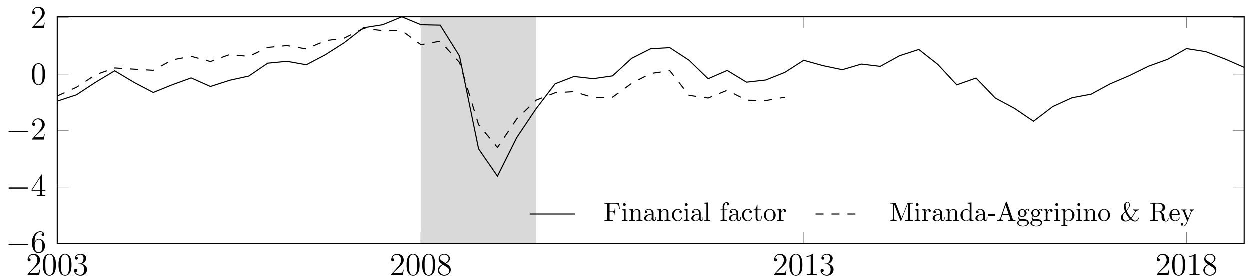

Figure 9: Comparison of the cyclical component of the cumulated financial factor with that of Miranda-Agrippino & Rey (2020)

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.

C A VAR expanded with our Estimated Factors

In this brief digression we explain the aim of the exercise of Section 2 in which we expand the original vector auto-regression formulation by Bruno & Shin (2015) by incorporating the factors we estimate. Indeed, in such paper the authors incorporate bank leverage into an otherwise standard VAR formulation in order to study the *linchpin* role of that sector in the monetary transmission mechanism, which thereafter is expanded to focus on cross-border flows. Here we consider the same basic framework of those authors, which we modify in order to include our factors so as to figure out the way in which customary monetary policy and risk-taking shocks impact the common forces that we identify. The results—pictured in Figure 10—are rather consistent with the impulse-response functions of the original paper and allow for a quantitative comparison of the dynamics of our estimated factors.

D Factor-augmented VAR

Here, we conduct an additional 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 the 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.[20]

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:

[20]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).

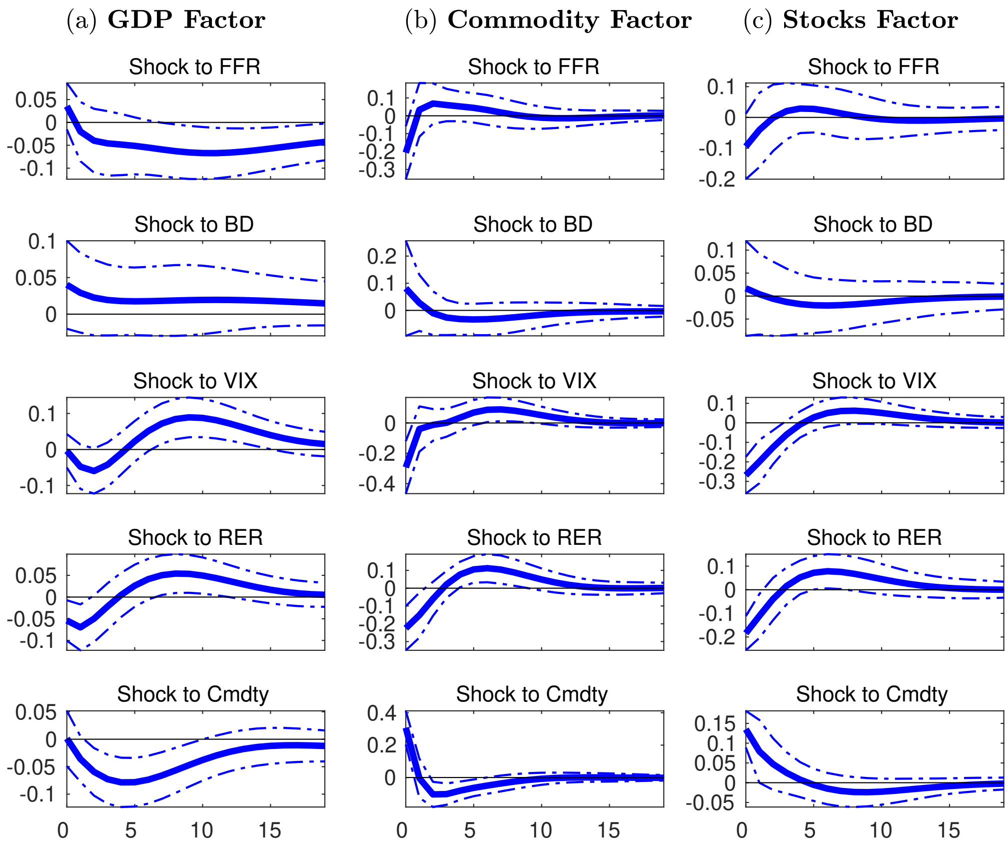

Figure 10: Factors' IRF to shocks in augmented Bruno & Shin (2015) VAR
Notes: Here we estimate the basic VAR of Bruno & Shin (2015) augmented with factors extracted from single variable subsamples, as in Section 2. Each column depicts the dynamic responses of the respective factor to 1 SD shocks to the U.S. Federal Funds Rate (FFR), Brokers-Dealers leverage (BD), VIX, U.S. real exchange rate (RER), IMF index of commodity prices (Cmdty). Dashed lines represent 90% bootstrapped confidence intervals.

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 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

$$X_t = \Lambda^o Y_t + \Lambda^u G_t + u_t, \tag{3}$$

$$\begin{pmatrix} Y_t \\ G_t \end{pmatrix} = \Phi(L) \begin{pmatrix} Y_{t-1} \\ G_{t-1} \end{pmatrix} + Be_t, \quad \mathbb{E}(e_t e_t') = I_q, \tag{4}$$

where $X_t = ((\mathrm{GDP}_{it}, \mathrm{FX}_{it}, \mathrm{CPI}_{it}, \mathrm{M1}_{it}, 10\mathrm{Y}_{it}, r_{it})_{i=1,\ldots,N})$, 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 (3)–(4) 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.

Figure 11 shows the estimation output of the factor-augmented VAR model in the case of shocks to the financial factor. Panel 11a 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 11b 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 11c. 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 11d 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 12 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.

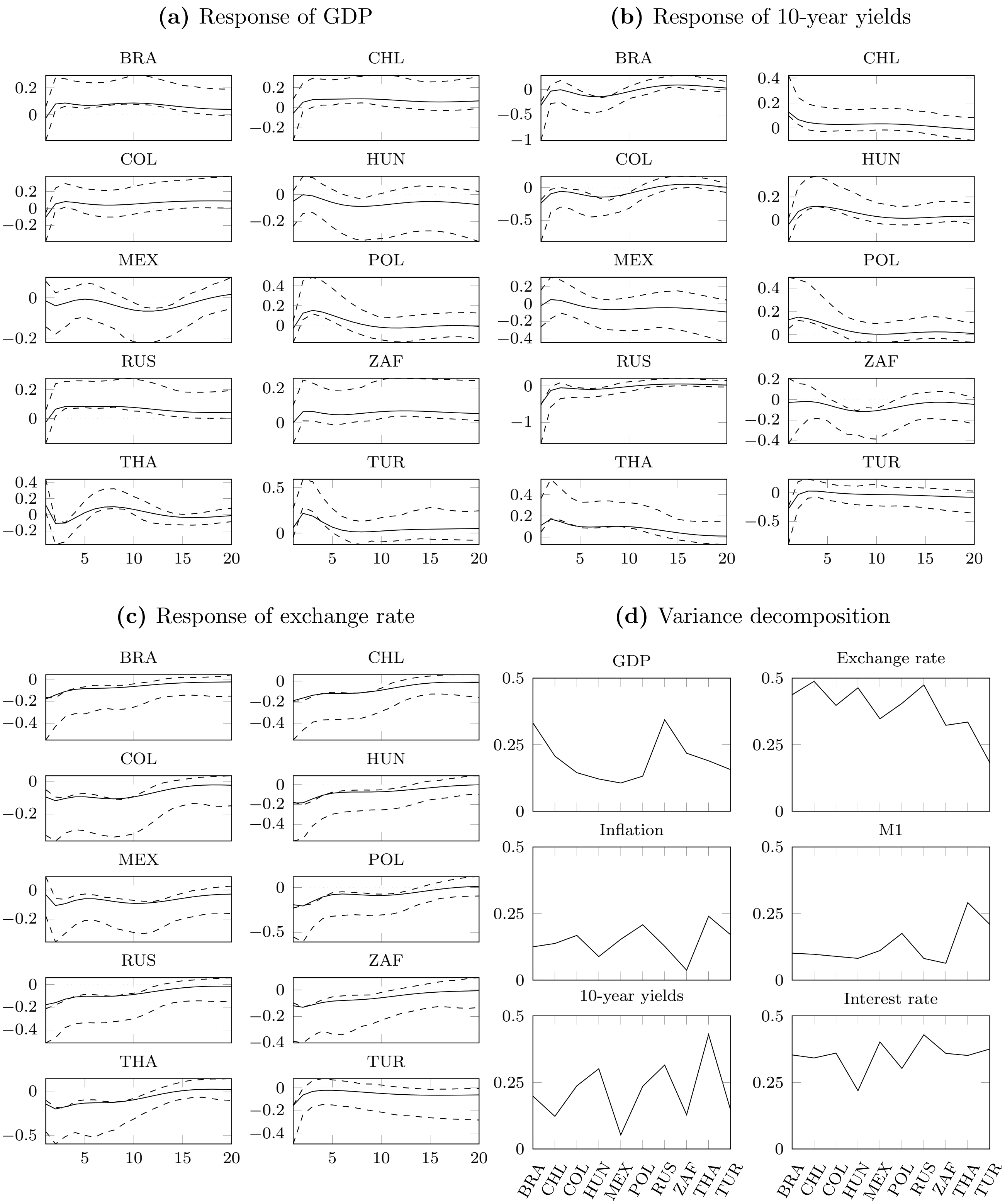

Figure 11: Factor-Augmented VAR — Shock to Financial factor

Notes: The figure shows impulse-response functions and variance decompositions from model (3)–(4). Dashed lines in figures (a)–(c) indicate 95% bootstrapped confidence intervals using Yamamoto's (2019) Procedure A.

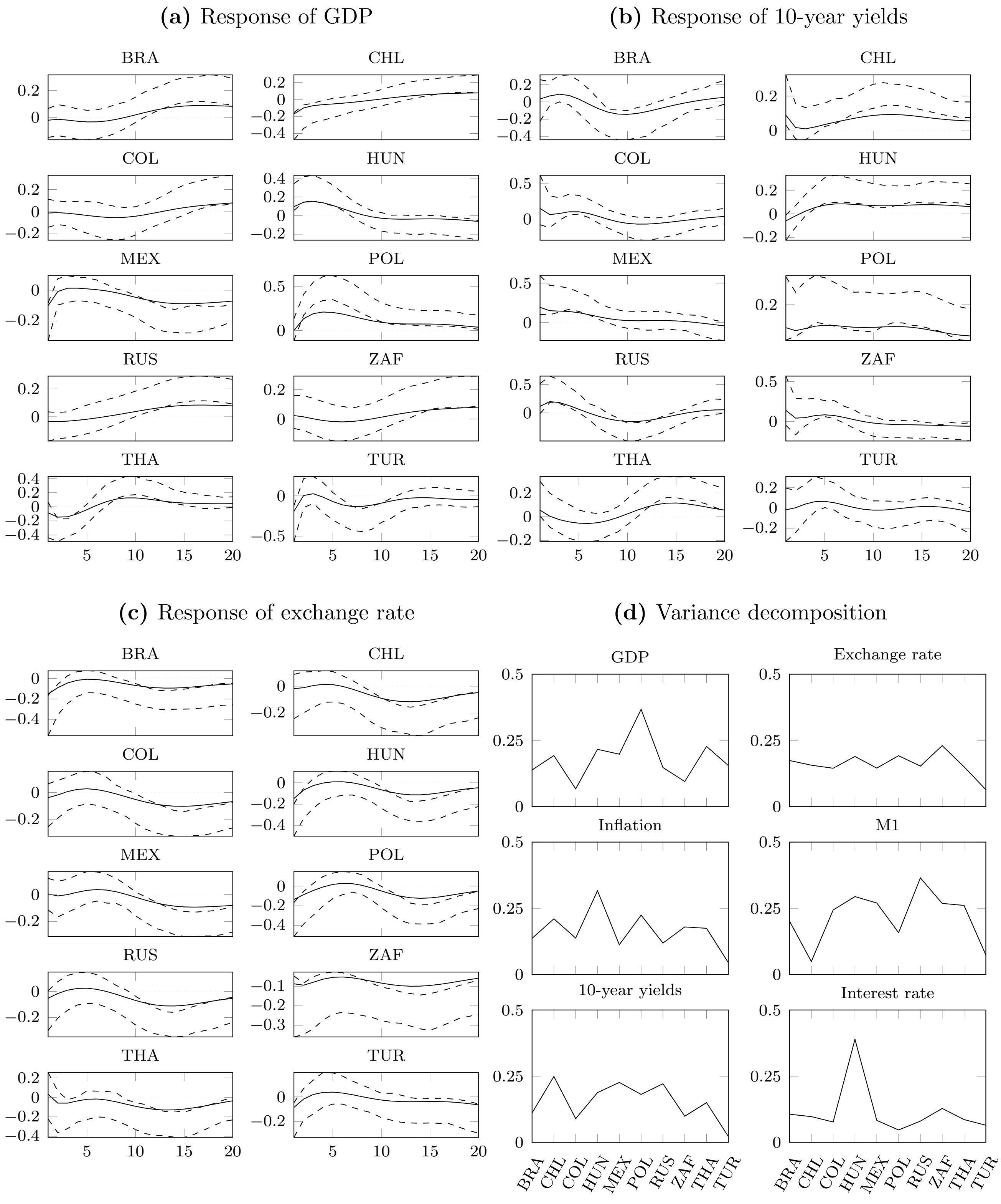

Figure 12: Factor-Augmented VAR — Shock to Commodity factor

Notes: The figure shows impulse-response functions and variance decompositions from model (3)–(4). Dashed lines in figures (a)–(c) indicate 95% bootstrapped confidence intervals using Yamamoto's (2019) Procedure A.

E Model fit

To get a notion of the fit of the model to the data, Figures 13–17 display the data with which the parameters were estimated along with the corresponding predicted values. The graphs tell a story consistent with Table 4. The model performs well at explaining the dynamics of the stock market indices, GDP, EMBI indices as well as the main commodities exported but less so in the case of inflation.

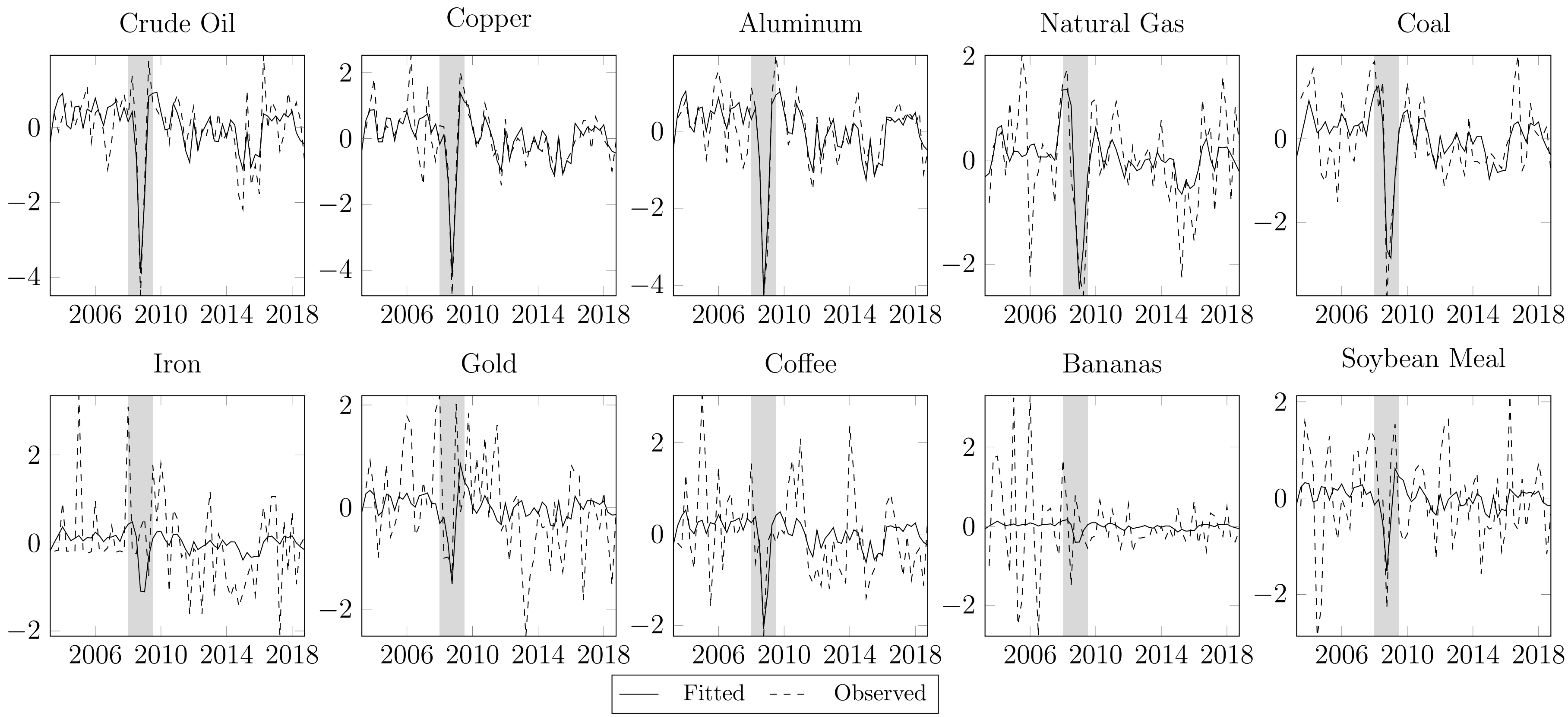

Figure 13: Comparison of fitted and observed values (Commodity Price Index)

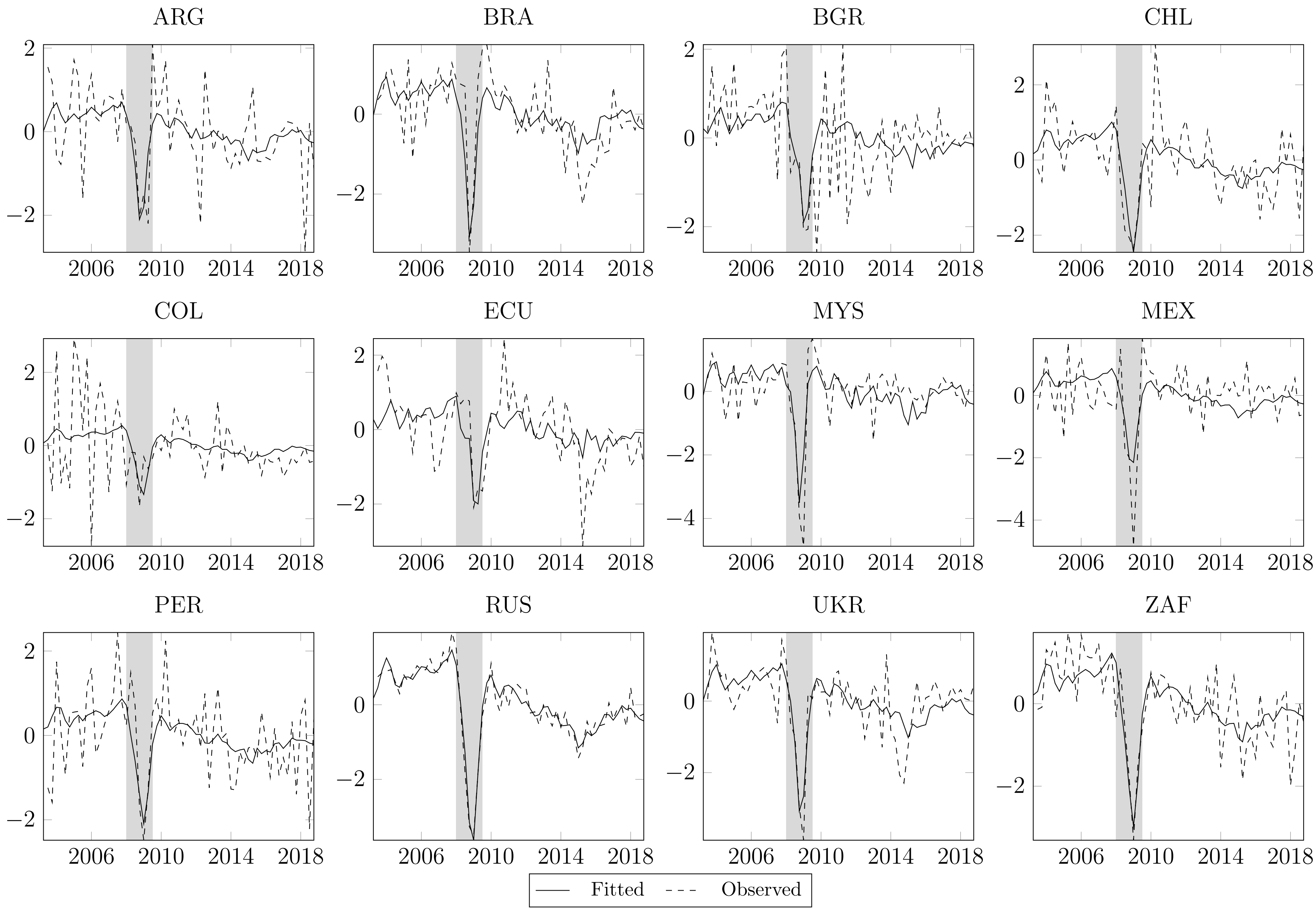

Figure 14: Comparison of fitted and observed values (GDP)

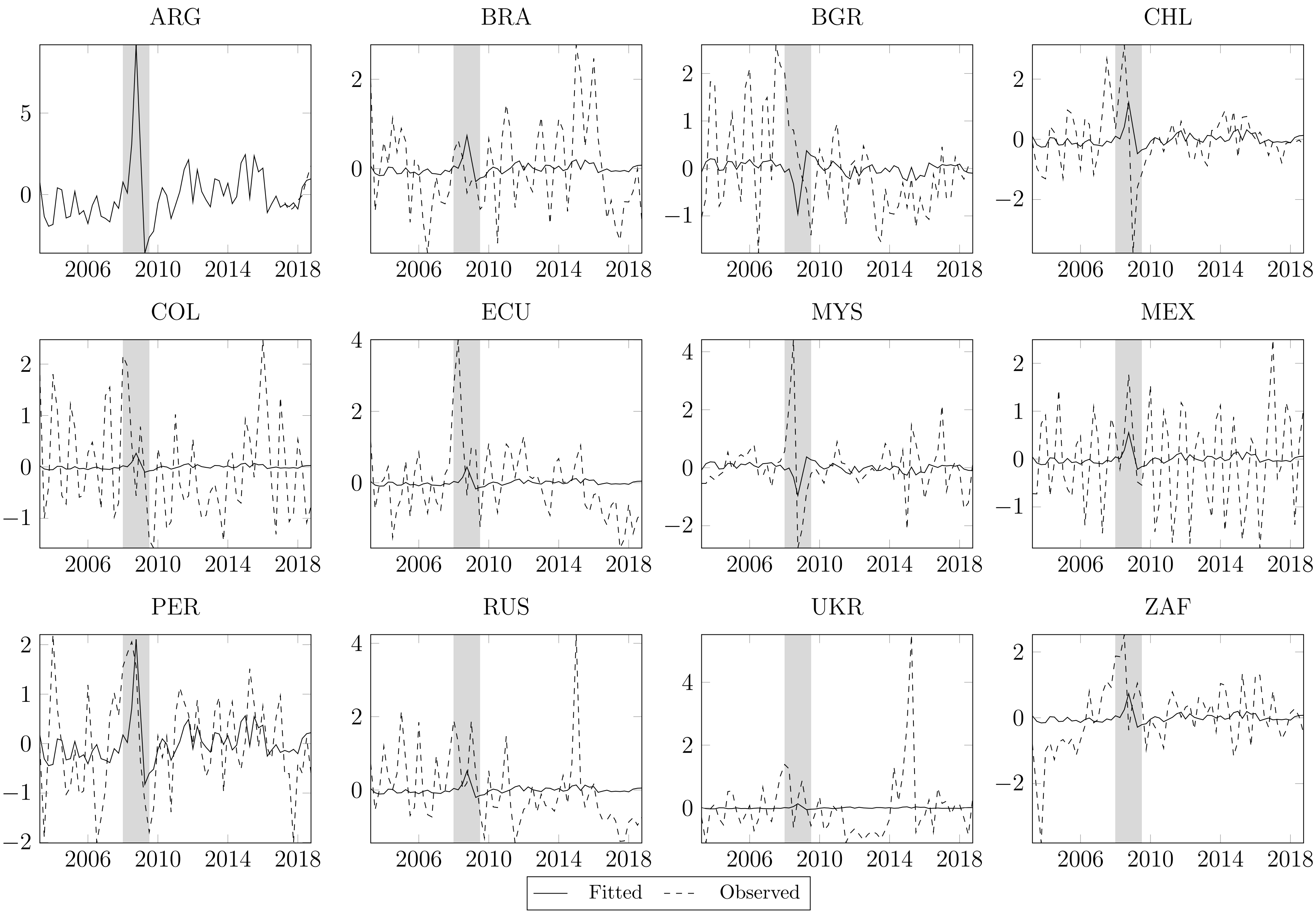

Figure 15: Comparison of fitted and observed values (Inflation)

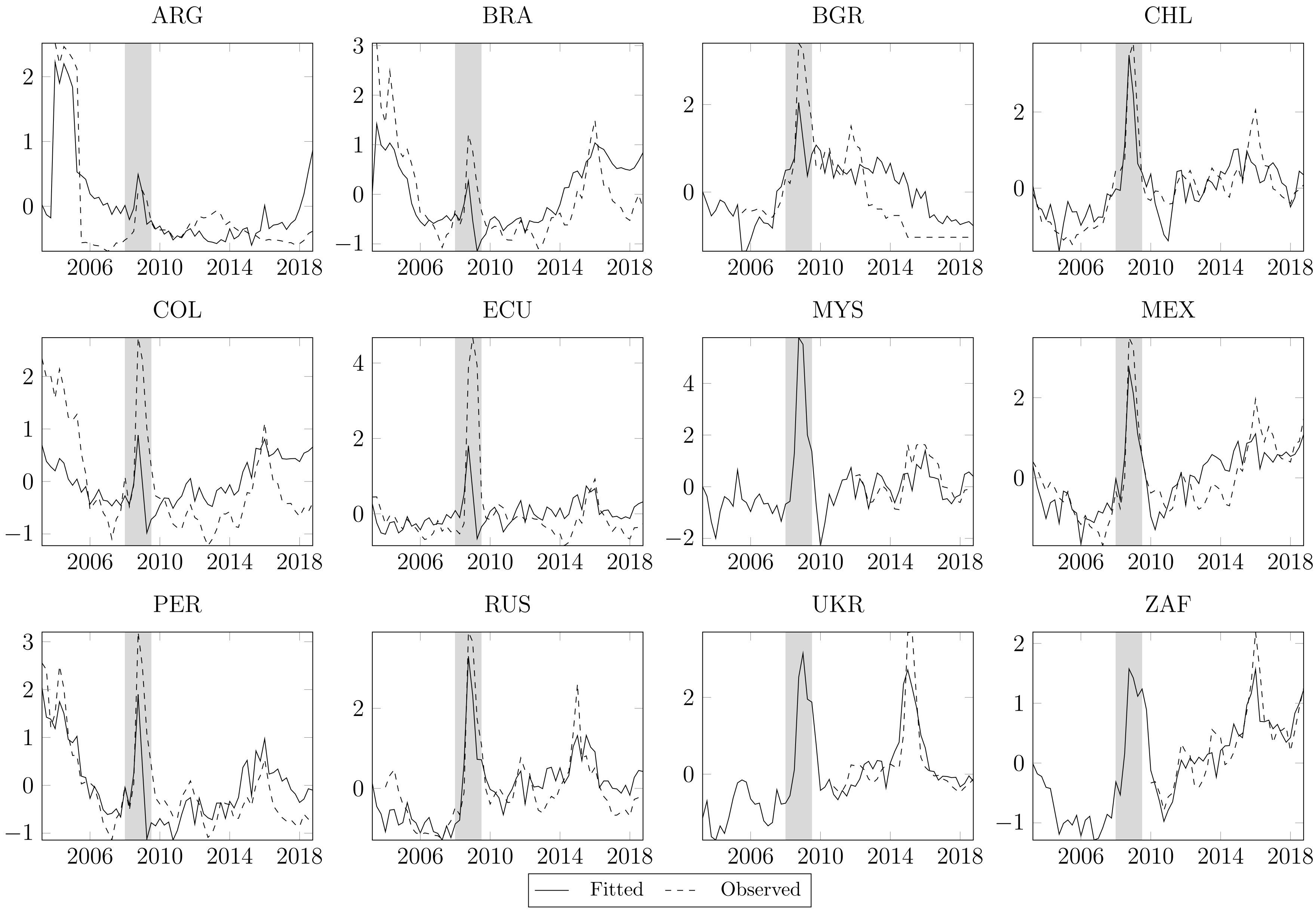

Figure 16: Comparison of fitted and observed values (EMBI Spreads deflated by growth and debt-to-GDP)

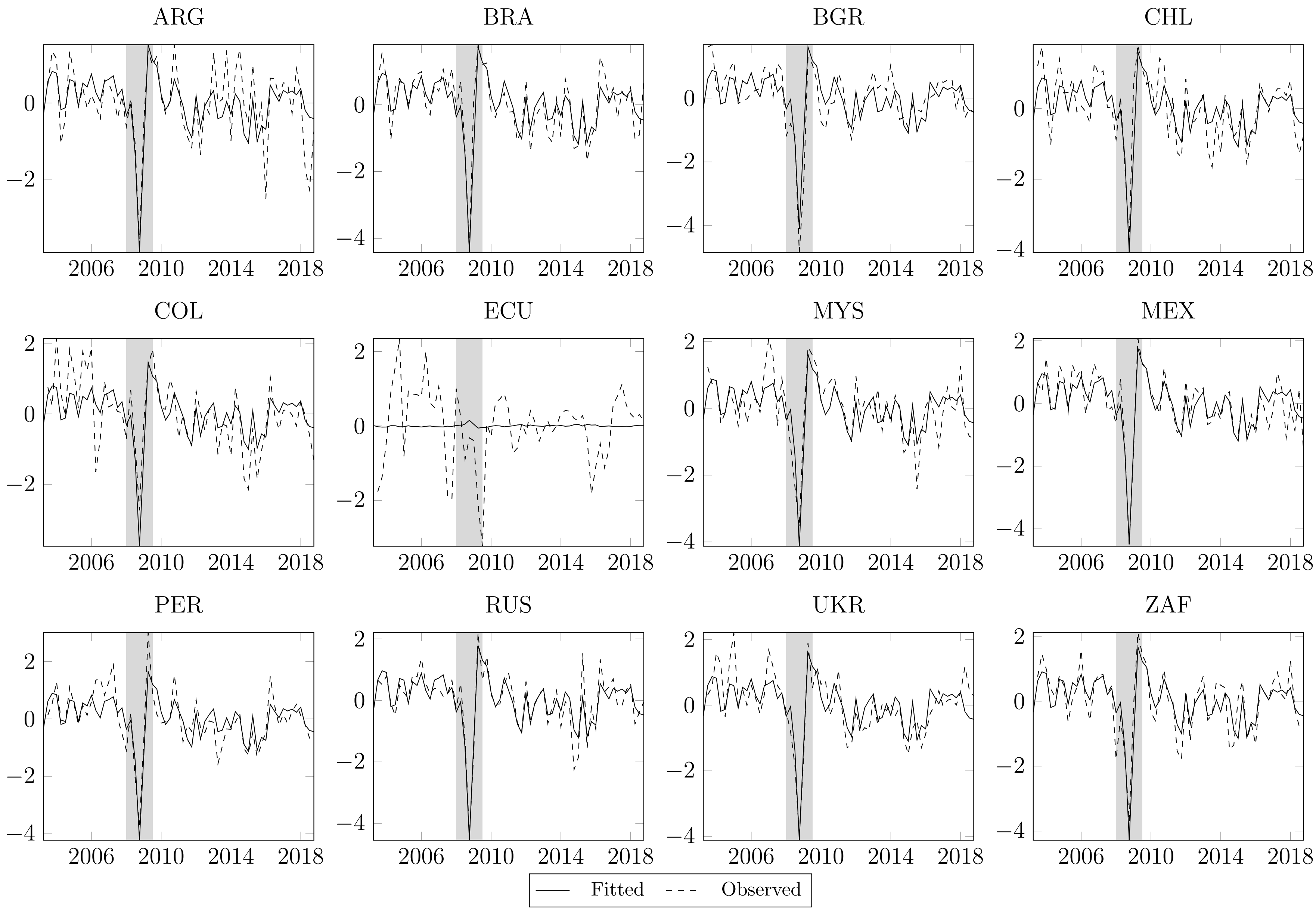

Figure 17: Comparison of fitted and observed values (Stocks)

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