

**EMERGING ECONOMIES
BUSINESS CYCLES: THE ROLE
OF THE TERMS OF TRADE
REVISITED**

Nadav Ben-Zeev, Evi Pappa and
Alejandro Viccondoa

Discussion Paper No. 16-10

November 2016

Monaster Center for
Economic Research
Ben-Gurion University of the Negev
P.O. Box 653
Beer Sheva, Israel

Fax: 972-8-6472941
Tel: 972-8-6472286

Emerging Economies Business Cycles: The Role of the Terms of Trade Revisited*

[PRELIMINARY VERSION. PLEASE DO NOT CIRCULATE]

Nadav Ben Zeev[†] Evi Pappa[‡] Alejandro Vicondoa[§]

September 27, 2016

Abstract

Common wisdom and standard open economy models suggest that terms-of-trade (TOT) shocks are an important driver of business cycle fluctuations in small open economies. Recently, [Schmitt-Grohe and Uribe \(2015\)](#) challenge this hypothesis by showing that unexpected TOT shocks explain only 10% of movements in aggregate activity on average for poor and developing countries. We confirm their findings for a sample of Latin American countries and show that TOT news shocks explain a bigger fraction of fluctuations in those countries. News shocks are identified as the shocks that best explain future movements in the TOT over an horizon of one year and that are orthogonal to current TOT. Our SVAR predictions imply that unexpected and news TOT shocks account on average for 37% of variations in output volatility. When feeding the standard small open economy model with both shocks, we show that we can match reasonably well model and empirical predictions for news shocks, while the model overstates the role of unexpected TOT shocks.

JEL classification: E32

Keywords: Terms-of-Trade Shocks, Small Open Economy DSGE Models

*We are grateful to participants at the GPEFM Alumni meeting 2015 for helpful comments and suggestions.

[†]Department of Economics, Ben-Gurion University of the Negev, Beer-Sheva, Israel. *E-mail:* nadavbz@bgu.ac.il.

[‡]Department of Economics, European University Institute, Florence, Italy; UAB, BGSE, and CEPR. *E-mail:* evi.pappa@eui.eu.

[§]Department of Economics, European University Institute, Florence, Italy. *E-mail:* Alejandro.Vicondoa@eui.eu.

1 Introduction

Until recently it has been commonly accepted in the international macroeconomics literature that terms of trade shocks - shocks to the price of exports relative to the price of imports - were an important determinant of macroeconomic dynamics in most emerging market economies (EMEs) (See, e.g., [Mendoza \(1995\)](#) and [Kose \(2002\)](#)). In their latest article, [Schmitt-Grohe and Uribe \(2015\)](#) have challenged this traditional view by estimating annual country-specific SVARs for 38 poor and emerging countries and showing that terms-of-trade shocks explain only 10% of movements in aggregate activity on average.¹ The literature on the important role of the terms of trade in propagating business cycles in EMEs countries is basically based on the analysis of calibrated business-cycle models. Indeed, [Schmitt-Grohe and Uribe \(2015\)](#) show that in standard estimated small open economy models terms-of-trade (TOT) shocks explain on average 30% of the variance of key macroeconomic indicators, three times as much as in their SVAR model. This disconnect between the empirical and theoretical models raises doubts about the validity of the existing models for explaining business cycle dynamics in emerging countries. The authors conclude their analysis by proposing improvements in both the theoretical model and the empirical one for resolving the disconnect between theory and data.

In the current paper we first try to examine whether the empirical findings of [Schmitt-Grohe and Uribe \(2015\)](#) can be challenged by analyzing different SVAR models. We confirm their results for almost all the specifications analyzed. Next, we try to reconcile evidence and theoretical predictions by introducing anticipated shocks to the terms of trade in their analysis, motivated by the observation that many movements in the terms of trade are anticipated. For example, the increases in the TOT observed during the 2000s for many economies were largely due to rising commodity prices, driven by strong economic growth in countries such as China and India ([Kilian and Hicks \(2013\)](#)). To the extent that agents recognize the underlying causes of changes in the TOT, its

¹ Also, [Lubik and Teo \(2005\)](#) estimating a small open economy model using full information Bayesian methods, find that interest rate shocks are a more important source of business cycles than terms of trade shocks, and [Aguirre \(2011\)](#) finds that in a theoretical small open economy model output and other macroeconomic aggregates display a larger response to terms-of-trade shocks than in an empirical SVAR model.

reasonable to assume that they are able to forecast these changes. Also, the existence of futures prices for many commodities confirms that part of the terms of trade movements are anticipated. Futures prices can be thought of as providing “forecasts“ of future commodity prices ([Chinn and Coibion \(2014\)](#)). However, the accuracy of those forecasts is not high since the options markets tell us that we should not put a lot of confidence in the price forecasts that can be obtained from the futures markets. Commodity prices are difficult to forecast because their expected price depends on both the spot price of the commodity in the future but also on a risk premium associated with the commodities risk exposure. Yet, we believe it is important to examine whether anticipated movements in the terms of trade matter for business cycle dynamics of small emerging countries.

There has recently been a renewed interest in theories of expectation-driven business cycles, focusing in particular on the effects of news shocks: shocks which are realized and observed before they materialize. [Beaudry and Portier \(2006\)](#) and [Jaimovich and Rebelo \(2009\)](#) present theoretical models in which news about future productivity is a primary source of business cycle fluctuations. [Beaudry and Portier \(2006\)](#) were the first to provide empirical evidence in favor of this hypothesis in the context of structural VARs. [Schmitt-Grohé and Uribe \(2012\)](#) estimate a DSGE model with flexible prices, which incorporates news about future technology, preference, government spending and markup shocks, and show that anticipated shocks account for around half of aggregate fluctuations in the U.S. Given the shortcomings of using futures on commodity prices to identify future shocks in the terms of trade, we employ an alternative identification scheme for extracting news about terms of trade movements in the data. Our identification strategy relies on “medium-run” constraints and builds on [Uhlig \(2003\)](#) and [Barsky and Sims \(2011\)](#). We identify TOT news shocks as the shocks that best explain future movements in the TOT over a horizon of one year, and that are orthogonal to current TOT movements using quarterly data for Latin American countries.

In particular, we estimate country-specific VARs for seven Latin American countries and construct average responses to anticipated and surprise shocks to the TOT by using the mean responses weighted by their relative precision. The benchmark VAR includes, the TOT, real output, consumption, investment, the trade balance to GDP ratio, the real exchange rate and one year ahead

commodity prices. Individual and mean responses confirm the findings of [Schmitt-Grohe and Uribe \(2015\)](#): Unexpected changes in the TOT explain on average 12% of business cycles fluctuations in EMEs. Yet, our identified TOT news shock explains on average 25% of output fluctuations in EMEs. Unanticipated improvements in the terms of trade improve significantly on impact the trade balance and induce prolonged increases in private investment and consumption and cause the country to become more expensive vis-a-vis the rest of the world. Similarly, anticipated increases in the TOT induce significant and persistent increases in output, and the trade balance and consumption. Investment drops on impact after the realization of the news but bounces back quickly and increases persistently until reaching its peak after five quarters. The TOT news shocks induces a significant impact response of futures prices that we leave unrestricted when identifying the shock. As in the case of unexpected shocks news TOT shocks appreciate the real exchange rate but with a significant lag. We perform various robustness analysis and show that our results hold even when we use annual data and the extended sample of developing countries considered in [Schmitt-Grohe and Uribe \(2015\)](#). They also hold when alternative commodity based TOT series are used in the VAR to identify the shocks and when we control for TFP movements.

Our empirical exercises reveal that the TOT hypothesis as a source of business cycle fluctuations in emerging markets is not dead. TOT news matter more than unexpected TOT shocks for business cycle fluctuations in emerging countries. Turning to theoretical results, we show that incorporating news about TOT in the model suggested by [Schmitt-Grohe and Uribe \(2015\)](#) augmented with variable capital utilization helps us replicate the empirical findings². To be able to compare consistently model and data predictions, we simulate series from our model and use our identification strategy in these series in order to recover the two types of TOT shocks identified in the empirical exercise. In particular, we simulate 1000 sets of data with 83 observations each using as the data generating process the standard small open economy model. For each simulation, we apply our identification method on the artificial data and include in the Monte Carlo VAR the same variables that we use in the empirical exercise. The two structural shocks in the model are

² We augment their model with capital utilization to capture more precisely the dynamics of investment and GDP.

the unanticipated and anticipated TOT shocks, which we calibrate by using the estimated TOT process for each country (See [Otrok and Kurmann \(2011\)](#)). The theoretical model matches reasonably well the empirical predictions for TOT news shocks. yet, as in the case of [Schmitt-Grohe and Uribe \(2015\)](#), it overstates the role of unexpected TOT shocks. Unexpected TOT shocks explain on average 28% of output fluctuation in the MC exercise while in the data they explain only 12% of output variations. On the contrary, TOT news explain on average 25% of output fluctuations both in the theoretical and the empirical model.

The remainder of the paper is organized as follows. Section 2 describes the econometric framework. Section 3 presents the benchmark empirical results and also reports results from additional robustness exercises and extensions. Section 4 describes briefly the small open economy model and presents forecast error variance decompositions based on simulated data and compares them with their empirical counterpart. Finally, Section 5 concludes.

2 Econometric Strategy

To identify news and surprise TOT shocks, we need to estimate first a SVAR that includes the main transmission channels of both shocks. In particular, we estimate a baseline VAR that includes: terms of trade series, which are defined as the price of exports relative to the price of imports; the trade balance, measured as net exports over output; GDP; consumption; investment; real exchange rate index; and an indicator of one-year ahead future commodity prices, computed as the principal component of the future prices of the main commodities. Our identification strategy relies on the Maximum Forecast Error Variance (MFEV) identification approach put forward by [Uhlig \(2003\)](#) and later extended by [Barsky and Sims \(2011\)](#). The TOT news shock is identified as the shock that best explains future movements in TOT over a horizon of one year and that is orthogonal to current TOT. Our underlying identifying assumption is that the TOT news shock is the only shock that affects future TOT while having no impact effect on it. This assumption is consistent with the reasonable notion that TOT does not respond to domestic economic variables in a small open

economy, which implies that it is driven by only two shocks, one being the traditional unanticipated TOT shock which moves TOT on impact and the other being the TOT news shock which moves TOT with a lag. An example of a process that would satisfy this condition is:

$$TOT_t = \rho TOT_{t-1} + \varepsilon_t^{sTOT} + \varepsilon_{t-s}^{TOTnews} \quad (1)$$

where $0 < \rho < 1$, ε^{sTOT} and $\varepsilon^{TOTnews}$ are the surprise and anticipated innovations in TOT, respectively, and the news shock is realized $s > 0$ periods in advance. As explained in [Barsky and Sims \(2011\)](#), an appealing way to identify news shocks to a fundamental that is driven by an unanticipated shock and a news shock, is to estimate a reduced-form multivariate VAR where all variables, including the fundamental itself, are regressed on their own lags as well as the other variables' lags, and then use the resulting reduced-form VAR innovations to search for the structural shock that is *i*) contemporaneously orthogonal to the fundamental and that *ii*) maximally explains the future variation in the fundamental over some finite horizon. We therefore consider a VAR that includes TOT together with other domestic macroeconomic variables.

Specifically, let the VAR in the observables be given by

$$y_t = F_1 y_{t-1} + F_2 y_{t-2} + \dots + F_p y_{t-p} + F_c + e_t \quad (2)$$

where y_t represents the vector of observables, F_i are 7×7 matrices, p denotes the number of lags, F_c is a 7×1 vector of constants, and e_t is the 7×1 vector of reduced-form innovations with variance-covariance matrix Σ . The reduced form moving average representation in the levels of the observables is

$$y_t = B(L)e_t \quad (3)$$

where $B(L)$ is a 7×7 matrix polynomial in the lag operator, L , of moving average coefficients and e_t is the 7×1 vector of reduced-form innovations. We assume that there exists a linear mapping

between the reduced-form innovations and structural shocks, ε_t , given as

$$e_t = A\varepsilon_t. \quad (4)$$

Equation (3) and (4) imply a structural moving average representation

$$y_t = C(L)\varepsilon_t, \quad (5)$$

where $C(L) = B(L)A$ and $\varepsilon_t = A^{-1}e_t$. The impact matrix A must satisfy $AA' = \Sigma$. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, \tilde{A} (we choose the convenient Cholesky decomposition), the entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a 7x7 orthonormal matrix ($D' = D^{-1}$ and $DD' = I$, where I is the identity matrix).

The h step ahead forecast error is

$$y_{t+h} - E_t y_{t+h} = \sum_{\tau=0}^h B_\tau \tilde{A} D \varepsilon_{t+h-\tau}, \quad (6)$$

where B_τ is the matrix of moving average coefficients at horizon τ . The contribution to the forecast error variance of variable i attributable to structural shock j at horizon h is then given as

$$\Omega_{i,j} = \sum_{\tau=0}^h B_{i,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B'_{i,\tau}, \quad (7)$$

where γ is the j th column of D , $\tilde{A}\gamma$ is a 7x1 vector corresponding to the j th column of a possible orthogonalization, and $B_{i,\tau}$ represents the i th row of the matrix of moving average coefficients at horizon τ . We index the unanticipated TOT shock as 1 and the TOT news shock as 2 in the ε_t vector. TOT news shocks identification requires finding the γ which maximizes the sum of contribution to the forecast error variance of TOT over a range of horizons, from 0 to H (the truncation horizon), subject to the restriction that these shocks have no contemporaneous effect

TOT. Formally, this identification strategy requires solving the following optimization problem

$$\gamma^* = \operatorname{argmax} \sum_{h=0}^H \Omega_{1,2}(h) = \operatorname{argmax} \sum_{h=0}^H \sum_{\tau=0}^h B_{1,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B'_{1,\tau} \quad (8)$$

$$\text{subject to } \gamma(1,1) = 0 \quad (9)$$

$$\gamma' \gamma = 1. \quad (10)$$

The first constraints impose on the identified news shock to have no contemporaneous effect on TOT. That is, our news shock is orthogonal to the unanticipated TOT shock. The second restriction that imposes on γ to have unit length ensures that γ is a column vector belonging to an orthonormal matrix. This normalization implies that the identified shocks have unit variance.

We follow the conventional Bayesian approach to estimation and inference by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters. Specifically, we take 1000 draws from the posterior distribution of reduced form VAR parameters $p(F, \Sigma \mid data)$,³ where for each draw we solve optimization problem (8); we then use the resulting optimizing γ vector to compute impulse responses to the identified shock. This procedure generates 1000 sets of impulse responses which comprise the posterior distribution of impulse responses to our identified shock. Our benchmark choices for the number of lags and truncation horizon are $p=4$ and $H=5$, respectively.⁴

3 Empirical Evidence

3.1 Data

We estimate seven country-specific VARs. Data are quarterly and samples are as follows: Argentina 1994:Q1-2013:Q3, Brazil 1995:Q1-2014:Q3, Chile 1996:Q1-2014:Q3, Colombia 1994:Q1-2009:Q4,

³ Note that F here represents the stacked $(6 \times (p + 1)) \times 6$ reduced form VAR coefficient matrix, i.e., $F = [F_1, \dots, F_p, F_c]'$.

⁴ We have confirmed the robustness of our results to different VAR lag specifications and truncation horizons. These results are available upon request from the authors.

Ecuador 2000:Q1-2013:Q4, Mexico 1994:Q1-2014:Q2, Peru 1994:Q1-2014:Q3. Appendix [A](#) contains a detailed description of the data. We focus on Latin America, but later we draw comparisons with samples with more emerging countries when relevant. We found that pooling all set of Latin American and Asian countries together in the benchmark regression, as [Schmitt-Grohe and Uribe \(2015\)](#) do, was not a good idea for several reasons: a) the two regions are different both in terms of trade performance and in terms of output dynamics, b) the relative importance of intra-regional trade in the two regions is significantly different, with higher indicators in Asia, c) in Latin America there is a lack of potential supply conditions to determine the terms of trade by smaller economies – instead in Asia some economies have become in a few years star cases in terms of export performance in manufactured products; and d) very importantly for the present argument, there are marked differences between the two regions with regard to the actual composition of intra-regional trade flows, with trade in Asia presenting a higher share of manufactures.

3.2 The Identified News Shock

Following the identification strategy outlined in section [3](#), we identify news and surprise TOT shock series for all the countries included in our sample. One way to assess the identification procedure is to see whether the identified TOT news shock matches with some events in the data. To provide an example, [Figure 1](#) displays this series for Brazil. In particular, we can see that the storm 'El Niño', which affected Brazil and other South American countries during the period under analysis, is associated with a positive news shock in this country. This storm generated changes of temperatures and increases in rainfalls that affected negatively the supply of many agricultural products and, therefore, was reflected in higher expected prices of agricultural products (i.e. better TOT for Brazil). This series also peaks in the expected way with the two main collapses of financial markets: the burst of the Dot-Com Bubble and the collapse in the end of 2008. In both cases, markets were uncertain about future demand for commodities and this is reflected as a negative peak in our news series. Finally, the series also reflects the recent oil discoveries in Brazil. These episodes, which occurred in years of higher oil prices, generated a wealth effect in the economy

and are captured as positive news shocks in our series. We conclude that our identified news series captures the most important events that affected the Brazilian TOT during the sample period. In the next subsection, we analyze the response of Latin American economies to surprise and news TOT shocks.

3.3 Impulse Responses and Forecast Error Variance Decomposition

Figure 2 shows the estimated cross country average of impulse responses of all variables to a one standard deviation unanticipated TOT shock from the benchmark VAR. The bands in the figures are one standard error bands where the standard error is the one corresponding to the standard error of the average estimate obtained from using the variances of the individual countries impulse responses. All responses should be interpreted as the typical responses of a Latin American country to an unexpected increase in the terms of trade. We present the individual responses in the Online Appendix.

The identification of the unexpected TOT shock does not actually differ from what other researchers have studied in the literature. In particular, Figure 2 is comparable with the findings of [Schmitt-Grohe and Uribe \(2015\)](#). Our responses are not qualitatively very different from theirs besides the fact that the sample and frequency of the data as well as the computation of average responses (we used weighted averages instead of simple averages) are different. The TOT shocks appreciates the real exchange rate and moves positively on impact the trade balance. Contrary to their findings, the initial consumption, investment, and output responses are small but positive and they increase with a lag to the unexpected TOT positive disturbance. Since [Schmitt-Grohe and Uribe \(2015\)](#) do not provide confidence bands for their responses we cannot appreciate whether the responses are significantly different, apart from the lag response of output and the real exchange rate the identified shocks seem to invoke similar dynamics to the macroeconomic variables. All variables seem to react in the same direction but less strongly to our identified innovation relative to the TOT shock identified in [Schmitt-Grohe and Uribe \(2015\)](#). Turning to the variance decom-

positions (see Table 3) we also confirm the [Schmitt-Grohe and Uribe \(2015\)](#) findings. Unexpected terms of trade shocks explain over a two-year horizon on average 10%-13% of fluctuations in output, consumption, investment, and the trade balance and they explain approximately 35% of terms of trade fluctuations. Those numbers are similar for all the countries apart from Ecuador and Peru. In the case of Ecuador, surprise terms of trade shocks seem to affect very slightly aggregate fluctuations, while in the case of Peru unexpected shocks to the terms of trade appear to matter a lot for aggregate fluctuations.

Turning to the news shock, in Figure 3 we plot the estimated average impulse responses of all variables to a positive news shock in the terms of trade. News about TOT increase terms of trade gradually and the TOT response reaches its peak before the horizon for which news shocks explain the biggest share of terms of trade variations. In response to the news about the positive shock to the terms of trade future prices increase on impact and continue growing, following the actual path of the terms of trade. Since we have not imposed any restrictions on those series, their impulses imply that our identified shocks seem to capture news about future movements in the terms of trade. The response of output and the trade balance is significant and economically important on impact. Consumption increases on impact and investment declines initially while bounces back in later periods, after the increase in TOT. The real exchange rate sluggishly appreciates. Turning to the variance decomposition in Table 4, we observe that TOT news shocks explain on average 25% of output fluctuations and 37% of terms of trade fluctuations, while they explain a considerable amount of future prices fluctuations (33% approximately).

There is more heterogeneity in the responses at the country level relative to the unanticipated shocks. TOT news seem to be an important source of fluctuations in Argentina and Chile and less important for the variations in output in Colombia and Ecuador. The case of Ecuador seems to stand out for both types of TOT shocks considered: TOT movements unexpected or anticipated explain a very small fraction of output fluctuations in Ecuador. Since petroleum is Colombia's main export, making over 45% of Colombia's exports and is a net oil exporter, production of oil might be adjusting to hedge against the news TOT shocks in this country. For Argentina, since agricultural

goods still account for over 50% of exports when processed foods are included (Soy products alone - soybeans, vegetable oil- account for almost one fourth of the total exports) its is not surprising to find that news shocks to the TOT might affect significantly the Argentina economy. Similarly Chile is mostly exporting mining products, news about changes in the price of cooperers might make firms adjust the production in the mining industry in advance affecting significantly the cycle fluctuations in Chile.

3.4 Alternative SVAR specifications

To clear any doubt about the robustness of our results, in this section we consider alternative VAR specifications for our empirical exercise. The impulse responses of all the exercises performed in this section are included in the Online appendix. Here, for ease of exposition, we only present the share of variance explained by the TOT unanticipated and news shocks shocks in every exercise on average in Tables 5 and 6, respectively.

3.4.1 Country spreads

According to [Uribe and Yue \(2006\)](#) country spreads respond endogenously to business cycle conditions in emerging economies and might be affected by external and anticipated shocks, such as the shocks in the terms of trade. For that reason its important to include this series in the VAR. We construct country spreads for each country by using the JPMorgan EMBI Global Index (Stripped Spread). Details of the series used are described in [Appendix A](#). We estimate the baseline SVAR including spreads instead of future prices as an endogenous variable in the system. The first row of Tables 5 and 6, respectively, presents the share of variance explained by the two identified TOT shocks in this exercise. The addition of country spreads in the analysis does not change results regarding the importance of the two identified shocks in explaining aggregate fluctuations in emerging countries. On average, surprise shocks explain 15% of output fluctuations and news TOT shocks explain 24% of output fluctuations. The numbers for the rest of the variables included in the SVAR are similar.

3.4.2 Government spending

Also, the government reaction to TOT shocks might be an important determinant of the role of TOT shocks in shaping business cycle fluctuations. [Ilzetzi and Vegh \(2008\)](#) provide evidence that fiscal policy is procyclical in developing countries. The problem of procyclicality seems to be more acute in commodity rich nations since commodity related revenues can be a large proportion of total government revenues (see [Sinnott \(2009\)](#)). [Cespedes and Velasco \(2014\)](#) study the behavior of fiscal variables across the commodity cycle and show that there is a negative relation between the fiscal balance and the behavior of commodity prices. In this exercise we introduce government expenditure as an additional endogenous variables in our benchmark SVAR. The second row of [Tables 5 and 6](#), respectively, presents the share of variance explained by the two identified TOT shocks when we control for movements in government spending in our analysis. The share of output variations explained by TOT news and surprises remains almost the same. Moreover, we learn from this exercise that government reacts much more to news about changes in the terms of trade relative to unexpected changes in the TOT. News shocks about the TOT explain 25% of government spending variability, while unexpected TOT shocks explain only 9% of the variability of government expenditure on average in our sample.

3.4.3 Commodity-based terms of trade

In their conclusions [Schmitt-Grohe and Uribe \(2015\)](#) suggest that an improvement in their empirical model could stem from entertaining the hypothesis that commodity prices are a better measure of the terms of trade than aggregate indices of export and import unit values, especially for countries whose exports or imports are concentrated in a small number of commodities. [Fernandez et al. \(2015\)](#) and [Shousha \(2016\)](#) estimate a VAR including commodity prices and find that they explain between 25% and 42% of fluctuations in GDP in emerging economies. In order to investigate whether their and our conclusions are sensitive to the measure of the terms of trade used in the empirical model, we have re-run our benchmark model substituting commodity-based terms of trade with our benchmark TOT index. We define the commodity-based terms of trade as the

ratio of weighted average price of the main commodity exports to weighted average price of main commodity imports. The index is available at annual frequency from IMF’s website⁵. Spatafora and Tytell (2009) constructed it from prices of six commodity categories (food, fuels, agricultural raw materials, metals, gold, and beverages) measured against the manufacturing unit value index (MUV) of the World Economic Outlook database. Relative commodity prices of six categories are weighted by the time average (over 1980–2009) of export and import shares of each commodity category in total trade (exports and imports of goods and services). Exports and imports by commodity category are obtained from the United Nations Common Format for Transient Data Exchange (COMTRADE) data at SITC second digit level. Results from the exercise with annual data and the alternative measure of terms of trade appear in the third row of Tables 5 and 6.

Using commodity-based TOT series in our baseline regressions does not change the fact that unexpected and anticipated movement in the TOT explain a big part of cyclical fluctuations in emerging countries. TOT shocks explain in total 34% of output fluctuations on average. Yet, the relative importance of unexpected TOT shocks in explaining output fluctuations increases from 12% in the benchmark model to 18% in the model with commodity based TOT series.

3.4.4 The Schmitt-Grohe and Uribe (2015) specification

We continue by analyzing the empirical specification used in Schmitt-Grohe and Uribe (2015) in order to compare directly our empirical results with theirs and to show that differences are not due to the different sample, different frequency, or different variables included in the VAR. In this exercise we use exactly the same specification and sample as Schmitt-Grohe and Uribe (2015). That is, we estimate country by country VARs using annual data for 38 countries that include log deviations of the TOT, real output, private consumption and gross investment per capita, and the real exchange rate from their respective time trends, as well as series for the ratio of trade balance to trend output. We present impulse responses to a positive one standard deviation shock to the unexpected TOT shock and to TOT news in the online appendix, and in the third row of

⁵ See <https://www.imf.org/external/pubs/cat/longres.aspx?sk=23307.0> for more information on this series.

Tables 5 and 6 we present the share of variance explained by the two identified TOT shocks in this exercise. The predictions concerning the importance of unexpected TOT shocks in generating business cycles is very similar with the numbers documented in [Schmitt-Grohe and Uribe \(2015\)](#). In this specification, news TOT shocks are also important, but slightly less relative to the benchmark specification in explaining the variance of output on average. Note that restricting our sample to the seven Latin American countries we consider in our benchmark exercise would make results deviate even further. In the fifth row of Tables 5 and 6 we present the corresponding number of the exercise with annual data and the specification used in [Schmitt-Grohe and Uribe \(2015\)](#) when we use only the sample of countries in our baseline SVAR. What we see, is that results are very different when looking at the forecast error variance of unexpected TOT shocks. The SVAR with annual data overstates the importance of surprises in generating aggregate fluctuations, while news, although still important, become less significant in generating cyclical fluctuations in annual data. Hence, we conclude that although the frequency of the sample might affect overall the relative importance of TOT surprises versus news in explaining cyclical fluctuations the joint importance of both shocks in generating aggregate variability in emerging countries remains relatively robust to the frequency of the data used.

3.4.5 TOT News and TFP shocks

For our identification procedure to be valid, terms of trade should be exogenous. Clearly, TOT is largely exogenous from a small open economy's perspective. Yet in many standard models, an adverse shock to the terms of trade acts like an adverse shock to productivity along many dimensions. We show that this is true also in our framework. Using annual Latin American country-specific VARs and annual data on TFP we show in the online appendix that both unexpected and anticipated increases in the TOT induce significant increases in the TFP; here we present in the sixth row of Tables 5 and 6 the shares of the two-year variation in the variables accounted for the unanticipated shock and the news shock, respectively. It is noteworthy that TOT unanticipated and news shocks account for 21% and 19% of the variation in TFP, respectively. We have also confirmed

that TFP unanticipated and news shocks also explain similar shares of the variation in TOT by using our identification strategy to identify TFP news shocks (15% and 20%, respectively).⁶ Hence, we can conclude that while there is some relation between TOT and TFP shocks, this relation seems to be quite limited and does not rule out the interpretation of the TOT shocks identified in this paper as being pure TOT shocks.

3.4.6 Exogeneity of TOT shocks

Another important concern is that, according to our methodology, the true TOT news shock is identified as the linear combination of all other VAR innovations apart from surprise TOT shocks that maximize the residual forecast error variance of TOT over a finite horizon. In other words, in our setting domestic variables may be relevant to identify news about TOT. Since such an assumption may raise suspicions about the validity of our results we implement an alternative VAR framework in which the terms of trade and future prices are included in the exogenous block of the VAR and the identification restriction of news shocks implies that only TOT and futures prices movements can affect the evolution of the terms of trade. Results regarding the quantitative contribution of the TOT news shocks to the forecast error variance decompositions of macroeconomic variables are robust to this specification. Moreover, using this specification, contrary to [Schmitt-Grohe and Uribe \(2015\)](#), the quantitative importance of unexpected changes in TOT doubles.

4 The Predictions of a Small Open Economy Model

In this section we adopt the theoretical model used in [Schmitt-Grohe and Uribe \(2015\)](#) in order to perform country-by-country comparisons of the predictions of the empirical SVAR model with the predictions of a theoretical model concerning the effects of unexpected and anticipated TOT shocks. As in the case of the latter authors, the comparison is disciplined by the same four principles: 1) The SVAR is based on the identification restriction that the terms of trade in poor and emerging

⁶ These results are available upon request from the authors.

countries are exogenous and are driven by an expected and an unexpected component; 2) we use an even more generalized version of the theoretical environment upon which the conventional wisdom was built by introducing apart from three sectors, importables, exportables, and nontradables, featuring production, domestic absorption, capital, and labor in all three sectors, also variable capital utilization in order to have an extra margin to match empirical and theoretical predictions; 3) the empirical SVAR model and the theoretical model share the same terms-of-trade processes for each country in the sample; 4) Both the parameters of the empirical SVAR model and key parameters of the theoretical model are estimated country by country using the same time series. Moreover, the estimation of the structural parameters of the theoretical model matches second moments conditional on terms-of-trade shocks implied by the SVAR model. Finally, an additional principle that disciplines our comparisons is that the terms of trade shocks are identified exactly the same way in the model and in the data. That is we use the same identification technique to recover the unexpected and news TOT shocks in the theoretical model as we do in the empirical one. In this way we can investigate the validity of our identification technique in recovering the true surprise and news shocks from the data. All in all, all the principles followed in the analysis should give the theoretical model a larger chance to match the data. In the next subsection we describe very briefly the model and the following subsection describes the Monte Carlo exercise we have performed in order to recover the shocks from our simulated series.

4.1 The model

The model includes three sectors: exportable (x), importable (m), and non-tradable (n). We augment the model of [Schmitt-Grohe and Uribe \(2015\)](#) by considering capital utilization in the three sectors, which helps us to match the responses of GDP and investment. We also include news and surprise shocks to the terms of trade, following the estimated processes from the empirical section. We choose this model because we want to evaluate if it is capable of generating the IRFs we identify in the previous section.

4.1.1 Households

The economy is populated by a continuum of homogenous households with preferences described by the following utility function:

$$U_t = \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left(\frac{(c_t - G(h_t^m, h_t^x, h_t^n))^{1-\sigma} - 1}{1-\sigma} \right) \quad (11)$$

where c_t denotes consumption and h_t^m, h_t^x , and h_t^n denote hours worked in the importable, exportable and non-tradable sector, respectively. In particular, $G(h_t^m, h_t^x, h_t^n)$ has the following functional form:

$$G(h_t^m, h_t^x, h_t^n) = \frac{(h_t^m)^{\omega_m}}{\omega_m} + \frac{(h_t^x)^{\omega_x}}{\omega_x} + \frac{(h_t^n)^{\omega_n}}{\omega_n} \quad (12)$$

Households are subject to the following budget constraint:

$$c_t + i_t^x + i_t^m + i_t^n + \frac{\phi_x}{2} (k_{t+1}^x - k_t^x)^2 + \frac{\phi_m}{2} (k_{t+1}^m - k_t^m)^2 + \frac{\phi_n}{2} (k_{t+1}^n - k_t^n)^2 + \rho_t^T d_t = \frac{\rho_t^T d_{t+1}}{1+r_t} + w_t^x h_t^x + w_t^m h_t^m + w_t^n h_t^n + u_t^x k_t^x + u_t^m k_t^m + u_t^n k_t^n \quad (13)$$

where $i_t^i, k_t^i, \phi_t^i, w_t^i$, and u_t^i denote investment, capital stock, capital adjustment costs, wages, and rents for each sector $i = m, x, n$. ρ_t^T denotes the relative price of the tradable composite good in terms of the final good c_t (to be defined below), d_t denotes the stock of debt that matures in period t , which is expressed in units of the tradable composite good, and r_t denotes the interest rate on debt. The capital stock dynamics of each sector are described by the following equations:

$$k_{t+1}^x = (1 - \delta (u_t^x)^{\gamma_x}) k_t^x + i_t^x \quad (14)$$

$$k_{t+1}^m = (1 - \delta (u_t^m)^{\gamma_m}) k_t^m + i_t^m \quad (15)$$

$$k_{t+1}^n = (1 - \delta (u_t^n)^{\gamma_n}) k_t^n + i_t^n \quad (16)$$

where u_t^i denotes the utilization rate and γ_i is the elasticity of marginal depreciation costs, which is negatively related to the responsiveness of utilization to shocks. When γ_i is large, the negative

effects of utilization on depreciation dominate the positive effects of utilization on output and firms choose to keep utilization constant.

4.1.2 Production of Final Goods

Final goods are produced using tradable and nontradable goods via the following technology:

$$B(a_t^\tau, a_t^n) = \left(\chi_\tau (a_t^\tau)^{1-\frac{1}{\mu_\tau}} + (1 - \chi_\tau) (a_t^n)^{1-\frac{1}{\mu_\tau}} \right)^{\frac{1}{1-\frac{1}{\mu_\tau}}} \quad (17)$$

where a_t^τ denotes the domestic absorption of the tradable composite good, and a_t^n denotes the domestic demand for non-tradable goods. Final goods are sold to households and can be either consumed or invested. Firms of this sector behave competitively. Their profits are given by the following expression:

$$B(a_t^\tau, a_t^n) - p_t^\tau a_t^\tau - p_t^n a_t^n \quad (18)$$

where p_t^n denotes the relative price of nontradable goods in terms of final goods.

4.1.3 Production of the Tradable Composite Good

The tradable composite good is produced using exportable and importable goods via the following technology:

$$a_t^\tau = A(a_t^m, a_t^x) = \left(\chi_m (a_t^m)^{1-\frac{1}{\mu_m}} + (1 - \chi_m) (a_t^x)^{1-\frac{1}{\mu_m}} \right)^{\frac{1}{1-\frac{1}{\mu_m}}} \quad (19)$$

where a_t^m and a_t^x denote the domestic absorption of importable and exportable goods, respectively. Firms in this sector also behave competitively. Profits are given by the following expression:

$$p_t^\tau A(a_t^m, a_t^x) - p_t^m a_t^m - p_t^x a_t^x \quad (20)$$

4.1.4 Production of Exportable, Importable, and Nontradable Goods

Exportable, importable, and Nontradable goods are produced with the following technologies:

$$y_t^x = A_t^x F^x(u_t^x k_t^x, h_t^x) = A_t^x (u_t^x k_t^x)^{\alpha_x} (h_t^x)^{1-\alpha_x} \quad (21)$$

$$y_t^m = A_t^m F^m(u_t^m k_t^m, h_t^m) = A_t^m (u_t^m k_t^m)^{\alpha_m} (h_t^m)^{1-\alpha_m} \quad (22)$$

$$y_t^n = A_t^n F^n(u_t^n k_t^n, h_t^n) = A_t^n (u_t^n k_t^n)^{\alpha_n} (h_t^n)^{1-\alpha_n} \quad (23)$$

where A_t^i and y_t^i denote productivity and output of each sector $i = x, m, n$. Firms in each sector are homogenous and behave competitively both in factor and product markets.

4.1.5 Market Clearing Conditions and Definitions

This is the market clearing condition for the final goods:

$$c_t + i_t^x + i_t^m + i_t^n + \frac{\phi_x}{2} (k_{t+1}^x - k_t^x) + \frac{\phi_m}{2} (k_{t+1}^m - k_t^m) + \frac{\phi_n}{2} (k_{t+1}^n - k_t^n) = B(a_t^\tau, a_t^n) \quad (24)$$

This is the market clearing condition for the nontradable good:

$$a_t^n = y_t^n \quad (25)$$

The economy wide resource constraint is:

$$p_t^\tau \frac{d_{t+1}}{1+r_t} = p_t^\tau d_t + m_t - x_t \quad (26)$$

where m_t and x_t denote aggregate import and export, respectively. They can be defined as:

$$m_t = p_t^m (a_t^m - y_t^m) \quad (27)$$

$$x_t = p_t^x (y_t^x - a_t^x) \quad (28)$$

Finally, we define two key variables for this economy. First, the terms of trade (tot_t) are characterized by the following expression:

$$tot_t = \frac{p_t^x}{p_t^m} \quad (29)$$

Second, we define the real exchange rate (rer_t) as:

$$rer_t = \frac{\epsilon_t P_t^*}{P_t} = \epsilon_t p_t^\tau \quad (30)$$

where ϵ_t denotes the nominal exchange rate. This definition is in line with the index we are using in the VAR (i.e. an increase (decrease) means an depreciation (appreciation)).

4.1.6 Exogenous Processes

In order to close the model we need to define the exogenous processes. First, to ensure a stationary equilibrium process for external debt, we assume that the country spread, which is defined as the difference between the domestic interest rate and the international one, is debt elastic:

$$r_t - r_t^* = \psi \left(e^{d_t - \bar{d}} - 1 \right) \quad (31)$$

where r_t^* denotes the world interest rate and ψ captures the sensitivity of the country spread with respect to deviations of debt with respect to its steady state. Finally, we define a process for the terms of trade that is subject to two sources of exogenous variations: surprise and news shocks.

$$tot_t = \sum_{i=1}^I \rho_i^{tot} tot_{t-i} + \sum_{j=1}^J \rho_j^{news} news_{t,t+j}^{tot} + \sum_{k=1}^K \rho_j^\epsilon \epsilon_{t-k}^{tot} + \epsilon_t^{tot} \quad (32)$$

where $news_{t,t+j}$ and ϵ_t^{tot} denote the news about changes in terms of trade that will occur in period $t+j$ and the surprise shock. In line with our empirical analysis, we use the estimated process for each country.

4.1.7 Calibration

We calibrate the model following [Schmitt-Grohe and Uribe \(2015\)](#). Since our empirical analysis is in quarterly frequency, we modify some parameters accordingly. Table 1 displays the values of the parameters common across countries.

Table 1: Calibration-Common Parameters

α_x	0.35	α_m	0.35	α_n	0.25	ω_x	1.455	ω_m	1.455	ω_n	1.455	σ	2
χ_m	0.898	χ_τ	0.813	r^*	0.0277	\bar{d}	0.2189	δ	0.025	μ_m	1	μ_τ	0.5

Following [Schmitt-Grohe and Uribe \(2015\)](#), we adjust the investment adjustment costs, the elasticity of depreciation with respect to utilization for each sector, and the interest rate elasticity to external debt to match the dynamics of trade balance and investment in response to both shocks for each country. Table 2 displays the values of the parameters for each country.

Table 2: Calibration-Country Specific Parameters

Country	ϕ_m	ϕ_x	ϕ_n	ψ	γ_m	γ_x	γ_n
Argentina	1.5	0.1	5.5	0.6	2.4	2.1	2.108
Brazil	1.2	0.87	0.4	0.4	7.2	2.1	2.108
Chile	0.55	0.87	1.4	0.2	2.4	2.1	2.108
Colombia	3	1.78	3.5	0.6	3.3	2.098	2.108
Ecuador	10	9	15	1.4	10	2.098	2.098
Mexico	0.7	1.01	0.61	0.12	9	2.098	2.108
Peru	2	2.2	0.6	0.05	10	2.098	2.108

4.2 Monte Carlo Exercise

In order to evaluate whether there is a disconnect between the theoretical and the empirical predictions, we need to find a way to compare data and theory consistently. The literature on the econometric relationship between DSGE models and VAR models is by now pretty extensive. In particular, if the model shocks cannot be recovered from the SVAR shocks, model estimation and validation become meaningless. This issue has been hotly debated in the literature, with [Chari et al. \(2008\)](#) in one camp arguing that SVAR models are not suitable for model validation and estimation and [Christiano et al. \(2007\)](#) in the opposite camp defending SVAR models as a useful tool but cautioning against their incorrect use.⁷ In order to avoid these critiques we will try to treat simulated and actual data in the same manner. Given that in our VAR exercise we have only identified TOT news and unexpected shocks, neglecting the identification of other shocks, we will try to use the same identification technique to recover news and unexpected TOT shocks also in the simulated data. This way the comparison between theoretical and empirical predictions would be direct.⁸

To this end, we simulate 1000 sets of data from the standard small open economy DSGE model presented in the previous section., where the sample sizes correspond to our empirical country specific sample sizes. For each simulation, we estimate the median impulse response from a Bayesian VAR based on 1000 draws from the posterior distribution of the VAR parameters; we include in the Monte Carlo VAR the same variables that we used in the empirical exercise. The only difference

⁷ It is worthwhile noting that much of the criticism by [Chari et al. \(2008\)](#) focuses on the unsuitability of using long-run restrictions for the identification of technology shocks. The MFEV identification method has been recently shown by [Francis et al. \(2014\)](#) to significantly outperform long-run restrictions based identification strategies in terms of estimation precision; moreover, [Barsky and Sims \(2011\)](#) have shown the effectiveness of a suitably extended MFEV identification strategy, as the one we use in this paper, in identifying news shocks. Hence, there is a good reason to believe, a priori, that our identification method is not susceptible to the criticism put forward in [Chari et al. \(2008\)](#). The results we present in this section confirm this belief.

⁸ [Schmitt-Grohe and Uribe \(2015\)](#) compare theoretical and empirical predictions by computing the share of variance explained by unexpected TOT shocks as the ratio between the variance conditional on terms-of-trade shocks predicted by the model divided by the unconditional variance implied by the empirical country specific SVAR model, implicitly assuming that SVAR and DSGE model are directly comparable. We perform their exercise in the appendix for the sake of comparing results, but we insist that the Monte Carlo exercise we perform is the only way to accurately compare theoretical and empirical predictions.

in our Monte Carlo exercise relative to the empirical VAR is that we do not include a commodities futures variable because our theoretical model does not contain a natural counterpart to the futures series we have in the empirical VAR.⁹ Also note that, to keep things simple, our model does not include any other structural shock apart from the unanticipated and anticipated TOT shocks; adding such shocks would not materially change our results as these shocks do not affect TOT. In general, our identification method would perform well as long as no other shock significantly affects TOT, which is a reasonable assumption since it is sensible to view TOT as an exogenous variable from the standpoint of a small open economy.

We draw the unanticipated and anticipated TOT shocks from the normal distribution. To avoid stochastic singularity, we add measurement errors to output, consumption, and investment. We calibrate the standard deviations of the measurement errors such that estimated contributions to the forecast error variance of output reasonably match their empirical counterparts. The standard deviations of the TOT shocks and measurement errors for our seven countries are presented in Table 7. These measurement errors are also drawn from the normal distribution.

In order to save on space, in Figures 5a and 5b we depict the the SVAR impulse response, theoretical model responses, and estimated median impulse responses averaged over the simulations to an unanticipated TOT shock and a TOT news shock in Brazil¹⁰. The SVAR responses are given by the plus-signed solid lines, theoretical responses are represented by the solid lines, and the average estimated median responses over the simulations are depicted by the dashed lines, with the dotted lines depicting the 2.5th and 97.5th percentiles of the distribution of estimated median impulse responses. The estimated responses are generally very close to the true ones, suggesting that our identification procedure enables us to properly identify the true effects of unanticipated and anticipated shocks to TOT. Responses to the unanticipated shock are comparable with the responses presented in Schmitt-Grohe and Uribe (2015). The trade balance expands in response

⁹ We have nevertheless confirmed that the simulation results are generally insensitive to adding a variable that is equal to the true news shock series and some reasonably calibrated measurement error that could proxy for future prices.

¹⁰In the appendix we depict the theoretical model responses and estimated median impulse responses averaged over the simulations to an unanticipated TOT shock and a TOT news shock for all seven Latin American countries.

to an improvement in the terms of trade and this increases also output. As in [Schmitt-Grohe and Uribe \(2015\)](#), both consumption and investment increase on impact in response to the improvement in the terms of trade, although in the SVAR the expansion of demand is delayed. In responses to TOT news, output and consumption expand with a delay as in the empirical model. The model fails to generate the more prolonged and moderate response of investment to surprise TOT shocks. The model also generates a prolonged response of the trade balance and anticipates the response of investment after a news TOT shock.

Table 8 and 9 presents the estimated contributions of the unanticipated and news shocks to the two-year variation in output along with their empirical counterparts from Section , respectively. It is apparent that the Monte Carlo estimated contributions are generally close to their empirical counterparts for TOT news shocks in all the countries. Instead, with respect to the unexpected TOT shock the model seems to always overstate their importance on generating business cycle fluctuations. In other words, our results concerning unexpected increases in TOT are in line with the findings in Aguirre (2011) who estimates a similar model and shows that in the theoretical model output displays a larger response to terms-of-trade shocks than in the empirical SVAR model. Trying to correct for the discrepancy between theoretical and empirical responses to an unexpected TOT shock is beyond the scope of this exercise and we leave this task for further analysis in our future research.

5 Conclusion

The terms of trade of many commodity-producing small open economies are subject to large shocks that can be an important source of macroeconomic fluctuations. The literature so far based on calibrated business-cycle models has traditionally suggested this to be the case. In their recent article [Schmitt-Grohe and Uribe \(2015\)](#) challenge this view by providing evidence from SVAR that show that unexpected changes in the terms of trade account for a small share of output variations in developing countries.

In this paper we confirm the findings of [Schmitt-Grohe and Uribe \(2015\)](#) and examine the sensitivity of their results when using quarterly instead of annual SVARs and when we complement their analysis with additional information such as country spreads, of futures commodity prices. We show that their results are robust when alternative commodity based terms of trade are used to identify TOT shocks and when we control for TFP movements and account for the exogeneity of the terms of trade. Yet, we also show that in all these specifications news TOT shocks are equally or even more important as sources of business cycle fluctuations in emerging economies.

Actually, when we feed their textbook theoretical model with unexpected and news TOT shock series we show that the variations of news TOT shocks can account for more around 25% of variation in output volatility in emerging countries matching on average the empirical predictions from our SVAR exercises. On the other hand, the model overstates the importance of unexpected changes in the TOT in explaining aggregate fluctuation in emerging countries. However, a word of caution should be at place here, since we consider just one source of fluctuations in our model economy and ignore variations in other variables that could affect significantly the cycle in emerging markets. [Lubik and Teo \(2005\)](#), for example, estimate a small open economy model using Bayesian methods and find that world interest rate shocks are a more important source of business cycles than terms of trade shocks. [Vicondoa \(2016\)](#) shows that anticipated world interest rate shocks are actually more important sources of fluctuations in emerging countries relative to unexpected changes in the world interest rate.

Given the lack of consensus about the source of business cycle fluctuations in small open economies, we humbly conclude that TOT shocks when controlling for anticipation effects matter more than what originally stated by [Schmitt-Grohe and Uribe \(2015\)](#).

Appendix A Data

We use quarterly data for the following countries and periods: Argentina 1994:Q1-2013:Q3, Brazil 1995:Q1-2014:Q3, Chile 1996:Q1-2014:Q3, Colombia 1994:Q1-2009:Q4, Ecuador 2001:Q1-2013:Q4, Mexico 1994:Q1-2014:Q2, and Peru 1994:Q1-2014:Q2. The sample varies across countries according to data availability. For each case, we use the following series: GDP, Gross Fixed Capital Formation, Private Consumption Expenditure, and Exports and Imports of Goods and Services. All these variables are expressed in current prices and local currency units. We deflate all the variables (except the last 2) using the GDP Deflator. Finally, we compute the trade balance (difference between exports and imports) as a share of current GDP. All these series were downloaded from the International Financial Statistics (IFS) database, which is published by International Monetary Fund. Additionally, we use the Export and Import Price index to compute the terms of trade series for each country. These indexes were downloaded from the national central banks (Brazil, Chile, Ecuador, Mexico, and Peru) and IMF (Argentina and Colombia). Finally, we use the Real Exchange Rate index computed by the Bank of International Settlements. This index is calculated as geometric weighted averages of bilateral exchange rates adjusted by relative consumer prices. We compute the quarterly average and reexpress the series such that an increase (decrease) indicates a depreciation (appreciation). All the series were seasonally adjusted using ARIMA X13.

In order to compute a commodity futures price index, we take the first principal component of the following contracts: Coffee (6th continuous contract), Cooper, Corn (6th continuous contract), Gas (11th continuous contract), Oil (12th continuous contract), Soybean (8th continuous contract), Soybean meal (9th continuous contract), and Wheat (6th continuous contract). We compute a daily principal component (the first component explains 82% of the total variation) and then a quarterly average of this series. These commodities constitute a representative bundle of products exported by Latin American economies. The data for commodity prices was downloaded from Quandl ¹¹. For the robustness exercise, we use the Emerging Markets Bond Index (EMBI) Global computed by JP Morgan as a measure of country spread. This index is a composite of different US dollar-

¹¹ <https://www.quandl.com> provides continuous series for many commodities based on data from CME.

denominated bonds. The Stripped Spread is computed as an arithmetic, market-capitalization-weighted average of bond spreads over US Treasury bonds of comparable duration.

For the annual specification, we use the same sample of poor and emerging countries and periods as [Schmitt-Grohe and Uribe \(2015\)](#). In particular, the panel contains data for the period 1980 to 2011 for the following countries: Algeria, Argentina, Bolivia, Botswana, Brazil, Burundi, Cameroon, Central African Republic, Egypt, Arab Rep., El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Korea, Rep. Madagascar, Malaysia, Mauritius, Mexico, Morocco, Pakistan, Paraguay, Peru, Philippines, Senegal, South Africa, Sudan, Thailand, Turkey, and Uruguay. All the data comes from the World Development Indicators (WDI) database, which is published by the World Bank. We add to this database the measure of TFP computed by the Conference Board, which is available for the period 1990-2014. <https://www.conference-board.org/data/economydatabase/index.cfm?id=27762> contains detailed information on how this variable is computed.

References

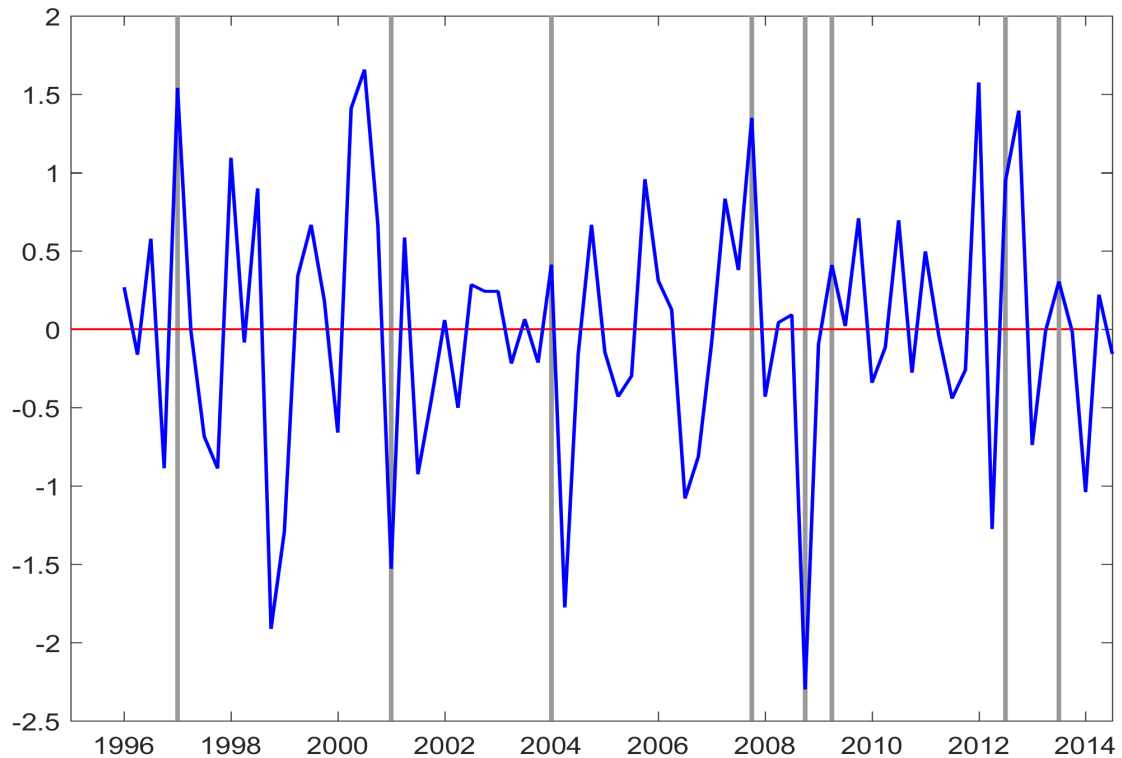
- Aguirre, E.: 2011, *Essays on exchange rates and emerging markets*, PhD thesis, Columbia University.
- Barsky, R. and Sims, E. R.: 2011, News shocks and business cycles, *Journal of Monetary Economics* **58**(3), 235–249.
- Beaudry, P. and Portier, F.: 2006, Stock prices, news, and economic fluctuations, *American Economic Review* **96**(4), 1293–1307.
- Céspedes, L. F. and Velasco, A.: 2014, Was this Time Different?: Fiscal Policy in Commodity Republics, *Journal of Development Economics* **106**(C), 92–106.
- Chari, V. V., Kehoe, P. J. and McGrattan, E. R.: 2008, Are structural vars with long-run restrictions useful in developing business cycle theory?, *Journal of Monetary Economics* **55**(8), 1337–1352.
- Chinn, M. D. and Coibion, O.: 2014, The predictive content of commodity futures, *Journal of Futures Markets* **34**(7), 607–636.
- Christiano, L. J., Eichenbaum, M. and Vigfusson, R.: 2007, Assessing structural vars, *NBER Macroeconomics Annual 2006, Volume 21*, MIT Press, pp. 1–106.
- Fernandez, A., Gonzalez, A. and Rodriguez, D.: 2015, Sharing a Ride on the Commodities Roller Coaster: Common Factors in Business Cycles of Emerging Economies.
- Francis, N., Owyang, M. T., Roush, J. E. and DiCecio, R.: 2014, A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks, *Review of Economics and Statistics* **96**(4), 638–647.
- Ilzetzki, E. and Vegh, C. A.: 2008, Procyclical Fiscal Policy in Developing Countries: Truth or Fiction?

- Jaimovich, N. and Rebelo, S.: 2009, Can news about the future drive the business cycle?, *American Economic Review* **99**(4), 1097–1118.
- Kilian, L. and Hicks, B.: 2013, Did unexpectedly strong economic growth cause the oil price shock of 20032008?, *Journal of Forecasting* **32**(5), 385–394.
- Kose, M.: 2002, Explaining business cycles in small open economies: how much do world prices matter?, *Journal of International Economics* **56**(2), 299 – 327.
- Lubik, T. and Teo, W. L.: 2005, Do Terms of Trade Shocks Drive Business Cycles? Some Evidence from Structural Estimation, *Computing in Economics and Finance 2005 377*, Society for Computational Economics.
- Mendoza, E. G.: 1995, The Terms of Trade, the Real Exchange Rate, and Economic Fluctuations, *International Economic Review* **36**(1), 101–37.
- Otrok, C. and Kurmann, A.: 2011, News Shocks and the Term Structure of Interest Rates: A Challenge for DSGE Models, *Technical report*.
- Schmitt-Grohé, S. and Uribe, M.: 2012, What’s news in business cycle?, *Econometrica (forthcoming)* .
- Schmitt-Grohe, S. and Uribe, M.: 2015, How important are terms of trade shocks?, *Working Paper 21253*, National Bureau of Economic Research.
- Shousha, S.: 2016, Macroeconomic Effects of Commodity Booms and Busts: The Role of Financial Frictions.
- Sinnott, E.: 2009, Commodity Prices and Fiscal Policy in Latin America and the Caribbean.
- Spatafora, N. and Tytell, I.: 2009, Commodity terms of trade: The history of booms and busts, *IMF Working Papers* pp. 1–34.
- Uhlig, H.: 2003, What moves real GNP?, *Unpublished manuscript*.

Uribe, M. and Yue, V. Z.: 2006, Country spreads and emerging countries: Who drives whom?, *Journal of international Economics* **69**(1), 6–36.

Vicondoa, A.: 2016, Monetary News, U.S. Interest Rates and Business Cycle in Emerging Economies.

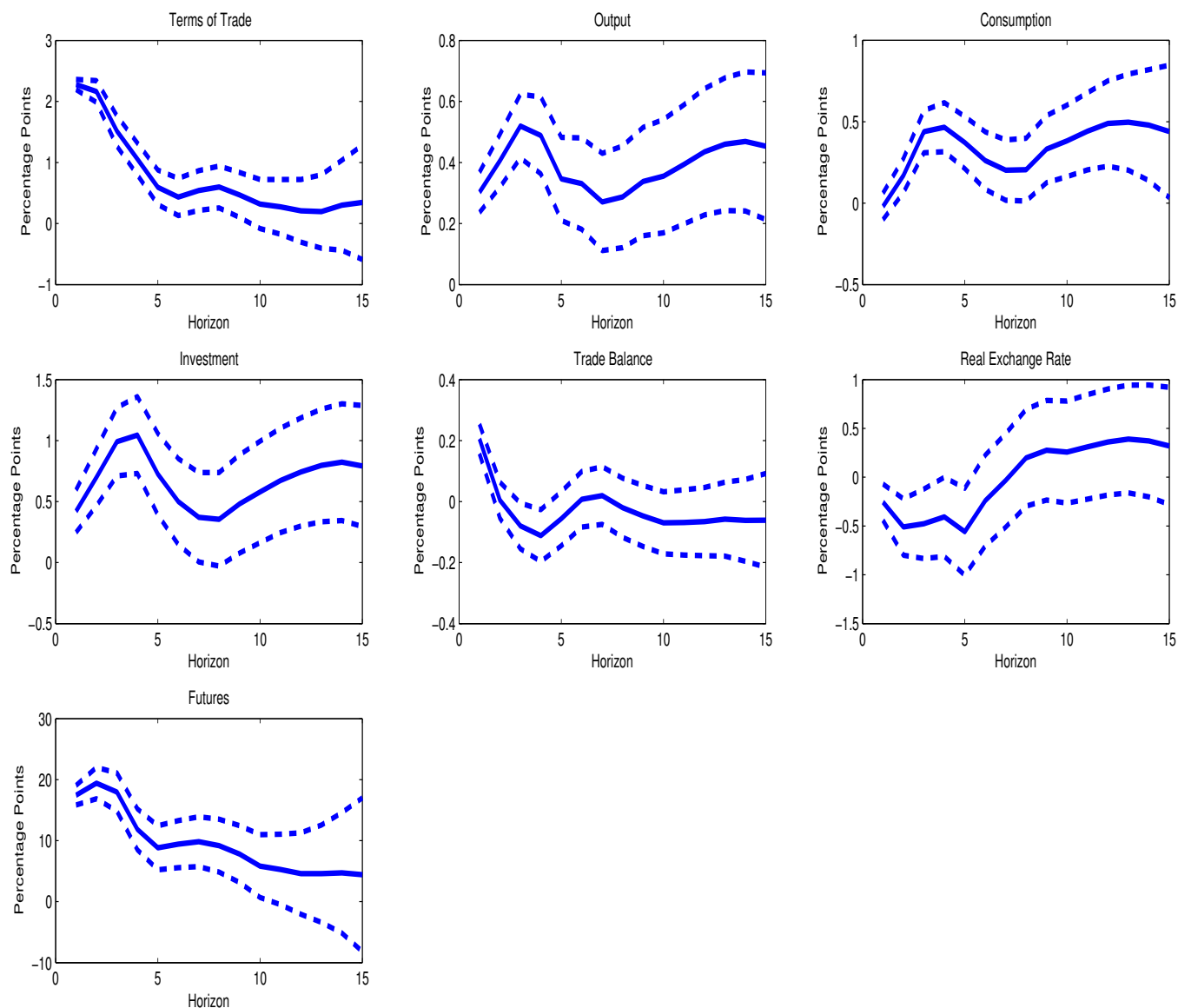
Figure 1: **Estimated Terms of Trade News Shocks for Brazil.**



Notes: Solid line denotes the estimated terms of trade news shocks for Brazil using our baseline VAR. Vertical lines denote the dates of these terms of trade events:

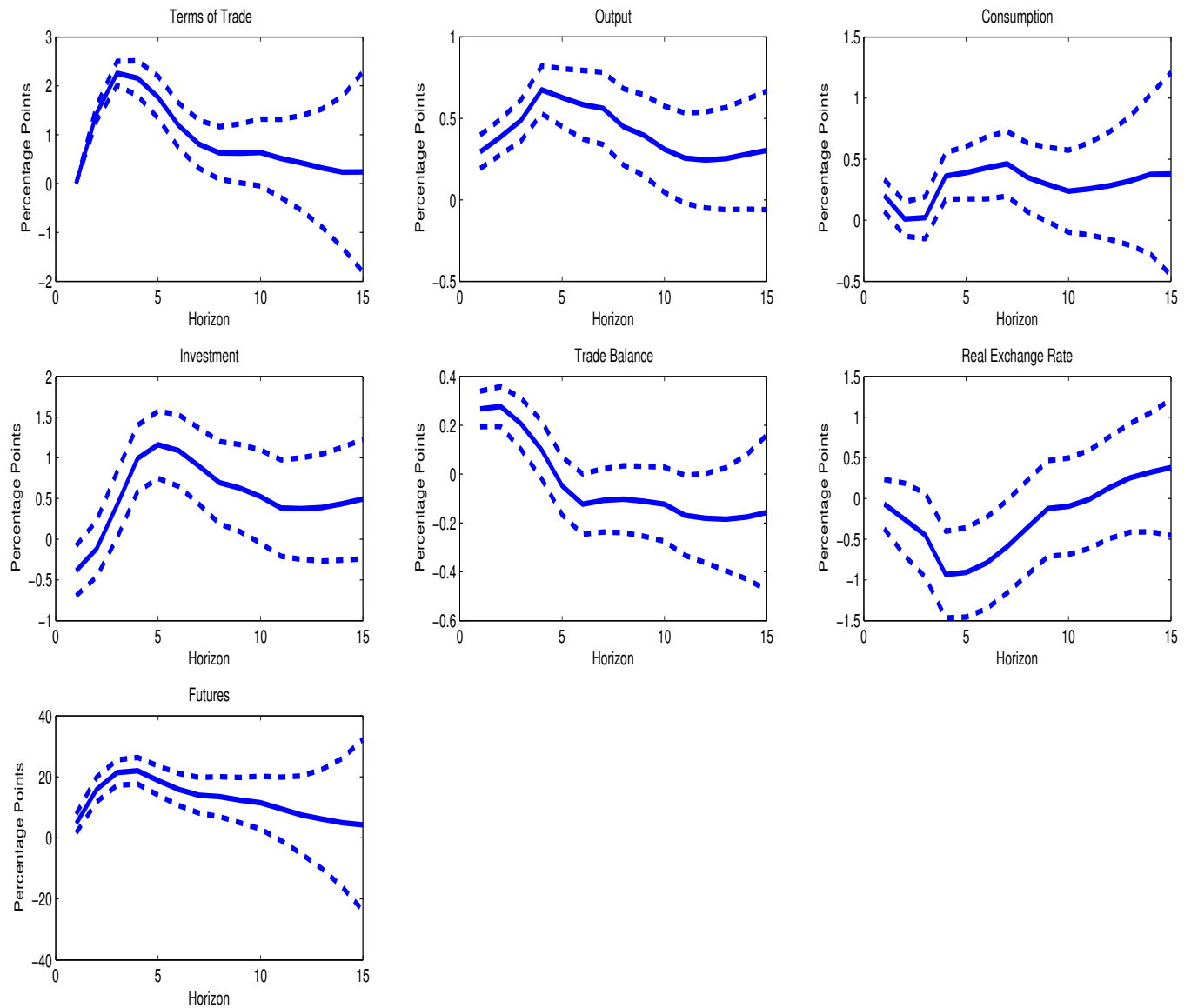
- 1997:Q1: Storm 'El Niño' affected Latin America.
- 2001:Q1: Burst of 'Dot-Com' Bubble U.S
- 2004:Q1: Storm 'El Niño' affected Latin America.
- 2007:Q4: Discovery of field of oil and forecast of record agricultural production
- 2008:Q4: World Recession
- 2009:Q2: Draught affected regions of Brazil
- 2012:Q3: Oil reservoir discovery
- 2013:Q3: Oil reservoir discovery

Figure 2: Impulse Responses to a One Standard Deviation Unanticipated TOT Shock from the Benchmark VARs (solid lines).



Notes: Solid line and dashed lines are the average of the country-specific median responses to the unanticipated TOT shock. The bands in the figure are one standard error bands where the standard error is the one corresponding to the standard error of the average estimate computed from the variances of the individual country-specific estimates. The underlying country-specific estimates are based on 1000 draws taken from the posterior distribution of the VAR parameters, where the unanticipated TOT shock is identified as the VAR innovation in TOT. Horizon is in quarters.

Figure 3: Impulse Responses to a One Standard Deviation TOT News Shock from the Benchmark VARs (solid lines).



Notes: Solid line and dashed lines are the average of the country-specific median responses to the TOT news shock. The bands in the figure are one standard error bands where the standard error is the one corresponding to the standard error of the average estimate computed from the variances of the individual country-specific estimates. The underlying country-specific estimates are based on 1000 draws taken from the posterior distribution of the VAR parameters, where the TOT news shock is identified in accordance with the MFEV estimation procedure described in Section . Horizon is in quarters.

Table 3: **Share of Forecast Error Variance Explained by Unanticipated TOT Shocks: Country-Level SVAR Evidence.**

Country	TOT	Output	Consumption	Investment	Trade Balance	Real Exchange Rate	Futures
Argentina	41	11	8	4	10	13	20
Brazil	53	13	7	19	4	24	18
Chile	30	9	16	14	11	16	15
Colombia	37	14	11	16	13	11	15
Ecuador	12	4	7	12	11	10	7
Mexico	44	12	10	6	18	19	33
Peru	30	22	11	22	14	11	27
Average	35	12	10	13	12	15	20

Notes: This table presents the estimated contribution of the terms of trade unanticipated shock to the two-year variation in the variables obtained from each of the 7 country-level VARs. Average estimate is simple mean of the country specific estimates. Shares are expressed in percent.

Table 4: **Share of Forecast Error Variance Explained by TOT News Shocks: Country-Level SVAR Evidence.**

Country	TOT	Output	Consumption	Investment	Trade Balance	Real Exchange Rate	Futures
Argentina	32	40	33	21	8	10	30
Brazil	29	19	35	20	26	27	21
Chile	46	45	32	22	16	35	40
Colombia	22	8	9	9	15	24	17
Ecuador	53	14	31	16	37	52	66
Mexico	32	29	16	19	21	10	27
Peru	44	18	12	22	34	5	30
Average	37	25	24	18	23	23	33

Notes: This table presents the estimated contribution of the TOT unanticipated shock to the two-year variation in the variables obtained from each of the 7 country-level VARs. Average estimate is simple mean of the country specific estimates. Shares are expressed in percent.

Table 5: **Robustness Table: Share of Forecast Error Variance Explained by Unanticipated TOT Shocks for Various Alternative SVAR Specifications.**

Specification	TOT	Output	Consumption	Investment	Trade Balance	Real Exchange Rate	Futures	Spreads	Government Spending	TFP
Country Spreads	32	15	13	13	15	14	13	17		
Federal Funds Rate	24	9	8	9	6	8	13			
Government Spending	38	12	12	14	17	18	23		9	
Annual Commodity-based TOT	72	18	16	17	13	20				
SGU Specification	72	16	16	15	17	19				
SGU (Our LA Sample)	75	27	22	19	14	24				
TFP	63	23	22	20	16	17				21
TOT and Futures in Exogenous Block	82	32	27	29	34	38	46			

Notes: This table presents the average estimated contribution of the TOT news shock to the two-year variation in the variables. Each row corresponds to an alternative SVAR specification described in Section 3.4. Shares are expressed in percent.

Table 6: **Robustness Table: Share of Forecast Error Variance Explained by TOT News Shocks for Various Alternative SVAR Specifications.**

Specification	TOT	Output	Consumption	Investment	Trade Balance	Real Exchange Rate	Futures	Spreads	Government Spending	TFP
Country Spreads	39	24	23	22	21	27	23	35		
Federal Funds Rate	21	15	12	15	12	13	18			
Government Spending	38	26	26	23	20	22	33		25	
Annual Commodity-based TOT	18	16	27	23	33	23				
SGU Specification	24	18	21	23	25	21				
SGU (Our LA Sample)	22	13	18	25	32	28				
TFP	31	17	15	20	26	23				19
TOT and Futures in Exogenous Block	18	23	22	24	22	22	54			

Notes: This table presents the average estimated contribution of the terms of trade unanticipated shock to the two-year variation in the variables. Each row corresponds to an alternative SVAR specification described in Section 3.4. Shares are expressed in percent.

Table 7: **Monte Carlo Experiment: TOT shocks and Measurement Error Standard Deviations.**

Country	Unanticipated Shock	News Shock	Measurement		
			Errors (Output, Invest- ment, Consump- tion)	Measurement Errors (Trade Balance)	Measurement Errors (Real Exchange Rate)
Argentina	0.023	0.012	0.02	0.002	0.004
Brazil	0.054	0.035	0.02	0.002	0.004
Chile	0.011	0.009	0.02	0.002	0.004
Colombia	0.013	0.004	0.02	0.002	0.004
Ecuador	0.029	0.018	0.02	0.002	0.004
Mexico	0.017	0.007	0.02	0.002	0.004
Peru	0.024	0.013	0.02	0.002	0.004

Notes: This table reports the standard deviations of the structural TOT shocks and measurement errors of output, consumption, investment, trade balance, and real exchange rate used to generate the data in the Monte Carlo experiment of Section 4.2. The idiosyncratic measurement errors are simply white noise errors whose purpose is to avoid singularity.

Table 8: **SVAR and Monte Carlo Estimated Forecast Error Variance Contributions of Unanticipated TOT Shocks.**

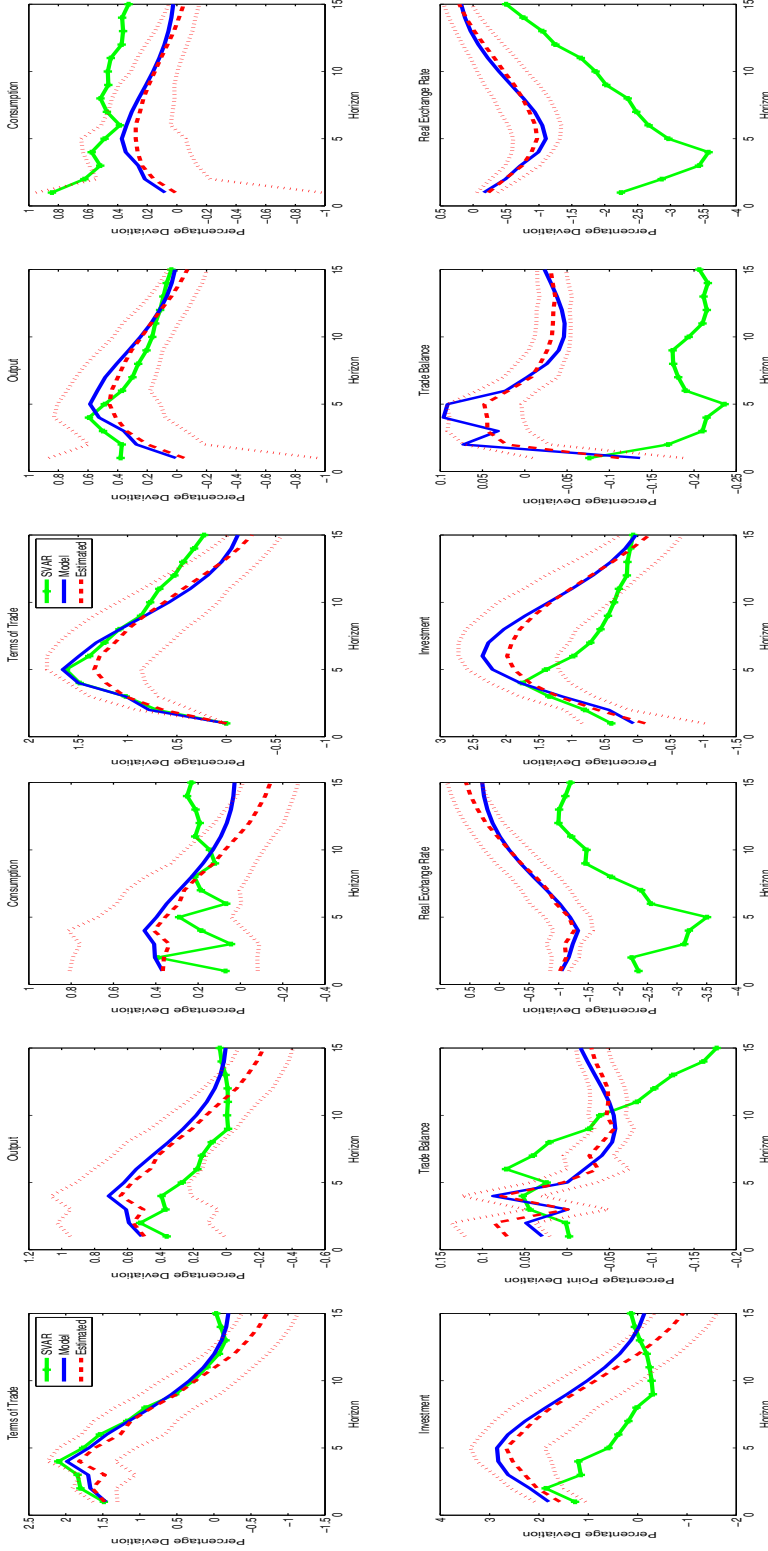
	Argentina		Brazil		Chile		Colombia		Ecuador		Mexico		Peru	
	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC
TOT	41%	54%	53%	55%	30%	47%	37%	48%	12%	24%	44%	56%	30%	56%
Output	11%	35%	13%	28%	9%	29%	14%	24%	4%	20%	12%	24%	22%	38%
Consumption	8%	24%	7%	20%	16%	21%	11%	20%	7%	18%	10%	16%	11%	21%
Investment	4%	51%	19%	54%	14%	43%	16%	38%	12%	23%	6%	51%	22%	47%
Trade Balance	10%	35%	4%	26%	11%	37%	13%	37%	11%	21%	18%	42%	14%	54%
REER	13%	55%	24%	53%	16%	47%	11%	47%	10%	24%	19%	55%	11%	50%

Table 9: **SVAR and Monte Carlo Estimated Forecast Error Variance Contributions of TOT News Shocks.**

	Argentina		Brazil		Chile		Colombia		Ecuador		Mexico		Peru	
	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC	Data	MC
TOT	32%	26%	29%	31%	46%	33%	22%	27%	53%	47%	32%	28%	44%	28%
Output	40%	22%	19%	22%	45%	24%	8%	21%	14%	37%	29%	20%	18%	23%
Consumption	33%	19%	35%	19%	32%	20%	9%	20%	31%	33%	16%	18%	12%	21%
Investment	21%	25%	20%	30%	16%	31%	9%	26%	16%	45%	19%	27%	22%	32%
Trade Balance	8%	26%	26%	24%	35%	31%	15%	25%	37%	41%	21%	25%	34%	17%
REER	10%	15%	27%	15%	40%	34%	24%	28%	52%	48%	10%	30%	5%	32%

Figure 4: Monte Carlo Evidence: (a) Unanticipated Shocks; (b) News Shocks.

Figure 5: here



(a) The SVAR Impulse Responses, Monte Carlo Estimated Mean and 97.5th and 2.5th percentile Median Impulse Responses, and the True Impulse Responses to the Unanticipated Shock. (b) The SVAR Impulse Responses, Monte Carlo Estimated Mean and 97.5th and 2.5th percentile Median Impulse Responses and the True Impulse Responses to the News Shock.

Notes: The figures are based on 1000 Monte Carlo simulations of the model of Section 4 for each country where in each simulation the impulse responses to the unanticipated and news shock were identified as the median values of impulse responses based on 1000 draws from the posterior distribution of the VAR parameters. These estimates were then averaged over the different country estimates to form the aggregated average impulse response estimate. The SVAR responses are given by the plus-signed solid lines, the solid line represents the true model impulse responses, the dashed line is the average estimated impulse response to the shock across Monte Carlo replications, and the dotted lines are the 97.5th and 2.5th estimated percentiles of the estimated monte carlo impulse responses.