Does the Commodity Super Cycle Matter?*

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Abstract

This paper investigates empirically the role of the commodity price super cycle in explaining real activity in developed and emerging economies. The commodity price super cycle is defined as a common permanent component in real commodity prices. Estimates using quarterly and annual data from 1960 to 2018 indicate that world shocks that affect commodity prices and the world interest rate explain more than half of the variance of output growth on average across countries. However, the majority of this contribution, more than two thirds, stems from stationary world shocks. These results suggest that world disturbances that are responsible for low frequency movements in commodity prices play an important but not dominant role in driving fluctuations in aggregate activity at the country level.

JEL classification: F41.

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1 Introduction

World commodity prices are known to display long cycles. These cycles have a periodicity of 20 to 30 years and are called commodity price super cycles. The existing literature on commodity price super cycles has mainly focused on documenting their frequency, amplitude, and turning points. Less work has been devoted to estimating the importance of commodity price super cycles for economic activity. The contribution of this paper is to identify global disturbances that cause regular cycles and super cycles in world commodity prices and to estimate the contribution of these global shocks to aggregate fluctuations in emerging and developed countries.

The econometric oriented related literature typically uses spectral analysis to identify commodity price super cycles. Cuddington and Jerrett (2008) pioneered the use of the asymmetric band pass filter of Christiano and Fitzgerald (2003) to identify super cycles in commodity prices with periodicity between 20 and 70 years. Specifically, they apply this technique to the prices of six metals traded on the London Metal Exchange. Subsequently, Erten and Ocampo (2013) apply this methodology to the identification of super cycles in real non-oil commodity prices.

The present paper proposes a different methodology to identify long cycles in world commodity prices. It identifies the commodity super cycle as a common permanent component in all commodity prices. The paper finds that this approach produces an estimate of the super cycle that is in line with the one delivered by the spectral approach. In particular, as in the works of Cuddington and Jerrett and Erten and Ocampo, the super cycle induced by the permanent component approach displays two peaks post 1960, one in the early 1980s and one in the early 2010s. In the academic and the financial-industry literatures, the upswing in commodity prices leading to the 1980s peak is typically attributed to the post World War II reconstruction of Western Europe and Japan and to the cartelization of the crude oil market. The second peak in the super cycle is often attributed to the accession of China and other south east Asian countries to world markets.

The proposed permanent component approach to identifying the commodity price super cycle has two desirable properties. First, the spectral approach applies the band pass filter to individual commodity price time series separately. As a result, it delivers one super cycle per commodity price. The super cycles estimated in this way are positively correlated with one another (Cuddington and Jerrett, 2008; Erten and Ocampo, 2013). This correlation has been interpreted as reflecting the existence of a common driver. The permanent component approach delivers this common driver by identifying the nonstationary world shock responsible for the super cycle in all commodity prices. The present paper finds that the common permanent component plays an important role in explaining movements in commodity prices at frequencies typically associated with the super cycle. Specifically, it explains on average across commodities between 67 and 91 percent of the forecast error variance of commodity prices at horizons between 5 and 30 years.

A second desirable property of the permanent component approach proposed in this paper for the identification of the commodity super cycle is that it allows for the simultaneous estimation of transitory and permanent domestic and world disturbances affecting aggregate activity in individual countries. As a result, the permanent component approach provides a natural environment for estimating the contribution of the shock responsible for the super cycle to explaining variations in output at the country level.

The paper formulates an empirical model that includes eleven commodity prices, the world interest rate, and output of over forty small open developed and emerging economies. All commodity prices are assumed to be cointegrated with a common nonstationary world shock. In addition, commodity prices and the world interest rate are assumed to be buffeted by stationary world shocks. Output at the individual country level is driven by the nonstationary and stationary worlds shocks, a nonstationary country specific shock, and a stationary country specific shock. Thus, a constellation of stationary and nonstationary world and domestic shocks compete for explaining movements in country-specific output. The nonstationary world shock is the one responsible for the commodity price super cycle. Thus, ascertaining the role of the super cycle in accounting for output movements in a given country amounts to estimating the share of the nonstationary world shock in the variance decomposition of the country's output.

Following Uribe (2018), the model is cast in terms of detrended endogenous variables and exogenous shocks. Since the exogenous shocks and the stochastic trends are unobservable, almost all variables in the model are latent variables. The estimation exploits the fact that the model delivers precise predictions for variables that are observed. In particular, the observable variables used in the estimation of the model are the growth rates of 11 commodity prices, the level of the world interest rate, and the growth rates of output of the countries included in the sample. The likelihood of the data is computed using the Kalman filter, and the econometric estimation employs Bayesian techniques. The model is estimated on quarterly data covering the period 1960 to 2018. For countries for which quarterly output data since 1960 is not available, the model is estimated on annual data.

The paper delivers two main results. First, world shocks that drive commodity prices and the world interest rate are major drivers of aggregate fluctuations in developed and emerging small open economies. Jointly the stationary and nonstationary world shocks explain more than half of the variance of output growth on average across countries. Second, the bulk (more than two thirds) of the explanatory power of world shocks stems from stationary shocks. These results obtain not only unconditionally but also conditionally on time horizons. Importantly, even at forecasting horizons typically associated with the super cycle (20 years or longer) stationary world shocks play a larger role than the nonstationary world shock in explaining the forecast error variance of the level of output in individual countries. Taken together these results suggest that the commodity price super cycle matters for explaining aggregate activity at the country level, but that its contribution is smaller than that of stationary world shocks.

This paper is related to a body of work on the role of world prices as mediators of world shocks for economic outcomes in small open economies. Mendoza (1995) and Kose (2001) using calibrated real business cycle models fed with estimated stochastic processes for the terms of trade find that disturbances to this international price accounts for more than thirty percent of fluctuations in aggregate activity. More recently, Miyamoto and Nguyen (2017) and Drechsel and Tenreyro (2018) find similar results using a Bayesian estimation approach. Schmitt-Grohé and Uribe (2018) apply a more agnostic approach based on structural vector autoregressions and find that the contribution of terms of trade shocks to explaining aggregate fluctuations in poor and emerging economies is only 10 percent. These authors argue for the need to consider more disaggregated measures of world prices to better capture the transmission of world shocks to individual economies. Fernández et al. (2017) employ a similar empirical strategy as Schmitt-Grohé and Uribe (2018) but expand the set of world prices from one to four, three commodity prices and the world interest rate, and find that world shocks mediated by this set of prices explain one third of output fluctuations on average in a set of 138 countries over the period 1960 to 2015. This figure more than doubles when the estimation is conducted on a more recent sample beginning in the late 1990s, as shown by Shousha (2016), Fernández et al. (2015), and Fernández et al. (2017). In the papers just cited shocks to commodity prices, if explicitly modeled, are assumed to be stationary, and as a result this body of work does not speak directly to the importance of commodity price super cycles.

Closer to the present investigation, as mentioned above, Cuddington and Jerrett (2008) and Erten and Ocampo (2013) are key references on the estimation of commodity price super cycles using spectral analysis. These papers and the early work by Pindyck and Rotemberg (1990) speculate on the existence of common drivers of commodity prices, which serves as motivation for the common component approach proposed in the present paper. Alquist et al. (2020) apply a factor-based identification strategy to estimate the role of commodity prices in explaining global economic activity. Benguria et al. (2018) identify the commodity price super cycle by HP filtering and analyze its transmission using firm-level administrative data from Brazil.

Finally, the present paper contributes to a literature assessing the role of transitory and permanent shocks in driving business cycles in developed and emerging economies (see, among others, Aguiar and Gopinath, 2007; García-Cicco et al., 2012; Chang and Fernández, 2013; and Miyamoto and Nguyen, 2017). It finds that for both developed and emerging countries transitory shocks play a larger role than permanent shocks even if one conditions on world shocks or on country-specific shocks.

The remainder of the paper is organized in seven sections. Section 2 presents the empirical model. Section 3 introduces the observables, the priors, and the estimation strategy. Section 4 presents the definitions and sources of the quarterly data on commodity prices, world interest rates, and output in twenty four predominantly developed economies spanning the period 1960Q1 to 2018Q4. Section 5 analyzes the estimated commodity price super cycle. Section 6 presents variance decompositions, forecast error variance decompositions, and impulse response analysis to ascertain the importance of the commodity super cycle for aggregate activity in the small open economies considered. Section 7 estimates the model on annual data from 1960 to 2018 for twenty-four emerging and seventeen developed countries. Finally, section 8 concludes.

2 An Empirical Model of the Commodity Super Cycle

The empirical model is an adaptation of the methodology developed in Uribe (2018) for the study of permanent monetary policy shocks to the study of permanent world shocks.

The world block consists of the vector p_t containing 11 real commodity prices and the gross real interest rate all expressed in logarithms. The commodity super cycle is modeled as a nonstationary exogenous variable X_t^p with the property of being cointegrated with the 11 commodity prices. We can then define a vector of transformed world prices, denoted $\hat{p}_t$, that is stationary as follows[1]

$$\hat{p}_t = \begin{bmatrix} \hat{p}_t^1 \\ \hat{p}_t^2 \\ \vdots \\ \hat{p}_t^{11} \\ \hat{r}_t \end{bmatrix} \equiv \begin{bmatrix} p_t^1 - X_t^p \\ p_t^2 - X_t^p \\ \vdots \\ p_t^{11} - X_t^p \\ \ln(1+r_t^*) \end{bmatrix}.$$

[1]For expositional purposes, constant terms are omitted. The model with constant terms is presented in the appendix.

The identification assumption that all commodity prices have the same cointegrating vector with X_t^p is based on the observation that in the raw data commodity prices do not seem to diverge from one another over time.

The vector $\hat{p}_t$ is assumed to be buffeted by a nonstationary shock, given by variations in the permanent component of world prices, X_t^p, and twelve stationary world shocks denoted z_t^p. The vector of world prices evolves according to the following autoregressive process

$$\hat{p}_t = \sum_{i=1}^{4} B_{pp}^i \hat{p}_{t-i} + C_{pX^p} \Delta X_t^p + C_{pz^p} z_t^p, \tag{1}$$

where B_{pp}^i for $i = 1, 2, 3, 4$, C_{pX^p}, and C_{pz^p} are matrices of coefficients of order 12-by-12, 12-by-1, and 12-by-12, respectively. Without loss of generality, assume that C_{pz^p} is lower triangular with ones on the diagonal. This is not an identification restriction. The elements of z_t^p should be interpreted as combinations of stationary world shocks affecting commodity prices and the interest rate. The present study does not aim to identify these shocks individually, but rather to ascertain their joint contribution to explaining movements in world prices and aggregate activity and to compare it to that of the nonstationary world shock X_t^p driving the commodity super cycle.

The domestic block consists of the vector y_t containing real output for 24 small open economies expressed in logarithms. In each country, output is assumed to be cointegrated with a linear combination of a country-specific nonstationary shock, denoted X_t^i for $i = 1, \ldots, 24$ and the nonstationary component of real world commodity prices, X_t^p. The rationale behind the assumption that X_t^p enters in the cointegrating relationship of output is that in models of small open economies with nonstationary commodity prices these prices can have permanent effects on output just like nonstationary technology shocks do. We note that this long-run relationship between output and the nonstationary component of world shocks is not subject to the observation made by Kehoe and Ruhl (2008) that depending on how real GDP is measured in the data, terms of trade shocks may not act like technology shocks. Their observation has to do with the direct effect of terms of trade shocks on measured GDP and not with the indirect effect on quantities. Allowing for the possibility that output is cointegrated with the permanent component of world shocks is justified on the grounds that in standard theories of the open economy, the former inherits the long-run stochastic properties of the latter.

Let $\hat{y}_t$ be a 24-by-1 vector of deviations of output from trend. Then,

$$\hat{y}_t = \begin{bmatrix} \hat{y}_t^1 \\ \hat{y}_t^2 \\ \vdots \\ \hat{y}_t^{24} \end{bmatrix} \equiv \begin{bmatrix} y_t^1 - X_t^1 - \alpha^1 X_t^p \\ y_t^2 - X_t^2 - \alpha^2 X_t^p \\ \vdots \\ y_t^{24} - X_t^{24} - \alpha^{24} X_t^p \end{bmatrix}.$$

For each country i, the country-specific shocks consist of the growth rate of the permanent component of output, ΔX_t^i, and a stationary shock, z_t^i. Detrended output is assumed to evolve according to the following autoregressive process:

$$\hat{y}_t = \sum_{i=1}^{4} B_{yp}^i \hat{p}_{t-i} + \sum_{i=1}^{4} B_{yy}^i \hat{y}_{t-i} + C_{yX^p} \Delta X_t^p + C_{yz^p} z_t^p + C_{yX} \Delta X_t + z_t, \tag{2}$$

where $\Delta X_t \equiv [\Delta X_t^1 \ldots \Delta X_t^{24}]'$ and $z_t = [z_t^1 \ldots z_t^{24}]'$, B_{yp}^i and B_{yy}^i, for $i = 1, \ldots, 4$, are 24-by-12 and 24-by-24 matrices of coefficients, respectively, and C_{yX^p}, C_{yz^p}, and C_{yX} are matrices of order 24-by-1, 24-by-12, and 24-by-24, respectively.

The exogenous shocks, ΔX_t^p, ΔX_t, z_t^p, and z_t follow univariate autoregressive processes. Specifically, let u_t denote the vector of exogenous shocks

$$u_t \equiv \begin{bmatrix} \Delta X_t^p \\ \Delta X_t \\ z_t^p \\ z_t \end{bmatrix}.$$

We assume that u_t obeys the law of motion

$$u_t = \rho u_{t-1} + \psi \nu_t, \tag{3}$$

where $\nu_t \sim$ i.i.d. $\mathcal{N}(0, I_{61})$. The matrices ρ and ψ are assumed to be diagonal. This implies that the permanent component of world prices, X_t^p, is uncorrelated with the stationary world shocks, z_t^p; that the permanent and transitory country-specific shocks are uncorrelated with each other and with other country-specific shocks; and that country-specific shocks, X_t^i and z_t^i, are uncorrelated with the world shocks, X_t^p and z_t^p. The latter assumption is motivated by the fact that the countries in the sample are small open economies and as such their idiosyncratic shocks do not affect world prices. We assume that all of the correlation of output across countries stems from world shocks. Accordingly, the matrices B_{yy}^i for $i = 1, \ldots, 4$, as well as the matrix C_{yX}, are restricted to be diagonal. The assumption that the world shocks X_t^p and z_t^p (as opposed to the contemporaneous world prices $\hat{p}_t$) enter directly in the domestic block, equation (2), allows for the possibility that world shocks affect country level output both directly and indirectly mediated by world prices. A direct effect of world shocks on country level output could occur, for example, via productivity shocks that are correlated across countries.

3 Observables, Priors, and Estimation Strategy

All variables in the system (1), (2), and (3) except for the interest rate, r_t^*, are latent variables and therefore unobservable. As a result, the system cannot be directly estimated on data. However, we will exploit the fact that the model has precise predictions for variables that are observable. Specifically, the data used in the estimation includes the growth rates of the commodity prices, Δp_t^i for $i = 1, \ldots, 11$, the level of the world interest rate, r_t^*, and the growth rates of output, Δy_t. The observable variables are related to the latent variables through the following identities:

$$\Delta p_t^i = \Delta \hat{p}_t^i + \Delta X_t^p; \quad i = 1, \ldots, 11, \tag{4}$$

$$\Delta y_t^i = \Delta \hat{y}_t^i + \Delta X_t^i + \alpha^i \Delta X_t^p; \quad i = 1, \ldots, 24, \tag{5}$$

and

$$\ln(1 + r_t^*) = \hat{r}_t. \tag{6}$$

The observable variables are assumed to be measured with error. Letting o_t denote the vector of observed variables, we have that

$$o_t = \begin{bmatrix} \Delta p_t^1 \\ \vdots \\ \Delta p_t^{11} \\ \ln(1 + r_t^*) \\ \Delta y_t^1 \\ \vdots \\ \Delta y_t^{24} \end{bmatrix} + \mu_t, \tag{7}$$

where μ_t is a 36-by-1 vector of measurement errors distributed i.i.d. $\mathcal{N}(0, R)$ and R is a diagonal matrix. We restrict the measurement errors to explain no more than ten percent of the variance of the data.

The relationship between the observables and the latent variables, the fact that the model is linear, and that all innovations are Gaussian, makes it possible to compute the likelihood of the data, which in turn allows for the estimation of the parameters of the model. To calculate the likelihood it is convenient to express the model in state space form. To this end, let

$$\hat{x}_t = \begin{bmatrix} \hat{p}_t & \hat{y}_t \end{bmatrix}' \quad \text{and} \quad \xi_t = \begin{bmatrix} \hat{x}_t & \hat{x}_{t-1} & \hat{x}_{t-2} & \hat{x}_{t-3} & u_t \end{bmatrix}'.$$

Then the state space representation of the model, equations (1)-(7), is given by

$$\xi_{t+1} = F\,\xi_t + P\nu_{t+1} \tag{8}$$

and

$$o_t = H'\xi_t + \mu_t, \tag{9}$$

where the matrices F, P, and H are known functions of the matrices B^i_{pp}, B^i_{yp}, B^i_{yy}, for $i = 1, \ldots, 4$, C_{pX^p}, C_{pz^p}, C_{yX^p}, C_{yz^p}, C_{yX}, ρ, and ψ. The model is estimated with Bayesian techniques. Draws from the posterior distribution are obtained by applying the Metropolis-Hastings algorithm. We construct an MCMC chain of 2.5 million draws and discard the first 1.5 million.

The prior distributions of the estimated parameters are summarized in table 1. We impose normal prior distributions to all elements of B^i_{pp}, B^i_{yy}, and B^i_{yp} for $i = 1, \ldots, 4$. In accordance with the Minnesota prior, we assume that at the mean of the prior parameter distribution the elements of $\hat{x}_t$ follow univariate autoregressive processes. So when evaluated at their prior mean, only the main diagonals of B^1_{pp} and B^1_{yy} take nonzero values and all other elements of B^i_{pp}, B^i_{yy}, and B^i_{yp} for $i = 1, \ldots, 4$ are nil. We impose an autoregressive coefficient of 0.95 in all equations, so that all elements along the main diagonal of B^1_{pp} and B^1_{yy} take a prior mean of 0.95. We assign a prior standard deviation of 0.5 to these elements, which implies a coefficient of variation close to one half (0.5/0.95). Also along the lines of the Minnesota prior, we impose lower prior standard deviations on all other estimated elements of the matrices B^i_{pp}, B^i_{yy}, and B^i_{yp} for $i = 1, \ldots, 4$, and set them to 0.25.

All estimated elements of the matrices C_{pX^p}, C_{pz^p}, C_{yX^p}, C_{yz^p}, and C_{yX} are assumed to have normal prior distributions with mean zero and unit standard deviation, with one exception: the diagonal elements of C_{yX}, which govern the responses of $\hat{y}^i_t \equiv y^i_t - X^i_t - \alpha^i X^p_t$ to an innovation in ΔX^i_t for $i = 1, \ldots, 24$, are assumed to have a prior mean of -1. This means that a shock that increases output in country i in the long run by 1 percentage point, under the prior, has a zero impact effect. This prior is motivated by a strand of the business cycle literature suggesting that the impact effect on output of a permanent productivity shock could have either sign depending on the strength of the wealth effect on labor supply

Table 1: Prior Distributions

Parameter	Distribution	Mean	Std. Dev.
Main diagonal elements of B^1_{pp} and B^1_{yy}	Normal	0.95	0.5
All other estimated elements of B^1_{pp}, B^1_{yy}, B^1_{yp}	Normal	0	0.25
Estimated elements of B^i_{pp}, B^i_{yy}, B^i_{yp}, $i = 2, 3, 4$	Normal	0	0.25
Estimated elements of C_{pX^p} and C_{pz^p}	Normal	0	1
Diagonal of C_{yX}	Normal	-1	1
Elements of C_{yX^p} and C_{yz^p}	Normal	0	1
Diagonal of ρ(1:25,1:25)	Beta	0.3	0.2
All other estimated elements of ρ	Beta	0.7	0.2
Diagonal of ψ	Gamma	1	1
α_i, $i = 1, \ldots, 24$	Normal	0	1
Diagonal elements of R	Uniform$\left[0, \frac{\text{var}(o_t)}{10}\right]$	$\frac{\text{var}(o_t)}{10\times 2}$	$\frac{\text{var}(o_t)}{10\times\sqrt{12}}$
Elements of A	Normal	mean(o_t)	$\sqrt{\frac{\text{var}(o_t)}{T}}$

Notes. T denotes the sample length, which equals 231 quarters. The vector A denotes the mean of the vector o_t and is defined in the appendix.

(see, for example, Galí, 1999).

The diagonal elements of the matrix ψ, representing the standard deviations of the innovations in the exogenous shocks are all assigned Gamma prior distributions with mean and standard deviations equal to one. We impose nonnegative serial correlations on the exogenous shocks (the diagonal of ρ), and adopt Beta prior distributions for these parameters. We assume relatively small means of 0.3 for the prior of the serial correlations of the nonstationary shocks (ΔX^p_t, and ΔX^i_t for $i = 1, \ldots, 24$) and a relatively high mean of 0.7 for the stationary shocks (z^p_t and z_t). The prior distributions of all serial correlations are assumed to have a standard deviation of 0.2. The variances of all measurement errors (the diagonal elements of the matrix R) are assumed to have a uniform prior distribution with lower bound 0 and upper bound of 10 percent of the sample variance of the corresponding observable indicator. Although not explicitly discussed thus far, the estimated model includes constants. These constants appear in the observation equation (9), for details see the appendix. The unconditional means of the 36 observables are assumed to have normal prior distributions with means equal to their sample means and standard deviations equal to their sample standard deviations divided by the square root of the length of the sample period.

Posterior means and error bands around the impulse responses shown in later sections are constructed from a random subsample of the MCMC chain of length 100 thousand with replacement.

4 The Data

The model is estimated on quarterly data on eleven world commodity prices, the world interest rate, and the gross domestic product of twenty-four small open economies. The sample period is 1961.Q1 to 2018.Q4. The eleven commodity prices included in the estimation are beverages, food, agricultural raw materials, fertilizers, metal and minerals, gold, platinum, silver, coal, crude oil, and natural gas. The raw data is monthly and expressed in current U.S. dollars. The source is the World Bank's Commodity Price database (Pink Sheet) with the exception of coal prices, which come from Global Financial Data (GFD). The GFD coal price is identical to the one in Pink Sheet, except that it begins in 1960.M1 whereas it begins only in 1970.M1 in Pink Sheet. Quarterly real commodity price indices are constructed by first deflating the monthly nominal price indices by the monthly CPI index of the United States, then taking a simple average of the deflated values across the corresponding months in each quarter. The data are normalized by dividing by each series' 2010.Q4 observation. The World Bank publishes data on prices of 40 individual commodities. The aggregation into 11 prices responds to the need to economize on degrees of freedom in the estimation. The prices that are aggregates of individual commodities are beverages, food, agricultural raw materials, fertilizers, and metal and minerals. The aggregated price indices are taken from Pink Sheet. Thus the eleven commodity prices included capture information from all 40 commodity prices in the World Bank's Commodity Price database.

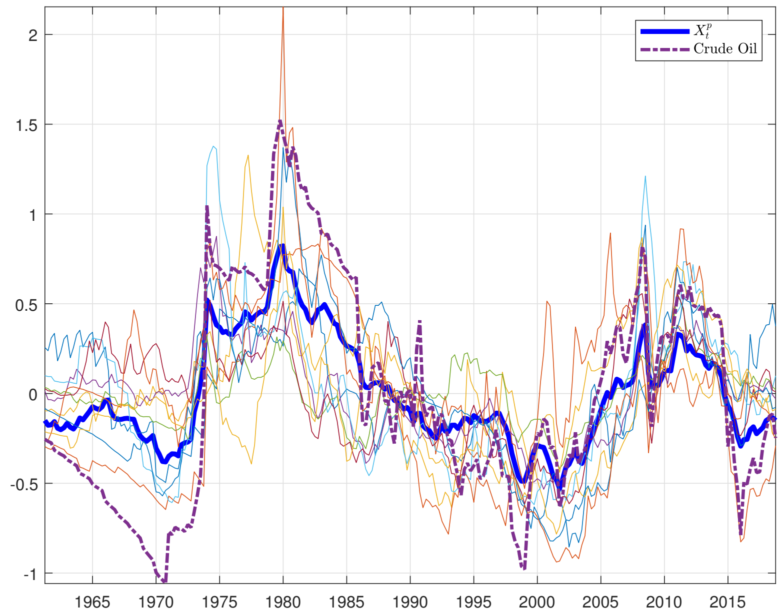
The quarterly time series for the world real interest rate, r_t^*, is constructed as $1 + r_t^* = (1 + i_t)E_t\frac{1}{1+\pi_{t+1}}$, where i_t denotes the nominal interest rate on three-month U.S. Treasury bills, and $1 + \pi_{t+1} = \frac{P_{t+1}}{P_t}$, denotes the gross growth rate of the consumer price index, P_t, as measured by the U.S. CPI index. The expected value of the inverse of gross inflation, $E_t\frac{1}{1+\pi_{t+1}}$ is approximated by the fitted component of an OLS regression of $\frac{1}{1+\pi_{t+1}}$ onto a constant, $\frac{1}{1+\pi_t}$, and $\frac{1}{1+\pi_{t-1}}$.

Output is measured by seasonally-adjusted real gross domestic product from the quarterly national accounts of the OECD.[2]

For a country to be included in the sample, we require at least 50 years of quarterly observations of real output. The rationale behind this restriction is that identifying the real effects of the commodity super cycle requires observing the behavior of output over a

[2]The OECD series name is VOBARSA. For Greece and Iceland the data appear not to have been seasonally adjusted at the source. Therefore, these two series were adjusted using the X-13 ARIMA-SEATS software produced, distributed, and maintained by the U.S. Census Bureau.

Figure 1: The Commodity Price Super Cycle



Notes. The permanent component of the eleven real commodity prices, X_t^p is computed by Kalman smoothing using the posterior mean of the parameter estimates. The thin solid lines are the eleven observed real commodity prices (beverages, food, agricultural raw materials, fertilizers, metal and minerals, gold, platinum, silver, coal, crude oil, and natural gas). All time series are constructed as cumulated demeaned growth rates.

relatively long period of time. In addition, since commodity prices and the world interest rate are assumed to be exogenous to the country, we exclude large economies. These selection criteria result in the following 24 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. The panel includes only four emerging economies, Korea, Mexico, South Africa, and Turkey. Section 7 estimates the model on annual data, which allows for the inclusion of a larger number of emerging economies.

5 The Commodity Price Super Cycle

Figure 1 displays the estimated common permanent component, X_t^p, of real commodity prices. It is constructed by Kalman smoothing at the posterior mean of the parameter estimate. The figure also displays the eleven observed commodity prices. We interpret the variable X_t^p as the commodity super cycle. The figure suggests that this interpretation is sensible as X_t^p appears to capture well the low frequency comovement of the individual commodity prices. Over the period 1960 to 2018 commodity prices display two distinct super cycles, one peaking in 1980 and the other in 2008. The rapid growth in X_t^p between the early 1970s and 1980 coincides with the OPEC oil price crises. As the market power of the oil cartel weakened in the 1980s and the supply of other countries (e.g., the United States and those located around the North Sea) rose, the downswing of the super cycle began. The expansionary phase of the second commodity-price super cycle begins around the time of China's accession to the WTO in 2001 and the peak is reached with the onset of the global financial crisis of 2008. The prediction of two commodity super cycles post 1960 and their dating is in line with the estimates reported in Erten and Ocampo (2013) using an asymmetric band pass filtering approach on real non-oil commodity prices that picks out cycles with periodicity between 20 and 70 years.

The permanent component of commodity prices, X_t^p, plays a significant role in explaining movements in these variables. Table 2 displays the fraction of the variance of changes in commodity prices accounted for by changes in their permanent component. On average across prices, ΔX_t^p explains more than one fourth of the variance of changes in commodity prices. The variance shares are estimated with precision, with standard deviations equal to two percentage points on average. The permanent component plays the largest role in explaining movements in crude oil prices with a variance share of 60 percent.

Estimating the price block of the model separately from the output block (not shown) yields similar results for the time path of X_t^p. Also this estimation approach yields a similar result for the average share of the variance of the growth rates of world prices explained by ΔX_t^p (21 percent when the price block is estimated separately versus 27 percent when it is estimated jointly with the output block). However, estimating the price block using only information on prices yields a smaller role for the permanent component, ΔX_t^p, in explaining the variance of the growth rate of crude oil prices (35 versus 60 percent). This finding suggests that even though the price block is independent of the output block, data on country level output is informative for the estimation of the parameters governing the dynamics of world prices.

Figure 2 presents the impulse responses of the eleven real commodity prices and the world interest rate to a unit long-run increase in the permanent component X_t^p along with 95-percent asymmetric confidence bands, computed using the methodology proposed by Sims and Zha (1999). In general, such an innovation is estimated to induce a positive but less than unity impact effect on commodity prices and a slow convergence to the permanently higher level, which by construction is equal to one. Outside of this pattern crude oil displays overshooting on impact and a convergence from above, and natural gas, fertilizers, gold, and

Table 2: Percent of Variance of the Growth Rate of Real Commodity Prices Explained by ΔX_t^p

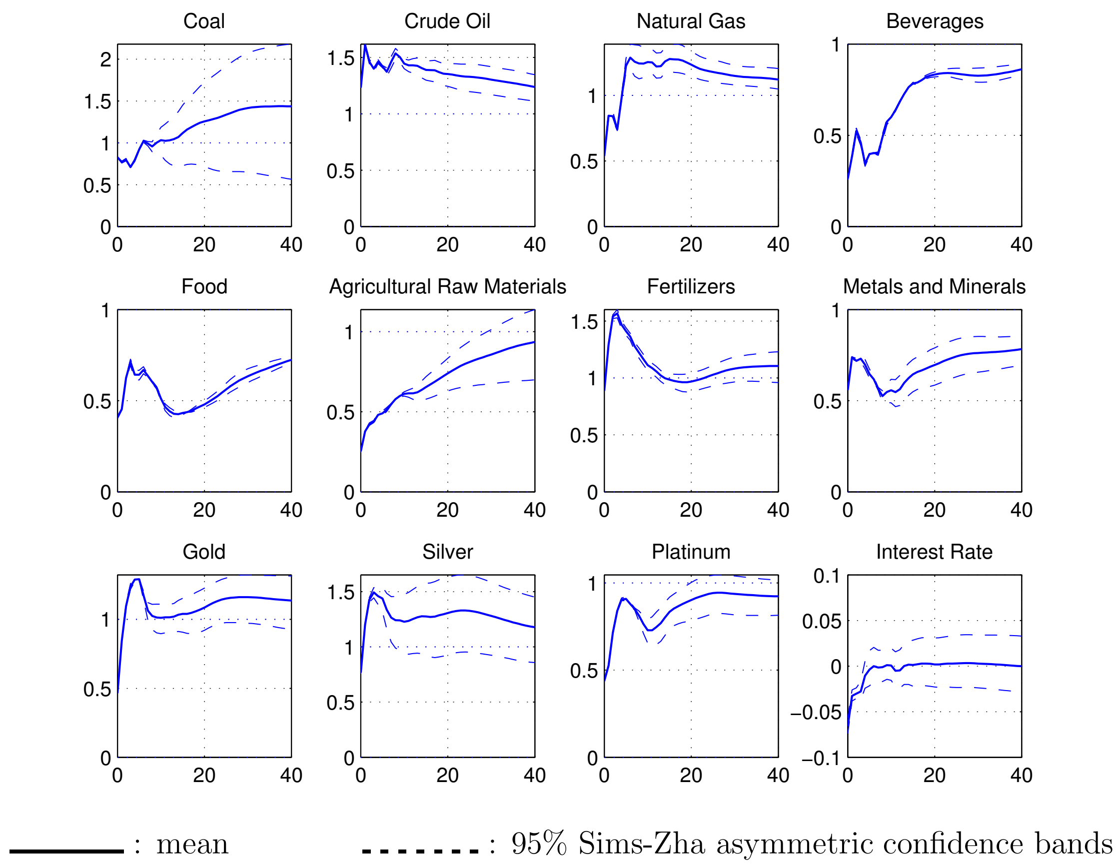
Price of	Mean	Std. Dev.
Coal	26	3
Crude Oil	60	2
Natural Gas	20	3
Beverages	11	1
Food	21	2
Agr. Raw Materials	20	3
Fertilizers	33	2
Metal and Minerals	30	2
Gold	30	2
Silver	28	2
Platinum	19	1
Mean of prices	27	2
Median of prices	26	2
Real Rate	15	8

Notes. The reported figures are based on 100,000 draws from the posterior distribution of the variance decomposition.

silver display delayed overshooting.

Notably, an increase in the permanent component of commodity prices has a negative effect on the world interest rate. The estimated negative conditional comovement between commodity prices and interest rates is of import for commodity exporters with external debt because it suggests that when commodity prices increase the country also benefits from favorable conditions in international financial markets. Similarly, during a downturn in commodity prices the costs of external debt rise. This result is in line with the work of Shousha (2016) who finds that movements in the interest rate are in part driven by variations in commodity prices. The novel aspect of the result documented here is that the negative comovement between commodity prices and interest rates is conditional on a permanent change in commodity prices. The finding that interest rates fall when commodity prices increase can also be interpreted as representing a particular manifestation of a phenomenon that Kaminsky, Reinhart, and Végh (2005) refer to as 'When it Rains, it Pours.'

Figure 2: Impulse Responses of World Prices to a Long-run Increase in X_t^p of Unity



6 How Important is the Commodity Super Cycle for Economic Activity

Thus far we have documented that the permanent component of commodity prices explains a sizeable fraction, over one fourth, of movements in commodity prices. In other words we have documented that there is a significant commodity super cycle. We now wish to ascertain the role of the commodity super cycle in explaining business cycle fluctuations in individual countries.

Table 3 displays the variance decomposition of output growth for the 24 countries in the sample. On average across countries the permanent component of commodity prices explains only 8 percent of the overall volatility of output growth. By contrast the transitory components of commodity prices jointly explain 62 percent of the variance of output growth. This result suggests that world shocks are important in explaining output movements in small open economies. However, the vast majority of the movements stem from stationary world disturbances. In this sense the role of the commodity super cycle is modest in accounting for business cycles. The importance of the commodity super cycle in explaining output fluctuations does not vary much across countries. The cross-sectional standard deviation of the variance share of output growth accounted for by ΔX_t^p is only 2.4 percentage points. This means that the relatively modest role played by the super cycle is not just valid on average but applies to most countries in the sample.

Table 3 also speaks to a large literature assessing the role of permanent versus transitory shocks in accounting for aggregate fluctuations in emerging and developed countries (see, for example, Aguiar and Gopinath, 2007). It shows that in the present sample of 24 countries the vast majority of fluctuations in output growth is driven by stationary shocks. Jointly the domestic and world stationary shocks (z_t^i and z_t^p) explain 80 percent of the variance of output growth on average across countries. Noticeably this result obtains not only for the developed countries in the sample but also for the emerging ones (Korea, 80 percent; Mexico, 93 percent; South Africa, 91 percent; and Turkey, 95 percent). The finding that stationary shocks explain the lion's share of output fluctuations in emerging countries is in line with those reported in García-Cicco, Pancrazi, and Uribe (2010), Chang and Fernández (2013) and Singh (2020).

It is of interest to ascertain the effects of the commodity price super cycle on commodity prices and aggregate activity at different time horizons. Table 4 presents forecast error variance decompositions of the level of commodity prices and the level of output at horizons of 5, 10, 20, and 30 years computed at the posterior mean of the parameter estimate. The top panel of the table shows that the commodity super cycle plays a sizeable role in explaining

Table 3: Variance Decomposition of Output Growth

	Shock			
Country	ΔX_t^p	z_t^p	ΔX_t^i	z_t^i
Australia	7	61	1	32
Austria	10	67	1	22
Belgium	8	84	7	1
Canada	10	71	1	19
Denmark	7	65	0	28
Finland	6	68	17	8
France	8	60	1	31
Greece	7	63	30	0
Iceland	5	47	45	2
Ireland	6	42	51	2
Italy	10	74	0	17
Korea, Rep.	11	60	10	20
Luxembourg	10	50	23	18
Mexico	7	71	0	22
Netherlands	8	58	33	1
New Zealand	5	51	36	8
Norway	4	55	19	22
Portugal	13	63	0	24
South Africa	9	61	0	29
Spain	12	69	0	19
Sweden	8	54	0	37
Switzerland	6	62	0	31
Turkey	4	51	0	44
United Kingdom	7	74	1	19
Mean	8	62	12	19
Median	8	62	1	20

Notes. The table presents the share (expressed in percent) of the total variance of output growth explained by shocks to the permanent component of commodity prices, ΔX_t^p, all twelve transitory commodity price shocks taken together, z_t^p, the country-specific nonstationary shock, ΔX_t^i, and the country-specific stationary shock, z_t^i. The reported numbers are averages over 100,000 draws from the posterior distribution of the variance decomposition.

the level of commodity prices at all forecasting horizons considered. The median share of X_t^p in the forecast error across the eleven commodity prices ranges from 67 percent at the 5-year horizon to 93 percent at the thirty-year horizon. This suggests that the commodity super cycle affects commodity prices not just at its own frequency of 20 years or higher, but also at shorter frequencies of 5 to 10 years.

By contrast, the commodity super cycle appears to play a secondary role in explaining movements in the level of output at horizons of 5 and 10 years, which are typically associated with business cycle fluctuations. The bottom panel of the table shows that the contribution of X_t^p in accounting for the forecast error variance is at most 12 percent at horizons of 10 years or less. At horizons of 20 and 30 years, which fall into the range of frequencies of the commodity super cycle itself, the contribution of X_t^p to explaining the variance of forecast errors of output increases to 19 percent. By contrast, stationary world shocks, the elements of the vector z_t^p, account for the majority of the forecast error variance of output at all horizons considered. Their median contribution ranges from 75 percent at the five-year forecasting horizon to 58 percent at the 30-year horizon. This indicates that the economic impact of the commodity super cycle on output relative to that of stationary world shocks is small at business cycle frequencies (10 years or less) and moderate at its own frequency (20 years or more).

The fact that the world and domestic stationary shocks, z_t^p and z_t^i, jointly explain the majority of the forecast error variance of output even at horizons of 20 and 30 years, 65 and 60 percent on average, respectively, indicates that the world and domestic nonstationary components, X_t^p and X_t^i, are not the dominant drivers of movements in output.

Figure 3 displays the impulse responses of the level of output, y_t, in each of the 24 countries to a permanent world shock, X_t^p, that increases commodity prices in the long run by 1 percent. In most countries the permanent commodity price increase is contractionary. One possible explanation for this finding is that the sample includes mostly developed open economies that are not important primary commodity producers. As we will see in section 7, in emerging countries the output response to an increase in the permanent component of world prices is in general positive. But even for primary commodity producers an increase in X_t^p could have an ambiguous effect on output for at least two reasons. One is that when X_t^p goes up, all commodity prices go up. To the extend that some commodities are imported and used as intermediate inputs in domestic production, an increase in X_t^p would result in an increase in marginal costs, which in turn, may lower domestic employment. The second reason is that because X_t^p represents a permanent increase in real commodity prices, it might entail a large positive wealth effect for the commodity producing country. In turn, this positive wealth effect could lead to a contraction in labor supply and in this way lower

Table 4: Forecast Error Variance Decomposition of the Level of Commodity Prices and Output

Shock	X_t^p				z_t^p				X_t^i				z_t			
Horizon (in years)	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30
Coal	52	66	77	82	48	34	23	18	0	0	0	0	0	0	0	0
Crude Oil	86	89	93	95	14	11	7	5	0	0	0	0	0	0	0	0
Natural Gas	73	83	90	93	27	17	10	7	0	0	0	0	0	0	0	0
Beverages	46	70	85	91	54	30	15	9	0	0	0	0	0	0	0	0
Food	38	52	76	85	62	48	24	15	0	0	0	0	0	0	0	0
Agr. Raw Materials	54	74	87	92	46	26	13	8	0	0	0	0	0	0	0	0
Fertilizers	68	78	87	91	32	22	13	9	0	0	0	0	0	0	0	0
Metal and Minerals	47	63	79	87	53	37	21	13	0	0	0	0	0	0	0	0
Gold	71	83	90	93	29	17	10	7	0	0	0	0	0	0	0	0
Silver	67	78	86	89	33	22	14	11	0	0	0	0	0	0	0	0
Platinum	67	81	90	93	33	19	10	7	0	0	0	0	0	0	0	0
Median	67	78	87	91	33	22	13	9	0	0	0	0	0	0	0	0
Interest Rate	8	7	6	7	92	93	94	93	0	0	0	0	0	0	0	0
Australia	5	2	2	7	82	89	87	80	5	6	8	11	8	3	2	2
Austria	19	27	33	36	74	70	65	63	1	1	1	1	6	2	1	1
Belgium	9	10	13	13	88	87	82	79	3	3	5	8	0	0	0	0
Canada	2	12	33	41	92	85	64	56	3	2	3	3	3	1	0	0
Denmark	6	13	22	24	88	84	76	74	0	0	0	0	6	3	2	2
Finland	5	8	11	10	60	59	50	42	34	32	39	48	1	0	0	0
France	20	27	36	41	70	69	61	56	2	2	2	2	8	2	1	1
Greece	1	2	5	5	95	96	92	91	3	2	2	3	0	0	0	0
Iceland	0	1	1	1	25	22	16	12	65	70	78	84	9	8	5	4
Ireland	4	2	1	2	26	18	11	7	69	79	88	91	1	1	0	0
Italy	12	14	15	14	81	83	83	84	0	0	0	1	7	3	1	1
Korea, Rep.	1	0	1	2	19	11	6	4	80	88	93	94	1	0	0	0
Luxembourg	29	35	36	33	43	36	27	22	25	28	36	44	3	1	1	1
Mexico	1	1	1	3	85	93	94	93	0	0	1	1	13	5	3	3
Netherlands	19	27	30	29	75	67	60	55	4	5	10	16	1	0	0	0
New Zealand	1	1	3	5	21	18	11	8	74	80	85	86	3	2	1	1
Norway	6	4	5	4	77	77	70	63	14	17	24	32	3	2	1	1
Portugal	24	23	25	25	69	74	74	73	0	0	0	0	7	3	2	1
South Africa	43	42	38	50	49	55	59	47	1	1	1	1	6	3	1	1
Spain	7	18	30	33	87	80	69	65	0	0	1	1	6	1	1	1
Sweden	8	36	59	67	74	58	38	30	2	2	1	2	16	5	2	1
Switzerland	8	15	29	33	75	75	65	61	1	1	2	3	16	9	4	3
Turkey	1	7	7	9	67	74	77	75	0	0	1	1	31	19	15	15
United Kingdom	17	28	39	42	77	67	56	52	2	3	4	5	4	2	1	1
Mean	10	15	20	22	67	64	58	54	16	18	20	22	7	3	2	2
Median	6	12	19	19	75	72	65	58	3	2	2	3	6	2	1	1

Notes. All shares are computed at the posterior mean of the estimated parameters and are expressed in percentage points.

equilibrium employment.

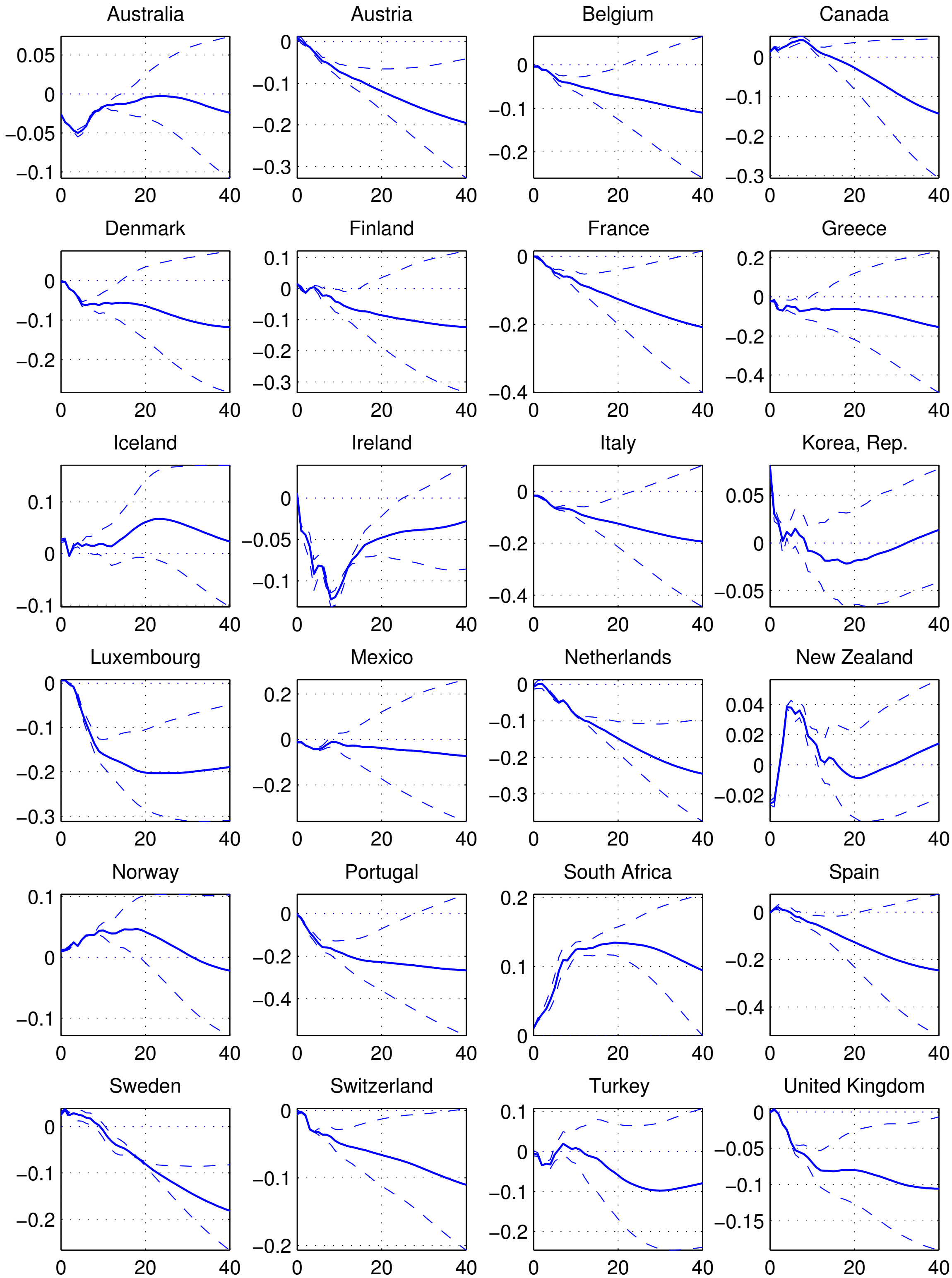
7 Emerging Countries

As mentioned earlier, long quarterly time series for output are available mostly for developed countries. As a result emerging countries are underrepresented in the sample. To shed light on the importance of the commodity super cycle in emerging countries, this section turns to an analysis based on annual data for which the coverage of this group of countries is more comprehensive. The empirical model is the one described in section 2 except for the number of lags and the number of commodity prices included. Because the data is annual, the model includes only one lag of prices and output, $\hat{p}_t$ and $\hat{y}_t$. To economize on the number of parameters estimated, the 11 commodity prices are aggregated into three indices, energy, non energy, and precious metals following the Pink Sheet aggregation scheme. Energy commodities include coal, crude oil, and natural gas. Non-energy commodities include beverages, food, agricultural raw materials, fertilizers, and metals and minerals. And precious metals comprise gold, silver, and platinum. The sample includes 24 emerging countries and 17 developed countries, which are listed in table 6. The output data comes from World Development Indicators. The selection of countries follows a number of criteria, which include data availability since 1960, a population of more than three million people in 2018, not having transitioned from a planned to a market economy, and having a common secondary data source for output. As in the analysis using quarterly data, the model is estimated using Bayesian techniques. The prior distributions for the model parameters are the same as those presented in table 1.

Figure 4 plots with thin lines the three real commodity price indices and with a thick line their estimated permanent component, X_t^p. As in the case of the estimation on quarterly data, the commodity super cycle is a smooth stochastic trend of the three prices, and displays two peaks since 1960, one in 1980 and the other in 2012. The peaks and troughs of the estimated commodity price supercycle line up with the ones identified using quarterly data on the more disaggregated commodity prices plotted in figure 1.

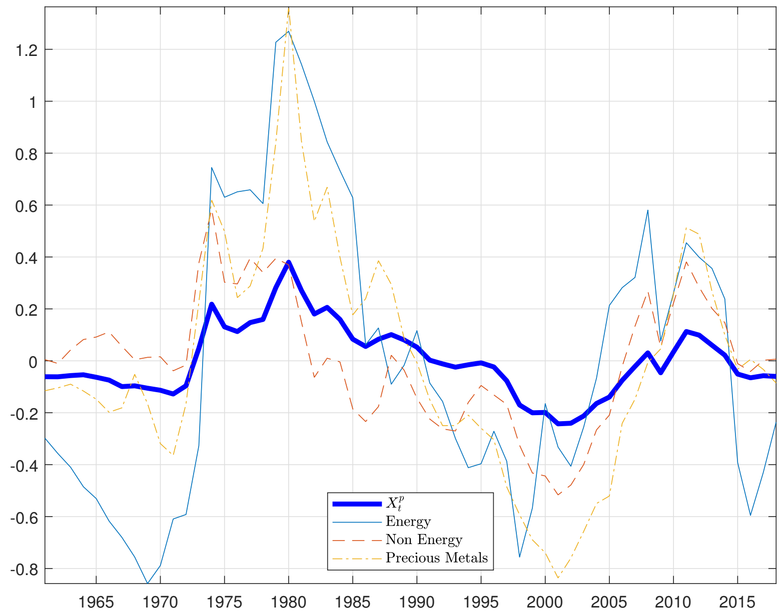
As shown in table 5, the permanent component, X_t^p, explains more than 90 percent of the variation in the growth rate of the three commodity indices. Thus, as in the quarterly estimation, the commodity super cycle is an important driver of commodity prices. A difference is that now the share of the variance of the growth rate of prices explained by the permanent component is much larger than the one estimated in quarterly data. This is to some extend expected since aggregation across time and across commodities tends to average away the effects of commodity specific and transitory disturbances. The table also shows that the

Figure 3: Impulse Responses of Output to a Long-run Increase in X_t^p of Unity



——— : mean - - - - - - - : 95% Sims-Zha asymmetric confidence bands

Figure 4: The Commodity Price Super Cycle in Annual Data



Notes. The permanent component of the three aggregate commodity price indices, X_t^p, is computed by Kalman smoothing using the posterior mean of the parameter estimates. All time series are constructed as cumulated demeaned growth rates.

commodity super cycle explains 25 percent of movements in the world interest rate, a share somewhat higher than the one obtained in the estimation on quarterly data (15 percent).

Table 6 displays the variance decomposition of output growth in the 24 emerging and 17 developed countries considered. As in the case of the analysis using quarterly data of mostly developed economies, it continues to be the case that all world shocks taken together, X_t^p and z_t^p, play a major role in explaining the variance of output growth. It also continues to be the case that of the contribution of world shocks to output fluctuations the majority is attributed to stationary disturbances, z_t^p. On average world shocks explain more than fifty percent of the variance of output in emerging countries and of this two thirds are attributable to stationary world shocks.[3]

The fact that stationary world shocks, z_t^p, explain a much larger share of the variance of output growth than of the variance of the growth rate of prices, indicates that these world

[3]The results are robust to estimating the model by maximum likelihood indicating that the findings are not due to the choice of priors. The maximum likelihood estimate assigns more importance (about 10 percentage points) to world shocks in explaining the variance of output growth. For emerging countries of this about one third is accounted for by the super cycle and two thirds by stationary world shocks. For developed countries, the relative importance of the super cycle is somewhat larger, with innovations to ΔX_t^p explaining about forty percent of the variance of output growth accounted for by world shocks.

Table 5: Percent of Variance of the Growth Rate of Annual World Prices Explained by ΔX_t^p

Price of	Mean	Std. Dev.
Energy Commodities	98	1
Non Energy Commodities	94	2
Precious Metals	94	1
Mean	95	1
Median	94	1
Real Rate	25	18

Notes. The reported figures are based on 100,000 draws from the posterior distribution of the variance decomposition.

shocks may be only partially mediated through commodity prices. An example of a world shock that could have an output effect both directly and through world commodity prices are productivity shocks that are correlated across countries.

Table 6 also speaks to the literature on the role of stationary and non-stationary shocks in explaining business cycles in emerging countries. The posterior mean joint contribution of stationary shocks, z_t^p and z_t^i, to the variance of output growth is 57 percent with the remaining 43 percent explained by non-stationary shocks, X_t^p and X_t^i. This result suggests that the majority of fluctuations in aggregate activity in the emerging countries considered stems from stationary domestic and world disturbances.

The explanatory preponderance of stationary world shocks in accounting for movements in output in emerging economies also manifests itself at different forecasting horizons. Table 7 displays the forecast error variance decomposition of the level of output at horizons 5, 10, 20, and 30 years. At forecasting horizons of 5 and 10 years, which are typically associated with business cycle frequencies, the mean share of variance explained by the stationary world shocks z_t^p is 40 and 38 percent, respectively, compared to 19 and 24 percent explained by the nonstationary world shock, X_t^p. At longer forecasting horizons of 20 and 30 years, the role of nonstationary world shocks increases, as expected, but does not clearly dominate that of stationary world shocks. Specifically, the variance of the forecasting error of output explained by X_t^p has a mean of 30 and 34 percent at horizons 20 and 30 years, compared to 34 and 31 percent for the stationary world shocks.

Figures 5 and 6 display the impulse response of output in the seventeen developed and twenty-four emerging economies, respectively, to a shock in X_t^p that increases energy, non-energy, and precious metal prices in the long run by 1 percent. The figures also include 95-percent confidence bands. In line with the results obtained in section 6 using quarterly data (figure 3), in developed economies a permanent increase in world commodity prices is

Table 6: Variance Decomposition of Output Growth — Annual Data

	Shock			
Country	ΔX_t^p	z_t^p	ΔX_t^i	z_t^i
Mean Emerging	18	32	24	25
Mean Developed	19	48	13	20
Argentina	16	8	74	1
Bangladesh	8	17	73	1
Bolivia	26	55	0	19
Brazil	21	33	0	45
Chile	10	18	0	71
Colombia	26	28	2	44
Costa Rica	25	42	28	4
Dominican Republic	8	8	0	84
Ecuador	34	32	33	1
Guatemala	20	78	1	1
India	10	24	63	2
Indonesia	15	50	32	2
Korea, Rep.	19	55	26	1
Malaysia	24	54	0	21
Mexico	12	40	47	1
Pakistan	8	35	57	1
Panama	14	16	0	70
Paraguay	30	19	0	50
Peru	18	19	0	63
Philippines	20	16	60	2
South Africa	35	27	1	36
Thailand	13	60	6	20
Turkey	4	16	79	0
Uruguay	18	21	0	61
Australia	6	27	64	4
Austria	25	51	1	22
Belgium	21	64	1	13
Canada	16	43	1	40
Denmark	21	54	2	21
Finland	17	60	19	3
France	18	77	2	4
Greece	22	47	0	30
Iceland	8	17	0	75
Italy	25	58	0	17
Luxembourg	28	22	50	1
Netherlands	18	50	0	32
Norway	10	39	3	49
Portugal	19	58	22	1
Spain	23	53	0	24
Sweden	14	63	21	2
United Kingdom	30	33	34	2

Notes. The table presents the share (expressed in percent) of the total variance of output growth explained by shocks to the permanent component of commodity prices, ΔX_t^p, all stationary world price shocks taken together, z_t^p, the country-specific nonstationary shock, ΔX_t^i, and the country-specific stationary shock, z_t^i. The reported numbers are averages over 100,000 draws from the posterior distribution of the variance decomposition.

Table 7: Forecast Error Variance Decomposition of the Level of Output — Annual Data

Shock	X_t^p				z_t^p				X_t^i				z_t			
Horizon (in years)	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30
Argentina	45	33	20	14	10	6	4	3	45	61	76	83	1	0	0	0
Bangladesh	15	12	9	9	26	41	38	33	55	45	52	57	4	2	1	1
Bolivia	1	6	48	65	63	69	41	30	0	1	1	1	36	25	10	5
Brazil	23	28	31	32	39	51	57	58	0	0	1	1	38	21	12	9
Chile	5	5	11	20	15	16	15	14	0	1	3	4	80	78	71	63
Colombia	34	42	58	69	29	30	25	18	1	2	2	2	37	26	15	10
Costa Rica	11	10	38	60	68	61	35	18	17	26	26	21	3	2	1	0
Dominican Republic	20	33	43	49	15	19	19	17	0	0	0	1	65	48	38	34
Ecuador	59	67	66	63	34	26	23	21	7	7	11	16	1	1	0	0
Guatemala	17	13	10	11	82	86	86	84	1	1	3	5	1	1	0	0
India	9	10	16	17	54	64	64	61	32	24	20	21	5	2	1	1
Indonesia	21	32	44	46	66	57	39	32	12	10	16	21	2	1	1	0
Korea, Rep.	9	7	5	9	77	54	49	45	12	38	45	46	3	1	0	0
Malaysia	16	18	31	42	50	43	36	32	0	1	2	2	33	38	31	24
Mexico	19	22	24	24	70	64	57	53	10	14	19	23	1	0	0	0
Pakistan	0	2	16	28	71	67	48	37	27	29	35	35	2	2	1	0
Panama	13	26	36	36	14	14	13	14	0	1	1	2	73	59	50	47
Paraguay	37	54	65	68	18	21	22	22	0	0	0	0	45	25	13	10
Peru	24	38	38	35	13	12	20	27	0	0	1	1	63	50	42	37
Philippines	19	19	12	10	5	5	10	14	74	75	77	75	2	1	1	1
South Africa	45	54	59	60	20	18	17	16	1	1	2	4	35	27	22	20
Thailand	1	1	6	14	66	63	67	65	1	3	7	8	32	32	20	13
Turkey	4	3	4	6	35	22	12	8	61	75	84	86	1	0	0	0
Uruguay	22	31	33	30	13	12	18	25	0	1	1	2	64	56	48	43
Mean–Emerging	19	24	30	34	40	38	34	31	15	17	20	21	26	21	16	13
Australia	0	0	0	0	69	62	46	36	24	34	52	62	7	4	2	1
Austria	4	2	1	2	86	93	95	94	1	1	1	2	9	4	2	2
Belgium	9	7	9	13	86	90	88	83	1	1	2	3	4	2	1	1
Canada	15	15	15	14	50	59	64	65	1	1	2	3	35	25	19	17
Denmark	13	12	8	7	68	75	81	82	2	3	5	6	16	9	6	5
Finland	7	4	3	3	86	87	85	81	3	6	10	14	4	3	2	2
France	2	1	5	13	94	96	92	84	1	2	2	2	3	2	1	1
Greece	21	30	38	41	55	59	57	55	0	0	0	0	24	11	5	4
Iceland	8	14	26	35	27	41	46	43	0	0	1	1	65	44	28	21
Italy	5	5	18	29	84	90	80	70	0	0	0	0	11	4	2	1
Luxembourg	28	37	33	27	47	32	22	18	23	31	45	55	1	1	0	0
Netherlands	3	5	6	6	72	81	85	86	0	1	1	1	24	13	8	7
Norway	1	6	17	24	48	66	69	65	3	4	4	4	48	23	10	7
Portugal	4	3	2	3	91	92	92	90	4	4	5	7	1	1	0	0
Spain	6	15	21	22	69	72	72	72	0	0	1	1	25	12	7	6
Sweden	4	3	6	10	89	88	77	66	5	8	16	23	2	2	1	1
United Kingdom	29	36	37	35	52	39	31	26	17	24	32	39	2	1	0	0
Mean–Developed	9	12	14	17	69	72	70	66	5	7	11	13	17	9	5	4

Notes. All shares are computed at the posterior mean of the estimated parameters and are expressed in percentage points.

contractionary for most countries. By contrast, for most emerging countries a permanent increase in commodity prices is expansionary. As pointed out in section 6, a possible explanation for this difference could be that in emerging countries the production of primary commodities represents a larger share of total output than it does in developed countries.

8 Conclusion

This paper aims to fill a gap in the literature on the transmission of world shocks through commodity prices to economic activity in open economies. An existing literature has documented the presence of a commodity price super cycle. An empirical techniques employed in many of these studies is based on spectral analysis and identifies one super cycle per commodity price. The resulting super cycles are positively correlated across commodities suggesting a common driver.

The first contribution of the present paper is to propose an alternative definition of the commodity price super cycle consisting in representing it as the common stochastic trend in all commodity prices. The so-identified super cycle turns out to share a number of key characteristics with the ones obtained using spectral analysis. An advantage of the common permanent component approach is that it lends itself to a joint estimation of the contributions of domestic and foreign transitory and permanent shocks to aggregate fluctuations in open economies.

The results of the paper suggest that world shocks are responsible for more than half of observed variations in aggregate activity in developed and emerging economies. However, more than two thirds of the contribution of world shocks is due to temporary disturbances leaving less than one third to the permanent world shock that drives the commodity supercycle. This result obtains both unconditionally and conditional on forecasting horizons. Importantly, even at horizons of 20 and 30 years, which are typically associated with the periodicity of the commodity price super cycle, the permanent world shock does not clearly dominate temporary world shocks in accounting for variations in aggregate activity.

Taken together these findings indicate that the permanent world shock that drives the commodity price super cycle does matter but does not play the central role in shaping short- or medium-run business cycle fluctuations.

Figure 5: Impulse Responses of Output to a Unit Long-Run Increase in X_t^p: Developed Economies

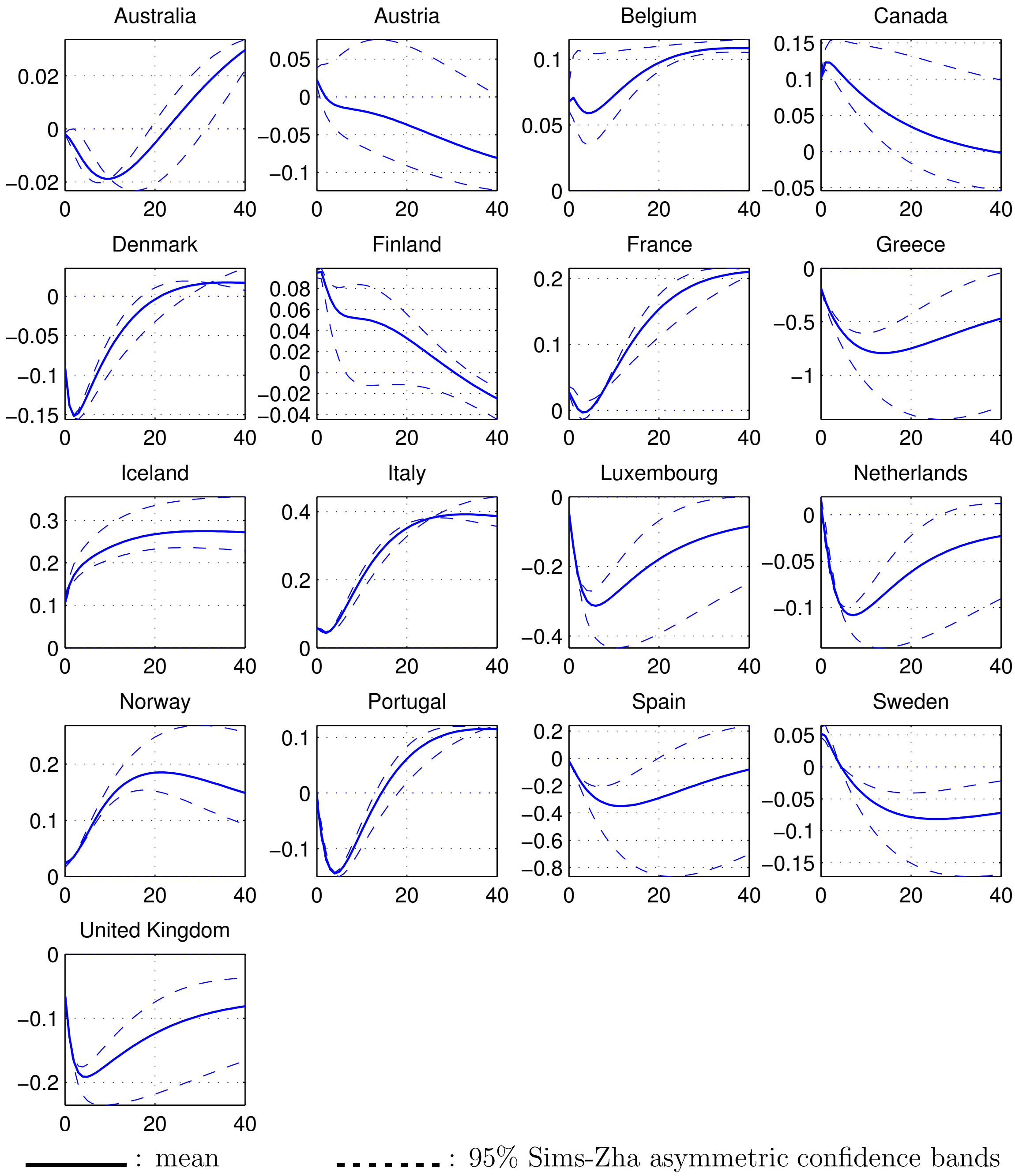
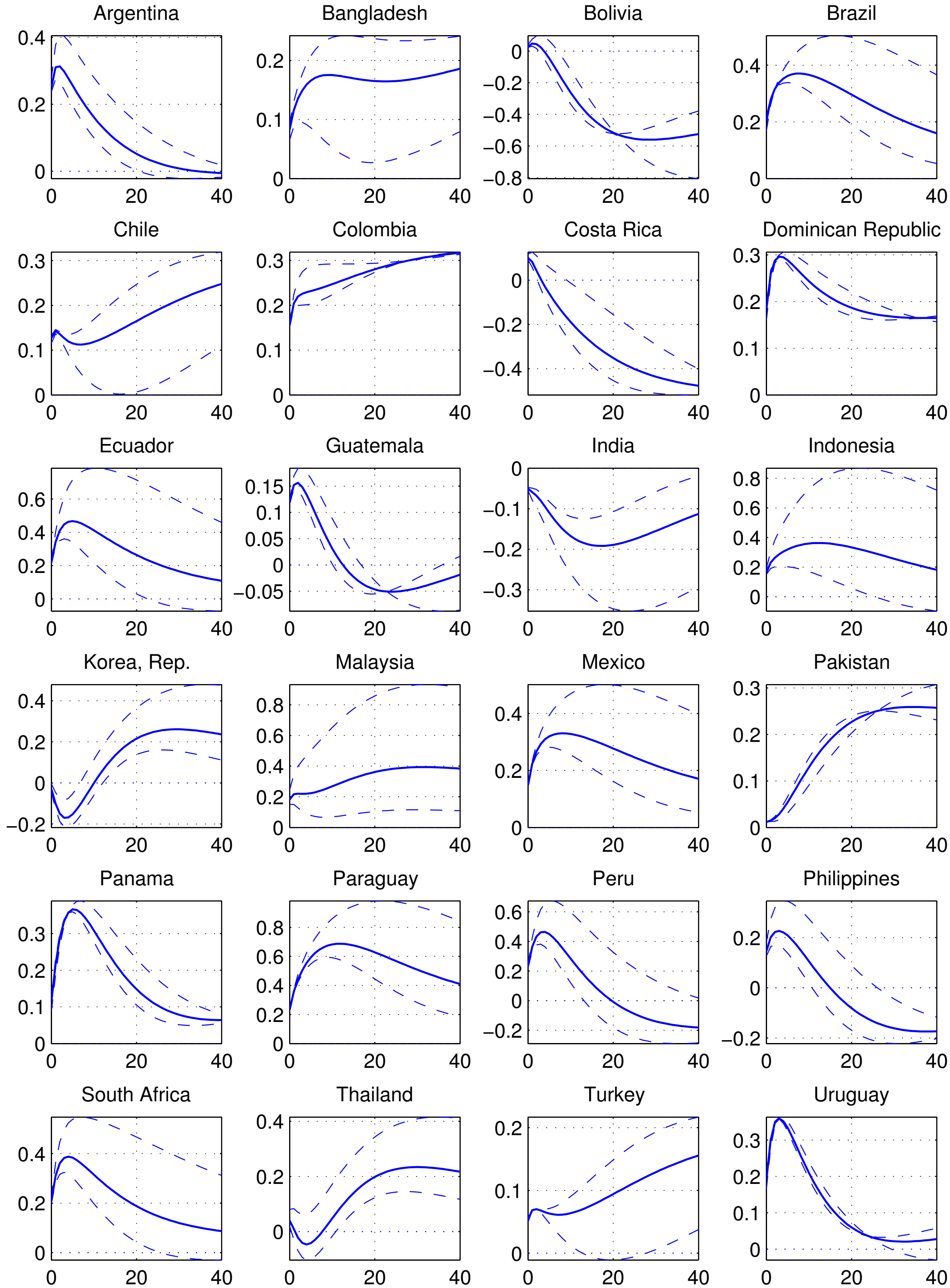


Figure 6: Impulse Responses of Output to a Long-Run Unit Increase in X_t^p: Emerging Economies



——— : mean - - - - - - - : 95% Sims-Zha asymmetric confidence bands

Appendix

In section 2, the presentation of the model omitted constant terms to facilitate the exposition. This appendix presents the model including those omitted constant terms. As we will see this will introduce a vector of constants, denoted A, into the observation equation (9). We will also derive expressions for the matrices F, P, and H of the state space representation of the model, equations (8) and (9).

Redefine the vectors $\hat{p}_t$, $\hat{y}_t$, and u_t as deviations from their respective means:

$$\hat{p}_t = \begin{bmatrix} p_t^1 - X_t^p - E(p_t^1 - X_t^p) \\ p_t^2 - X_t^p - E(p_t^2 - X_t^p) \\ \vdots \\ p_t^{11} - X_t^p - E(p_t^{11} - X_t^p) \\ \ln(1+r_t^*) - E(\ln(1+r_t^*)) \end{bmatrix}; \quad \hat{y}_t = \begin{bmatrix} y_t^1 - X_t^1 - \alpha^1 X_t^p - E(y_t^1 - X_t^1 - \alpha^1 X_t^p) \\ y_t^2 - X_t^2 - \alpha^2 X_t^p - E(y_t^2 - X_t^2 - \alpha^2 X_t^p) \\ \vdots \\ y_t^{24} - X_t^{24} - \alpha^{24} X_t^p - E(y_t^{24} - X_t^{24} - \alpha^{24} X_t^p) \end{bmatrix},$$

and

$$u_t \equiv \begin{bmatrix} \Delta X_t^p - E\left(\Delta X_t^p\right) \\ \Delta X_t - E\left(\Delta X_t\right) \\ z_t^p - E(z_t^p) \\ z_t - E(z_t) \end{bmatrix}.$$

The evolution of the vector $\hat{p}_t$ is

$$\hat{p}_t = \sum_{i=1}^{4} B_{pp}^i \hat{p}_{t-i} + C_{pX^p}\left(\Delta X_t^p - E\left(\Delta X_t^p\right)\right) + C_{pz^p}\left(z_t^p - E(z_t^p)\right). \tag{10}$$

The evolution of $\hat{y}_t$ is

$$\begin{aligned} \hat{y}_t \quad = \quad & \sum_{i=1}^{4} B_{yp}^i \hat{p}_{t-i} + \sum_{i=1}^{4} B_{yy}^i \hat{y}_{t-i} \\ & + C_{yX^p}\left(\Delta X_t^p - E\left(\Delta X_t^p\right)\right) + C_{yz^p}\left(z_t^p - E(z_t^p)\right) \\ & + C_{yX}\left(\Delta X_t - E\left(\Delta X_t\right)\right) + \left(z_t - E(z_t)\right). \end{aligned} \tag{11}$$

The evolution of the exogenous shocks, u_t, is

$$u_t = \rho u_{t-1} + \psi \nu_t. \tag{12}$$

Let

$$\hat{x}_t = \begin{bmatrix} \hat{p}_t & \hat{y}_t \end{bmatrix}'; \quad \text{and} \quad \xi_t = \begin{bmatrix} \hat{x}_t & \hat{x}_{t-1} & \hat{x}_{t-2} & \hat{x}_{t-3} & u_t \end{bmatrix}'.$$

The system of equations (10), (11), and (12) can then be expressed as:

$$\hat{x}_{t+1} \quad = \quad B \begin{bmatrix} \hat{x}_t \\ \hat{x}_{t-1} \\ \hat{x}_{t-2} \\ \hat{x}_{t-3} \end{bmatrix} + Cu_{t+1}, \tag{13}$$

where

$$B \equiv \begin{bmatrix} B^1_{pp} & \emptyset_{12\times 24} & B^2_{pp} & \emptyset_{12\times 24} & B^3_{pp} & \emptyset_{12\times 24} & B^4_{pp} & \emptyset_{12\times 24} \\ B^1_{yp} & B^1_{yy} & B^2_{yp} & B^2_{yy} & B^3_{yp} & B^3_{yy} & B^4_{yp} & B^4_{yy} \end{bmatrix}$$

and

$$C \equiv \begin{bmatrix} C_{\hat{p}X^p} & \emptyset_{12\times 24} & C_{\hat{p}z^p} & \emptyset_{12\times 24} \\ C_{\hat{y}X^p} & C_{\hat{y}X} & C_{\hat{y}z^p} & I_{24\times 24} \end{bmatrix}.$$

The vector ξ_t evolves over time as

$$\xi_{t+1} = F\xi_t + P\nu_{t+1},$$

where

$$F = \begin{bmatrix} B & C\rho \\ I_{108\times 144} & \emptyset_{108\times 61} \\ \emptyset_{61\times 144} & \rho \end{bmatrix}; \quad \text{and} \quad P = \begin{bmatrix} C\psi \\ \emptyset_{108\times 61} \\ \psi \end{bmatrix}.$$

Given the redefinition of $\hat{p}^i_t$, the observation equations (4), (5), and (6) become

$$\Delta p^i_t = \Delta\hat{p}^i_t + (\Delta X^p_t - E(\Delta X^p_t)) + E(\Delta X^p_t); \quad i = 1, \ldots, 11,$$

$$\Delta y^i_t = \Delta\hat{y}^i_t + (\Delta X^i_t + \alpha^i\Delta X^p_t - E(\Delta X^i_t + \alpha^i\Delta X^p_t)) + E(\Delta X^i_t + \alpha^i\Delta X^p_t); \quad i = 1, \ldots, 24,$$

and

$$\ln(1 + r^*_t) = (\ln(1 + r^*_t) - E(\ln(1 + r^*_t))) + E(\ln(1 + r^*_t)).$$

In vector form the observation equations can be expressed as

$$o_t = A' + H'\xi_t + \mu_t$$

where

$$A = \begin{bmatrix} E(\Delta X^p_t) & \ldots & E(\Delta X^p_t) & E(\ln(1 + r^*_t)) & E(\Delta X^1_t + \alpha^1\Delta X^p_t) & \ldots & E(\Delta X^{24}_t + \alpha^{24}\Delta X^p_t) \end{bmatrix},$$

$$H' = \begin{bmatrix} I_{36\times 36} & H_2 & \emptyset_{36\times 72} & H_4 & H_5 & \emptyset_{36\times 36} \end{bmatrix}$$

with

$$H_2 = -\begin{bmatrix} I_{11\times 12} & \emptyset_{11\times 24} \\ \emptyset_{1\times 12} & \emptyset_{1\times 24} \\ \emptyset_{24\times 12} & I_{24\times 24} \end{bmatrix}$$

$$H_4 = \begin{bmatrix} 1_{1\times 11} & 0 & \alpha^1 & \dots & \alpha^{24} \end{bmatrix}'$$

$$H_5 = \begin{bmatrix} \emptyset_{12\times 24} \\ I_{24\times 24} \end{bmatrix}.$$

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