World Shocks, Commodity Prices and Domestic Inflation

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Abstract

World shocks to global commodity prices can explain fluctuations in domestic inflation, but the extent to which these shocks affect inflation is debatable. Using a factor model, I extract the common factors from a set of commodity prices, characterizing their co-movement to proxy for world prices. I then devise a structural vector autoregressive model for a set of 67 advanced and emerging countries for the period 1970-2014. World shocks affect these countries' domestic economies through changes in common factors of commodity prices and the world interest rate. My results show that world shocks can explain between 26% and 38% of inflation fluctuations in the median country in the set considered in this study. These results have implications for monetary policymakers in that they highlight the need to use multiple commodity prices factors to assess the effects of world shocks on domestic inflation. Previous studies that used single-world-price vector autoregression models have significantly underestimated the importance of world shocks for domestic business cycles. Similarly, I find that the fraction of the inflation variance explained by world shocks falls by more than half (below 13% in the median country) when a single world price is included in the model. This study extends the literature by using three commodity price factors to explain their effects on domestic inflation.

Key words: world shocks, commodity prices, domestic inflation

JEL classification: E31, E32, F44, F62

1 Introduction

World shocks have impacts on domestic inflation. However, there is no consensus about the extent to which world shocks mediated by commodity price changes can affect domestic inflation. The results of a counterfactual exercise by Kilian (2008a) suggest that the evolution of the consumer price index (CPI) in the G7 countries is similar overall to the observed path of inflation even in the absence of exogenous shocks to oil production. However, Gelos and Ustyugova (2017) contradict these results when studying the importance of commodity price changes on explaining inflation fluctuations. They find that food price shocks alone explain less than 10% of inflation fluctuations. Moreover, Fernández, Schmitt-Grohe, and Uribe (2017) find that commodity prices are an important way by which world disturbances can spread to domestic economies. This result points to the drawback of relying on a single-price model to capture the volatility resulting from commodity shocks. This paper investigates this impact using commodity price factors rather than indices to obtain the highest variations of commodity price fluctuations.

In this paper, I use commodity price factors to proxy for world shocks to re-visit the importance of world shocks in explaining changes in domestic inflation. To do so, I include a large set of commodity prices which I aggregate using a factor model. Kamber and Wong (2020) use a similar foreign-domestic SVAR structure with commodity price indices and the common factors of the macroeconomic indicators of advanced economies to proxy for global economic indicators. They separate trends and cycles in inflation measures to find the contribution of world shocks to inflation gap. My approach is based on the idea that there is a co-movement among commodities in the short run as in suggested by Rossen (2015) and Byrne, Fazio, and Fiess (2011). They document a statistically significant degree of co-movement due to a common factor in commodities. Thanks to the use of common factors, I can summarize factors characterizing the co-movement in commodity prices and, in turn, measure their impact on inflation fluctuations (Forni, Hallin, Lippi, & Reichlin, 2000; Stock & Watson, 1998). This method allows me to measure the fraction of domestic fluctuations in inflation that commodity price factors can explain.

To investigate the impact of commodity price shocks on domestic inflation, I incorporate commodity price factors obtained from a factor model into a structural vector-autoregressive (SVAR) model. Furthermore, since the prices of internationally traded commodities, such as food, metal, and fuel, reflect changes in the supply and demand conditions of the world markets, these prices are also informative about world shocks (Jiménez-Rodríguez & Sánchez, 2005; Kilian, 2008b). To incorporate this assumption in my study, I adopt the SVAR model proposed by Fernández et al. (2017). They focus on the impact of changes in commodity price indices, weighted averages over spot prices, on variations in output, investment, and consumption. In contrast, I study the effect of changes in commodity prices on domestic inflation fluctuations. To do this, I extract factors characterizing the co-movement of commodity prices over 43 commodities. The model is built on the insight that world shocks are transmitted to small open economies via changes in world prices (commodity price factors). Even though my approach does not identify the structural shocks that directly drive world prices, it provides a means through which to assess the historical contribution of world shocks to inflation fluctuations. Thus, the main statistic of interest is the fraction of the variance of inflation (for each of the 67 countries in the sample) that can be attributed to world shocks that are mediated by commodity price factors. The results suggest that commodity price shocks have a 26% impact on domestic inflation.

My paper builds on several empirical studies that link the co-movements of commodity prices with inflation. Gospodinov and Ng (2013) extract common factors from a panel of 23 commodity convenience yields to forecast inflation. Using a dynamic latent factor model, Neely and Rapach (2011) find that common fluctuations in international inflation rates around their long-run averages, or global inflation, explain 35% of inflation fluctuations. In contrast, my results use commodity prices to explain the cross-sectional variation in domestic inflation. My paper also investigates the impact of commodity price shocks on domestic prices: through commodity prices alone. This is known as the first-round effect (Auer, Borio, & Filardo, 2017; Gelos & Ustyugova, 2017; Kaldor, 1976; Kose, 2002; Neely & Rapach, 2011). World shocks could accordingly spill over into the prices of goods and services other than commodities through production costs in other industries. This is known as the second-round effect (Sekine & Tsuruga, 2018).

My paper also contributes to the literature on world-price models that are used to capture world shocks. Some studies focus on the role of single-price models, most notably of oil prices and their impact on inflation. Barsky and Kilian (2001) argue that significant oil price increases were not nearly as essential as thought in terms of their role as a causal mechanism of the stagflation of the 1970s. They document that only ten percentage point of inflation fluctuations are explained by economic contraction during 1973-1975. Hooker

(2002) identifies a structural break in core U.S. inflation-unemployment Phillips curves that show that oil prices substantially contributed to inflation before 1981 whereas the pass-through has been negligible in 1986, a six percent in the case with a break. Gisser and Goodwin (1986) find no support that oil price shocks Granger-cause inflation post-1973. However, I find that single measures of world prices may not provide sufficient information to explain the channels through which world shocks are transmitted to domestic inflation. Empirically, Gelos and Ustyugova (2017) estimate country-by-country Phillips curves augmented by commodity prices for the period 2001–2010 using food/oil price indices. They find that the median long-term pass-through of a 10 percentage point food price shock to domestic inflation is 0.2 percentage points for advanced economies and almost 0.8 percentage points for emerging economies. I find that commodity price factors explain 26% of inflation fluctuations for the median country after correcting for the small-sample bias.

To my knowledge, my paper is the first to test the importance of world shocks using commodity price factors to explain inflation fluctuations. The analysis in this paper includes 67 advanced and emerging economies over the period 1970-2014.[1] My results suggest that commodity price factors can explain 26% of inflation fluctuations. This statistic implies an increased contribution of world shocks to changes in domestic inflation rates compared to previous studies. I also investigate the impact of commodity price shocks through the second-round effect, which suggests that headline inflation fluctuations explained by world shocks are almost 10 percentage points higher than core inflation fluctuations. This finding is consistent with the definition of core inflation does not include price information on the food and energy sector (Sekine & Tsuruga, 2018).

Finally, this paper highlights the importance of other mechanisms contributing to domestic inflation fluctuations. For instance, I confirm the importance of the world interest rate as an additional transmission channel through which world shocks affect domestic inflation (Gruber & Vigfusson, 2018; Kose, 2002). When the world's real interest rate is included in the SVAR model, the fraction of inflation explained by world shocks increases to 34%. Furthermore, Halka and Kotlowski (2017) discuss the impact of the global economic environment on domestic inflation using the SVAR approach to identify the global shocks. These authors document that low inflation in the examined countries

[1] Compared to previous studies, I include more commodity series (43 commodities) in the factor model to extract commodity price factors to proxy for commodity price shocks.

results from favorable commodity price shocks and weak domestic and external demand pressures. Thus, I also include a global economic index in an SVAR that explains 38% of inflation fluctuations. My results show that When a single world price is used in the estimation, less than 13% of inflation fluctuations are explained by commodity price shocks. In this respect, my results echo the conclusions of Fernández et al. (2017) and Fernández, González, and Rodríguez (2018), who demonstrate the importance of using multiple world prices for output fluctuations.

These findings have implications for monetary policy, particularly in dealing with the inflation-unemployment trade-off. As monetary policy aims to maintain low, stable inflation, policymakers need to consider the importance of commodity price changes and the extent to which they influence domestic inflation. This study adds to the literature as it introduces three commodity price factors in a model that includes a large sample of countries. The results provide a novel way to define world prices and the extent to which world shocks affect domestic inflation. These are issues monetary policymakers are interested in.

The rest of the paper is organized as follows. Section 2 describes how to obtain factors characterizing the co-movement in commodity prices. Section 3 describes the empirical strategy and the data. Section 4 presents the main results. Section 5 describes the alternative specifications. Section 6 concludes.

2 Commodity price factors

Commodities play an essential role in international supply chains, production, and final goods' prices. Commodities such as oil or metals are in high demand in advanced economies and often represent the main source of revenue of emerging economies (Deaton, 1999; Murphy & Hall, 2011). Thus, commodity price shocks can have significant impacts on both global economic activity and macroeconomic performance and living standards in many countries (Kyrtsou & Labys, 2006). Previously, Chen, Turnovsky, and Zivot (2014) use a single commodity price index constructed as the weighted average of fuel, metals, and agricultural spot prices to explore in-sample predictive regressions in forecasting inflation. They document that the information obtained from global commodity markets has low predictive power in forecasting inflation. However, I find that using a single measure underestimates the impact of commodity price shocks on domestic inflation. My results also suggest that three factors extracted from all commodity prices have a more substantial impact on inflation than using three price indices as world shocks.

In this paper, I include the data on 43 commodity prices. It is not practical to include all these series in a VAR model due to reduced degrees of freedom. Previous papers propose using a factor model with a large panel of commodity series as a useful method to reduce the dimensionality of the parameters while extracting factors characterizing the co-movement in commodity prices (Cuddington & Jerrett, 2008; De Nicola, De Pace, & Hernandez, 2016; Gospodinov & Ng, 2013). West and Wong (2014) empirically document that factor models do better compared to any other models since commodity prices consistently display a tendency to revert toward the extracted factor to mitigate the impact of world shocks on domestic business cycles. In this regard, Byrne et al. (2011) use factor analysis and find significant evidence of co-movement for a variety of metal commodities.

I use the factor model to extract the co-movements of 43 commodity prices to document the impact of world shocks. This allows me to capture the global commodity movements that carry important implications for researchers and policymakers. I use the HP-filter method over the series of commodities to take the cyclical component of real commodity prices and normalize each series by its standard deviation. Then, I extract factors characterizing the co-movement in commodity prices. Table 1 lists the factor loadings of the 1^{st}, 2^{nd}, and 3^{rd} components of the commodity price series obtained from the factor model. From the table, it is clear that none of those factors solely explains the variability of fuel, metals, and agricultural prices. In other words, multiple factors are required to capture the co-movement in commodity prices to proxy for world shocks.This finding is consistent with my result in section 4.4 that single-world-price models underestimate the importance of world shocks on domestic business cycles. Following the method suggested by Bai and Ng (2002), I find that the first three leading factors optimally explain the variability of commodity prices. This is why I use these three particular factors in my analysis. Table A1 shows the test results.

Figure 1 shows the 1^{st}, 2^{nd}, and 3^{rd} factors of the commodity series, over the period 1970-2014—the black lines. Two observations are worth pointing out. First, commodity price factors are volatile, and this suggests that commodity price changes could be a potentially important source of inflation fluctuations. Second, there is a relatively strong co-movement among these commodity series. These features are confirmed in Table A2, which shows the second moments of the commodity price factors. I also use a scree plot to

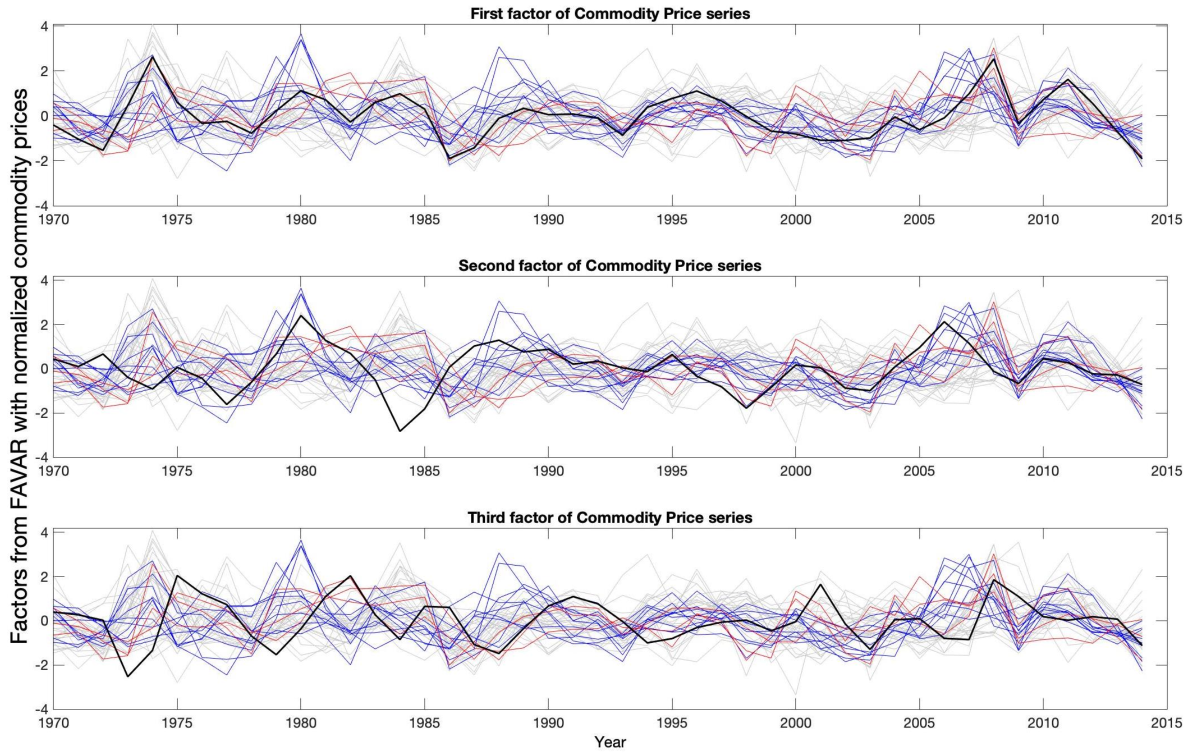
Table 1: Factor loadings associated with commodities

Commodity	Coefficient of 1^{st} factor	Commodity	Coefficient of 2^{nd} factor	Commodity	Coefficient of 3^{rd} factor
			Agricultural prices		
Urea	0.21	Sugar, world	0.17	Wheat	0.28
Maize	0.21	Rubber, SGP/MYS	0.12	Logs	0.23
Rice, Thai 5%	0.21	Orange	0.10	Coffee	0.21
DAP	0.20	Beef	0.09	Banana, US	0.19
TSP	0.20	Sawnwood, Malaysian	0.07	Phosphate rock	0.13
Sorghum	0.20	coffee	0.07	Potassium chloride	0.00
Soybean oil	0.20	Logs	0.07	Tobacco, U.S. import u.v.	-0.01
Barley	0.20	Wheat	0.07	Orange	-0.01
Coffee	0.19	Banana, US	-0.01	Tea	-0.01
Logs	0.19	Rice, Thai 5%	-0.02	Sugar, world	-0.01
Palm oil	0.19	Urea	-0.03	TSP	-0.04
Wheat	0.19	TSP	-0.03	Sorghum	-0.07
Rubber, SGP/MYS	0.18	DAP	-0.06	Maize	-0.10
Copra	0.18	Cotton, A Index	-0.06	DAP	-0.11
Coconut oil	0.17	Potassium chloride	-0.06	Groundnut oil	-0.12
Soybeans	0.17	Barley	-0.08	Urea	-0.14
Groundnut oil	0.15	Sorghum	-0.14	Rice, Thai 5%	-0.14
Sugar, world	0.14	Shrimps, Mexican	-0.14	Barley	-0.16
Cotton, A Index	0.14	Copra	-0.14	Shrimps, Mexican	-0.16
Potassium chloride	0.14	Coconut oil	-0.16	Meat, chicken	0.02
Phosphate rock	0.10	Soybeans	-0.16	Sawnwood, Malaysian	0.01
Sawnwood, Malaysian	0.10	Phosphate rock	-0.16	Soybean oil	0.29
Banana, US	0.03	Maize	-0.17	Cotton, A Index	0.28
Cocoa	0.02	Palm oil	-0.20	Cocoa	0.25
Tea	0.02	Groundnut oil	-0.21	Beef	0.05
Orange	0.01	Soybean oil	-0.22	Soybeans	0.01
Beef	-0.04	Cocoa	-0.23	Palm oil	-0.02
Tobacco, U.S. import u.v.	-0.04	Tobacco, U.S. import u.v.	-0.25	Rubber, SGP/MYS	-0.17
Meat, chicken	-0.09	Tea	-0.27	Coconut oil	-0.22
Shrimps, Mexican	-0.10	Meat, chicken	-0.28	Copra	-0.24
			Fuel prices		
Crude oil, average	0.16	Crude oil, average	0.04	Coal, Australian	0.14
Coal, Australian	0.16	Coal, Australian	0.03	Gas	0.11
Gas	0.05	Gas	-0.02	Crude oil, average	0.32
			Metal prices		
Tin	0.19	Platinum	0.31	Iron ore, cfr spot	0.23
Gold	0.18	Copper	0.22	Tin	-0.05
Silver	0.18	Nickel	0.20	Nickel	-0.07
Copper	0.17	Aluminum	0.20	Gold	-0.08
Lead	0.15	Lead	0.18	Silver	-0.10
Zinc	0.12	Gold	0.16	Lead	-0.11
Iron ore, cfr spot	0.11	Silver	0.14	Platinum	-0.11
Nickel	0.09	Zinc	0.07	Zinc	-0.11
Aluminum	0.07	Iron ore, CFR spot	0.02	Copper	-0.14
Platinum	0.07	Tin	-0.06	Aluminum	-0.01

Note: This table shows the factor loadings of the 1^{st}, 2^{nd}, and 3^{rd} components of a commodity price series of a factor model of 43 commodities. The commodity prices are standardized in my estimation.

select the number of factors that carry sufficient information on these commodity series. Figure 2 displays the scree plot for the common factors (of the commodity series) that confirm that three leading factors explain 90% of the fluctuation in the commodity price series. Thus, in this paper, I apply three commodity price factors to proxy for commodity price shocks. Table A3 in the appendix lists all of the commodity series used in this sample. I regress the normalized commodity price series on the common factors obtained from the factor model to show how much these factors can explain each commodity (R^2). Table A4 reports the R^2 of the OLS analysis that includes one, three, six, and ten factors. This table shows that if I use three factors in the SVAR model, they can explain 54% of

Fig. 1: Factors characterizing the co-movement in commodity prices over the period 1970-2014

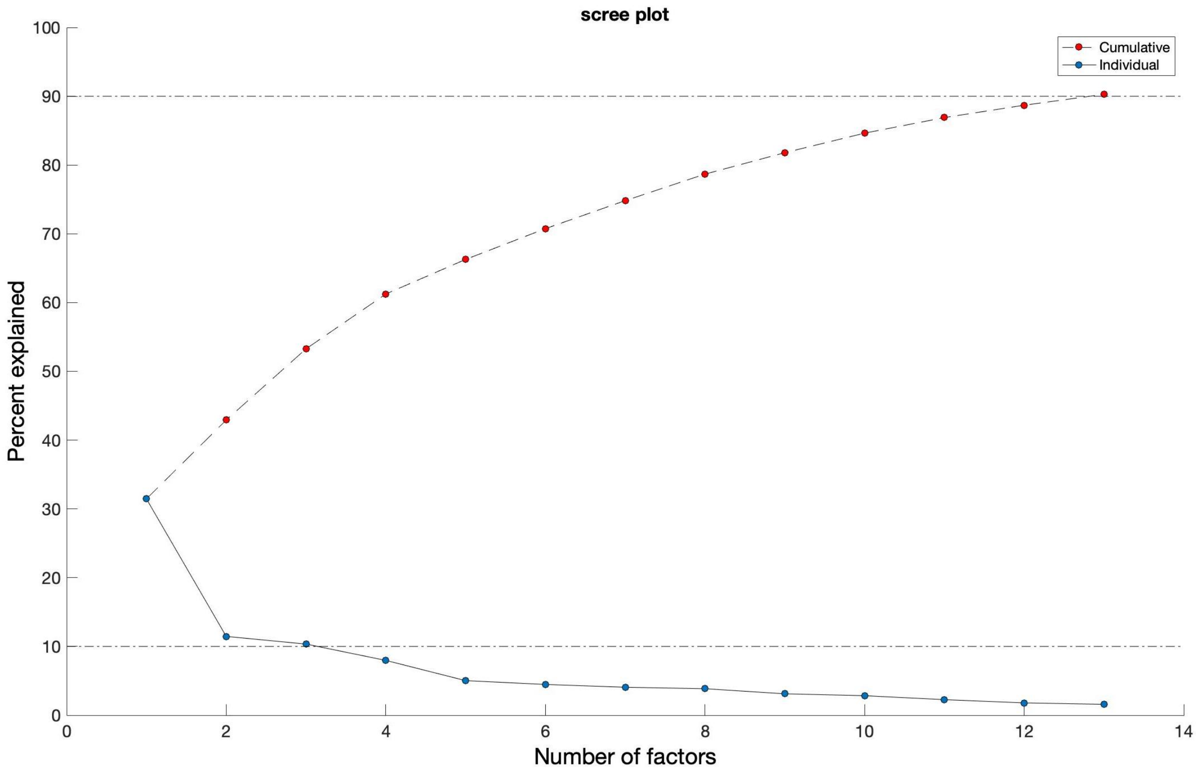


Note: The grey, blue, and red lines are the cyclical components of agricultural, metal, and fuel price series in percent deviations from the trend obtained using HP(100) filtering. The black lines represent the 1^{st}, 2^{nd}, and 3^{rd} factors of the commodity price series over the period 1970-2014. These factors capture the highest volatilities of the series that proxy for world shocks in this paper, according to the definition of principle component analysis.

these commodity series.

The approaches that are the most related to my own are those of Yin and Han (2015) and Gospodinov and Ng (2013). Yin and Han (2015) uses a monthly data set of 24 commodities in a dynamic latent factor model that extracts factors characterizing the co-movement in commodity prices and decomposes commodity returns into global, sectoral and idiosyncratic components. Gospodinov and Ng (2013) decomposes commodity convenience yields into factors and uses these estimated factors to forecast inflation. They explore what occurs when they model the co-movements of real commodity prices via a static factor model for 23 commodity convenience yields. They find that the two leading factors of convenience yields incorporate useful information for predicting inflation and commodity prices.

Fig. 2: The scree plot of factor loadings for commodity series.



Note: The panel shows that 90% of the fluctuation in the commodity price series can be explained by the first three factors. The red dots show the cumulative percentage that can be explained by these factors and the blue dots show the percentage that can be explained by the i^{th} factor.

Data on commodity price series Data on commodity prices are obtained from the World Bank Pink Sheet.[2] I use the annual series of globally traded commodities for which there is no missing data, yielding a total of 43 commodities. These series are expressed in U.S. dollars in real prices and include commodity prices for agricultural, fuel, and metal products. The agricultural series includes prices for beverages (e.g., cocoa and tea), food (e.g., fats, grains, and other foods), and agricultural raw materials (e.g., timber and other raw materials). The metals and minerals series include aluminum, copper, lead, nickel, steel, tin, and zinc. Fuel prices include crude oil, coal, and gas.[3] In my estimation, I apply the cyclical components of these series in percent deviations from the trend obtained using an HP filter with a smoothing parameter of 100. I then extract factors characterizing the co-movement in commodity prices. I also use these commodity price indices to proxy for world prices, in section 4.3, as an alternative measure for world shocks.

[2]This data is publicly available at http://www.worldbank.org/en/research/commodity-markets.
[3]Table A3 in the appendix lists all of the commodity series used in the sample.

3 Empirical strategy

3.1 SVAR model

My empirical framework includes a factor model to extract the common factors of commodity prices as a proxy for world shocks. These commodity price factors are included in the foreign block. My focus is on the annual inflationary changes in the domestic block as a critical macroeconomic indicator. Specifically, I study the joint behavior of the world price vector p_t and the vector of domestic macroeconomic indicators for country i, denoted by ${Y_t}^i$, from the perspective of a small open economy. A block-recursive SVAR model characterizes this behavior as suggested by Fernández et al. (2017).

The foreign block In my baseline specification, the world price vector consists of the real prices of three factors: agricultural products, fuel, and metals: pc_t^1, pc_t^2, and pc_t^3, which I obtained from the factor augmented autoregressive model applied in section 2.

$$p_t = \begin{bmatrix} {pc_t}^1 \\ {pc_t}^2 \\ {pc_t}^3 \end{bmatrix}$$

I later augment this price vector to include other world prices, such as the world interest rate, r_t. I assume that world prices are independent of each individual country's domestic macroeconomic variables. Further, I assume that these prices follow a first-order vector autoregressive system, as follows:

$$p_t = Ap_{t-1} + \mu_t, \tag{3.1}$$

where A represents a matrix of the coefficients, and μ_t is an i.i.d mean-zero random vector with the variance matrix Σ_μ. The vector μ_t captures the effects of unobservable structural world shocks. It is important to note that no assumptions are imposed to identify these shocks in the model. Instead, the focus here, as in Fernández et al. (2017), is on estimating the *joint contribution* of μ_t to individual countries' domestic inflation.

The domestic block The vector of domestic macroeconomic indicators ${Y_t}^i$ includes annual changes in the inflation rate. I later augment this vector to include other country-specific macroeconomic indicators. These domestic variables are influenced by country-specific shocks ε_t^i and world shocks μ_t. I assume that ε_t^i and μ_t are uncorrelated. As a result, there are no restrictions on the domestic block in terms of the Cholesky decomposition in my model. Further, I assume that the world shocks in my model affect the small open economies only through changes in the contemporaneous or past world prices, p_t. These assumptions give rise to the following model,

$$Y_t^i = B^i p_t + C^i\, Y_{t-1}^i + D^i\, p_{t-1} + \varepsilon_t^i. \tag{3.2}$$

The innovations vector ε_t has mean-zero with the variance matrix $\Sigma_{\varepsilon_t}^i$.

The SVAR model Combining 3.1 into equation 3.2, I obtain a first-order block-recursive structural vector autoregressive model in the form

$$\begin{bmatrix} p_t \\ Y_t^i \end{bmatrix} = \begin{bmatrix} A & 0 \\ B^i A + D^i & C \end{bmatrix} \begin{bmatrix} p_{t-1} \\ Y_{t-1}^i \end{bmatrix} + \begin{bmatrix} I & 0 \\ D^i & I \end{bmatrix} \begin{bmatrix} \mu_t \\ \varepsilon_t^i \end{bmatrix}, \tag{3.3}$$
$$E \begin{bmatrix} \mu_t \mu_t^{'} & \mu_t \varepsilon_t^{i'} \\ \varepsilon_t^i \mu_t^{'} & \varepsilon_t^i \varepsilon_t^{i'} \end{bmatrix} = \begin{bmatrix} \Sigma_\mu & 0 \\ 0 & \Sigma_\varepsilon^i \end{bmatrix}.$$

The coefficients of the foreign blocks A and Σ_μ are estimated using OLS, equation by equation, and annual data for the period 1970-2014. The $R^2 = [0.41\ 0.18\ 0.45]$ for the three equations in the model suggests the extent to which the contemporaneous shocks explain commodity price factors in the foreign block. I then estimate the domestic block, equation 3.2, using OLS for all countries in the sample. Finally, with the parameters of the SVAR at hand, I perform variance decomposition to estimate the joint contribution of world shocks μ_t to the movements in each specific country's macroeconomic indicators. To do so, I apply a Cholesky decomposition of the covariance matrix of VAR residuals to determine the proportion of the variation of domestic inflation that can be explained by the three factors of the commodity price series.

Implementation details To overcome the problems that arise when using a relatively small number of observations, I follow the suggestions of Fernández et al. (2017). I begin by estimating the parameters of the domestic block, in two ways: First, I include only one domestic indicator (the inflation rate) in Y_t to estimate the annual price changes of each country. Second, I include two country-specific indicators (the inflation rate with another macroeconomic indicator, in my extended model) in the vector Y_t^i, which results in a maximum number for the degrees of freedom.

Another issue is the possibility of small-sample upward bias in the estimation of the model. This bias might occur for two reasons: First, any negative or positive correlation between the foreign and domestic blocks may result in a positive share of commodity price shocks in the variance matrix Σ_{ε}^{i}. Second, when a sample is small, the estimates obtained from OLS regressions are known to be biased. To overcome these issues, I follow the Monte Carlo procedure to create artificial data. To estimate the model, I use real data to calculate the non-corrected estimates and subtract the small-sample bias obtained from the Monte Carlo procedure to obtain the corrected estimates. I explain this procedure step by step in section .1 in the appendix. In discussing the results, I will focus on the corrected estimates for the small-sample bias.

3.2 Data

My analysis relies on country-specific headline and core inflation rates and country-specific macroeconomic variables.

The macroeconomic variables are obtained from the World Development Indicators (WDI).[4] The inflation rate is the key variable of interest and is measured by annual changes in the CPI. This variable, headline inflation, reflects the cost to the average consumer of acquiring a basket of goods and services. The conventional Augmented Dickey-Fuller test suggests using annual changes in inflation due to the stationarity of the data. Section 4.2 investigates the impact of core inflation, instead of headline inflation, in the SVAR model. I obtain annual changes in core inflation by taking the averages of the quarterly samples, by country, over the period 1980-2014. Core inflation contains the CPI for all urban consumers. All items are in indices of U.S. city averages, monthly, seasonally adjusted (1982-1984=100).

In my estimation, I include countries where the number of observations for the domestic block is at least twenty observations. This results in 94 countries remaining in the sample. I notice that there are countries with data that are highly volatile or where there are high standard deviations for their CPIs in different years. I exclude these countries from my sample and those that have experienced hyperinflation for multiple years as they result in highly volatile data for the estimation. Table A5 in the appendix lists excluded countries from my sample and provides information on each country's CPI over the period 1970-2014. Thus, the baseline sample contains 67 countries for the period 1970-2014. The data

[4] The WDI database is publicly available at http://data.worldbank.org.

set for the annual samples is unbalanced. The longest sample consists of data covering 45 years (1970-2014), and the shortest sample covers 20 years (1994-2014).

Quarterly data In the robustness section, using data from the OECD, I also work with quarterly samples of headline inflation rates for 29 of the countries. A country must have at least 100 consecutive quarterly observations to be included in the quarterly sample. Table A6 in the appendix provides country-by-country information on this sample period and the data source.

4 Results

In this section, I start with a baseline model with three factors extracted from 43 commodity prices in real terms to explain the contribution of world shocks to inflation fluctuations (Section 4.1). I then consider several variations of the model: In section 4.2, I compare the results using core inflation versus headline inflation. In section 4.3, I report how world shocks contribute to domestic inflation while controlling for different macroeconomic indicators in the domestic block. In section 4.4, I examine the role of including other specifications for commodity prices with inflation in an SVAR. I also analyze the impact of using a single proxy for world prices. Finally, in section 4.5, I investigate the role of including other world prices in the foreign block in the SVAR.

4.1 Commodity price shocks and inflation fluctuations

To answer the question posed in this paper, I include commodity price factors in the foreign block and inflation in the domestic block of the model. Then, I use the estimated SVAR system to perform variance decomposition country by country. Column 1 in Table 2 shows the cross-country median shares of the variances in inflation that are explained by commodity price shocks. In this estimation, I consider only one domestic macroeconomic indicator–inflation–in equation 3.2. These statistics are computed by estimating the VAR model, calculating the relevant variance decomposition for each of the 67 countries in the study, and computing the median values. The cross-country median absolute deviation (MAD) shows the interval of the estimated variance share. Column 2 in Table 2 shows the averages of the inflation fluctuations explained by world shocks mediated by commodity price shocks. In this estimation, I also consider only one domestic macroeconomic indicator in the domestic block. The estimation result is the same for both the median and the average share of variances for all countries in the sample.

Table 2: Share of inflation fluctuations explained by world shocks—baseline result

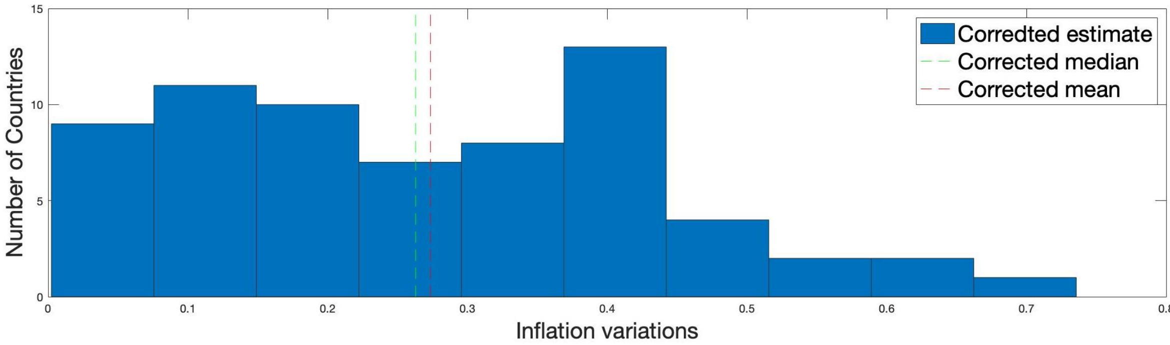
	Median	Mean
Non-corrected estimate	0.37	0.38
Small-sample bias	0.11	0.11
Corrected estimate	**0.26**	**0.27**
MAD of corrected estimate	0.08	
Number of countries	67	67

Note: Variance decompositions are based on country-by-country estimates of the SVAR system over the period 1970-2014. In columns 1 and 2, vector Y_t of the domestic variables contains only one domestic indicator, the inflation rate. The small-sample bias in the variance decomposition of inflation is, on average, almost 11 percentage points. MAD stands for the cross-country median absolute deviation, which displays the interval of the estimated variance share. Statistics are computed across 67 advanced and emerging economies.

The non-corrected estimates show that commodity price shocks explain, on average, 37% of the variation in the inflation rate for the median country and 38% of inflation fluctuations for the average share of variances over 67 counties. After correcting for the small-sample bias, between 26% and 27% of the variation in inflation can be explained by world shocks for the median country and the average share of the variances in the inflation rate. I treat the results obtained in the corrected estimates for inflation fluctuations (26%) as the baseline result in my paper. Figure 3 displays the variance in the inflation rate, in terms of the frequency distribution for all countries. Table A7, in the appendix, reports the results for each country (σ^{π}), separately. Note that the sample is unbalanced because the number of observations for the domestic block is different across countries (from 20 to 45 across 67 countries). This table also reports the confidence intervals for the estimates for each country to show the uncertainty of the baseline results at the 5% level. Figure 5, in the appendix, presents each country's inflation fluctuations to commodity price shocks over the period 1970-2014.

It is useful to put my estimates in the context of the literature. For example, Gelos and Ustyugova (2017) estimate the impact of a change in one world price on fluctuations in domestic inflation. They indicate that the median long-term pass-through of a 10 percentage-point food price shock to domestic inflation is 0.2 percentage points for advanced economies and almost 0.8 percentage points for emerging economies. They sug-

Fig. 3: The frequency distribution of inflation fluctuations of each country to commodity price shocks, over the period 1970-2014.



gest that economies with higher food shares in their CPI baskets, higher fuel intensities, and pre-existing inflation are more prone to experiencing sustained inflationary effects from commodity price shocks. Furthermore, Sekine and Tsuruga (2018) find that the effects of commodity price shocks on headline inflation, on average, are an increase by 1.87 percentage points in response to a 10 percentage-point increase in commodity prices. My paper finds that commodity price shocks can explain 26% of the variation in inflation fluctuations. This result indicates an increased contribution of world shocks to changes in domestic inflation rates, compared to previous studies. This can be an interesting result for policymakers because it compels them to consider the importance of commodity prices on inflation when monetary policy aims to maintain low and stable inflation rates.

4.2 Headline inflation versus core inflation's results

To determine how much commodity price shocks can explain country-specific core inflation fluctuations, I include common factors of commodity prices in the foreign block and core inflation and headline inflation (inflation rate) in the domestic block, separately. To briefly recap, headline inflation measures the cost of many goods and services such as food and energy. However, core inflation excludes the prices of these two commodities. Thus, I expect that world shocks that are mediated by factors characterizing the co-movement in commodity prices contribute more to explaining fluctuations in headline inflation compared to core inflation (see e.g., Sekine and Tsuruga (2018)).

In this section, I perform variance decomposition country by country, using the estimated SVAR system obtained in section 3.1. I work with a quarterly sample of commodities that make up the core inflation rate in 24 countries, using the OECD database. Due

Table 3: Shares of variances explained by world shocks—core & headline inflation

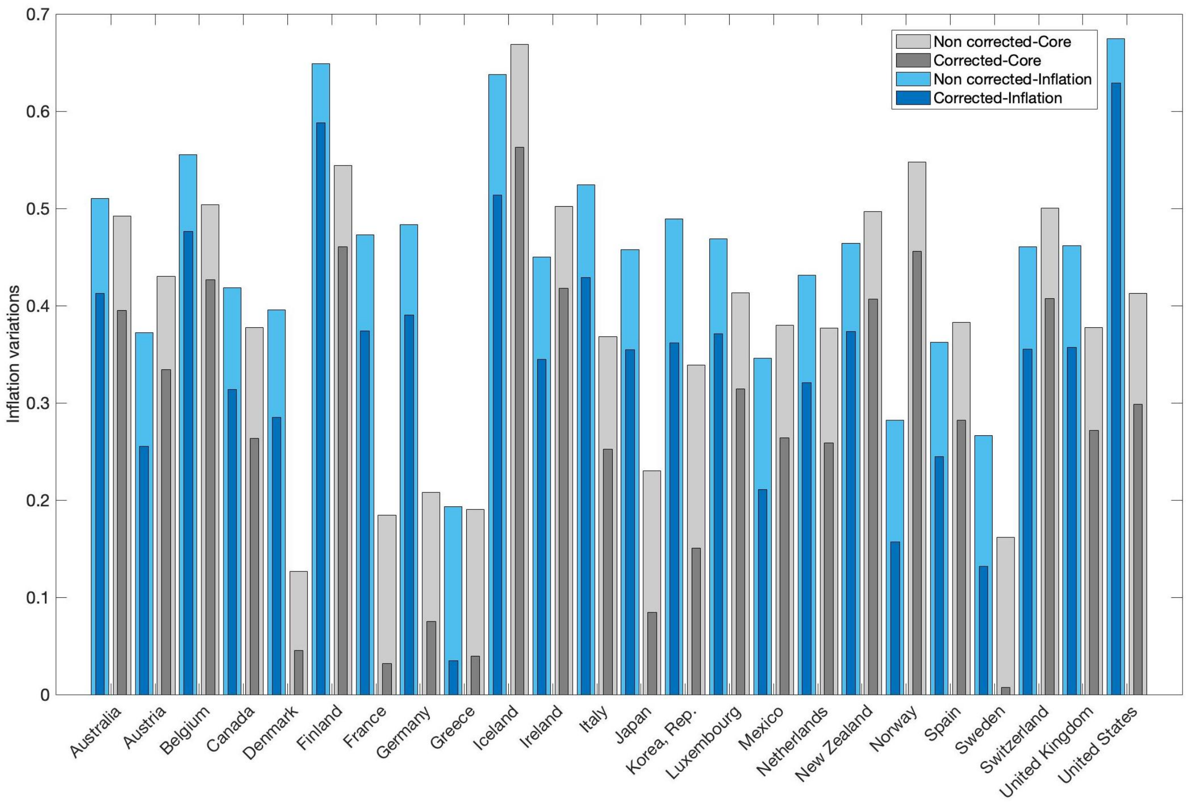
	Median		Mean	
	A. Core inflation	B. Inflation	C. Core inflation	D. Inflation
Non-corrected estimate	0.38	0.45	0.38	0.46
Small-sample bias	0.12	0.11	0.11	0.11
Corrected estimate	0.27	0.35	0.28	0.36
MAD of corrected estimate	0.08	0.07		
Number of countries	24	24	24	24

Note: Variance decompositions are based on country-by-country estimates of the SVAR system over the period 1980-2014. The small-sample bias in the variance decomposition for inflation is, on average, almost 11 percentage points. MAD stands for the cross-country median absolute deviation, which displays the interval of the estimated variance share. Statistics are computed across 24 advanced and emerging economies.

to limited data availability for core inflation, I include 24 countries for both estimations to have a consistent comparison. In the first column, vector Y_t of the domestic variables contains only core inflation. In the second column, vector Y_t contains only the headline inflation rate. In the third and fourth columns, I show the same estimation results for the average responses of both domestic indicators (core inflation and the inflation rate) to world shocks mediated by commodity price shocks over 24 countries. Table A8, in the appendix, shows the list of countries included in this section.

The non-corrected estimates in Table 3 show that commodity price shocks explain, on average, 38% of the variation in core inflation and 45% of the inflation fluctuations for the median country. They also explain 38% of the variation in core inflation and 46% of the changes in headline inflation, on average, over 24 countries. After correcting for the small-sample bias, world shocks explain 27% of the variation in core inflation and 35% of the fluctuations in headline inflation for the median country, and 26% of the variation in core inflation and 32% of the fluctuations in inflation for the average share of commodities over 24 countries on the median country. Thus, the estimation results in this section show that headline inflation responds to world shocks by almost ten percentage points more than core inflation. This result is consistent with what Sekine and Tsuruga (2018) suggest theoretically. Since core inflation is the change in the cost of the bundle of goods and services that does not include those from the food and energy sectors, changes in food and energy prices are not included in this measure. Figure 4 shows the results for the responses of headline inflation, the indicator I use in the baseline estimation. The figure also shows

Fig. 4: Headline inflation and core inflation fluctuations in response to commodity price shocks, over the period 1980-2014.



each country's core inflation fluctuations to commodity price shocks from 1980-2014.

4.3 Results with the extended domestic block

In this section, I extend the domestic block to control for country-specific macroeconomic indicators to investigate the impact of commodity price shocks on inflation fluctuations. To answer the question posed in this section, I include three factors characterizing the co-movement in commodity prices in the foreign block (equation 3.1) and the inflation rate and the other macroeconomic indicator, both separately and jointly in the domestic block (equation 3.2).

To investigate the impact of commodity price shocks on inflation fluctuations, I control for real interest rates because of the inverse correlation between interest rates and inflation. Central banks adjust short-term interest rates to stabilize the rate of inflation in the economy (Mundell, 1963). Thus, this cost channel for monetary policy transmission matters for the inflation dynamics within industrialized countries. In the estimations, I also control for the exchange rates to investigate the impact of commodity price shocks on country-specific inflation fluctuations. The increase in the foreign exchange rate contributes to cheaper domestic goods for foreign consumers, increasing exports and total demand. As a result, exchange rate fluctuations can significantly affect the general level of prices in countries (Mishkin, 2007; Shapiro, 1975). In column C, I control for the output and the real interest rate to estimate the importance of commodity price shocks on domestic inflation inflation. In general, when interest rates decrease, the economy grows, and inflation increases. In contrast, when interest rates rise, the economy slows down, and inflation reduces (Mishkin, 2007; Trigari, 2009).

Data. This section describes the data used for the extended domestic block. In column A in Table 4, I use the annual changes in interest rates. I apply the conventional Augmented Dickey-Fuller tests to check the stationarity of the data. Due to data availability, only 38 countries are included in this estimation. These are listed on Table A9 in the appendix.

In column B in Table 4, the exchange rate is the official exchange rate. The exchange rate data includes local currency units per USD, in averages for each period. In this estimation, 53 countries are included due to limited data availability for country-specific exchange rates. Table A10, in the appendix, lists of countries included in this section.

In column C in Table 4, for the output, I consider the GDP data in constant local currency units and use the cyclical component of the natural logarithm of real GDP as captured by an HP filter with a smoothing parameter of 100. In this estimation, 38 countries are included, again due to data issues for country-specific real interest rates. Table A9, in the appendix, lists the countries included in this section.

Table 4: Share of inflation fluctuations explained by world shocks—Extended domestic bloc

	A. Real interest rate		B. Exchange rate		C. Output and interest rate	
		Extended model		Extended model		Extended model
	Inflation	Inflation	Inflation	Inflation	Inflation	Inflation
Non-corrected estimate	0.39	0.39	0.36	0.36	0.39	0.44
Small-sample bias	0.14	0.14	0.11	0.11	0.14	0.13
Corrected estimate	0.26	0.25	0.25	0.25	0.25	0.32
MAD of corrected estimate	0.07	0.07	0.08	0.07	0.08	0.06
Number of countries	38	38	53	53	38	38

Note: Variance decompositions are based on country-by-country estimates of the SVAR system over the period 1970-2014. In each panel (A, B, C), the first column reports the estimation results when only inflation is included in the domestic block. The second column shows the results when I control for other macroeconomic indicators in domestic block: the real interest rates, the exchange rates, and the output and the real interest rates.

Results. Table 4 reports the estimation results for the extended domestic block in section 4.3. Column A in Table 4 shows the estimation results for inflation fluctuations, separately and jointly, while I control for real interest rates in the extended domestic block. The non-corrected estimates show that commodity price shocks explain, on average, 38% and 39% of the variation in inflation fluctuations for both estimations in 38 countries. After correcting for the small-sample bias, 26% of inflation fluctuations in both estimations can be explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is not affected by the real interest rate when I control for this indicator.

Column B in Table 4 shows the estimation results for inflation fluctuations, separately and jointly, while I control for the exchange rate in the extended domestic block. The non-corrected estimates show that commodity price shocks explain, on average, 36% of the variations in both inflation and the exchange rate in all 53 countries. After correcting for the small-sample bias, 25% of inflation fluctuations for both settings are explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is the same as when I control the exchange rate.

Column C in Table 4 shows the estimation results for inflation fluctuations, separately and jointly, while I control for output and the real interest rate in the extended domestic block. In the first column, vector Y_t for the domestic variables contains only the inflation rate. In the second column, vector Y_t contains three domestic indicators: the inflation rate, output, and the real interest rate. The uncorrected estimates show that commodity price shocks explain, on average, 39% and 44% of the variation in inflation fluctuations for both settings, respectively, in all 38 countries. After correcting for the small-sample bias, 25% of the inflation fluctuations and 32% of the variation in inflation in the extended model are explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is almost seven percentage points lower than when I control for both indicators.

4.4 Results using various commodity prices

I include different commodity prices in the foreign block (equation 3.1) to investigate the impact of commodity price shocks on inflation fluctuations. Fernández et al. (2017) suggest going beyond single-world-price model and using three price indices corresponding to major commodity groups. Thus, to examine commodity price shocks' importance in explaining domestic inflation fluctuations, I use commodity price indices to proxy for world shocks. My results suggest that three factors extracted from all commodity prices have a stronger impact on inflation than the three price indices.

Commodity price indices. I compute factors characterizing the co-movement in commodity prices in the baseline results to proxy for world shocks. Then, I re-estimate the baseline model using the cyclical components of the commodity price indices obtained with the HP filter with the smoothing parameter $\lambda = 100$ to compare this result with the baseline estimation. The use of indices has been criticized on different grounds. For instance, the choice of three indices included in the foreign block is arbitrary. Another concern is that the commodity price indices are the weighted averages of oil, fuel, and agricultural commodities. They might not capture the volatility of commodity prices as much as the factor model would. Thus, I investigate whether including more factors of commodity prices in the foreign block would affect fluctuations in domestic inflation and, if so, by how much.

Table A11, in the appendix, shows the correlations between the three factors obtained from the factor model in section 2 and the commodity price indices (agricultural, fuel, and metal prices). It shows that the first factor is highly correlated with these three commodities' indices. In contrast, the second factor is highly correlated with the metals index, and there is some correlation between the third factor and fuel prices.

Results. Column 1 in Table 6 reports the results using four factors of commodity prices. The non-corrected estimates show that commodity price shocks explain, on average, 52% of the variation in the fluctuations in the inflation rate when I use four factors in a foreign block. After correcting for the small-sample bias, the results for the median country show that 42% of the fluctuations in inflation are explained by the impact of world shocks on domestic inflation. This result indicates that using more factors (more world prices) in the foreign block (equation 3.1) has more explanatory power for fluctuations in domestic inflation.

The second column of Table 6 shows the results using commodity price indices instead of three factors of commodity price series obtained from the factor model. The corrected estimates show a difference between these two measures as a proxy for world shocks. The results show a twelve percentage points decrease in the importance of world shocks for inflation, relative to the baseline results shown in Table 2. Thus, I find that using factors characterizing the co-movement in commodity prices provides better statistical characteristics of commodity markets, compared with commodity price indices, and is, therefore, better able to capture the impact of world shocks on inflation fluctuations. This is consistent with the idea that the principal component analysis preserves as much of the data's variation possible. The first factor of commodity prices can equivalently be defined as a direction that maximizes the variance of the commodity series.

Single-world-price model specification. Many previous studies focused on the impact of a single commodity price, such as the price of oil or food, on domestic inflation. Schmitt-Grohé and Uribe (2016) and Fernández et al. (2017) demonstrate that such an approach underestimates the importance of world shocks in explaining output fluctuations. In this section, I analyze the implications of using a single measure to proxy for the impact of world shocks on fluctuations in inflation. To this end, I include one factor and a single price index at a time in the foreign block (equation 3.1). Then, I estimate the number of single-world-price SVAR models to compare the results of these models relative to the SVARs with commodity price factors and the world interest rate. Overall, these results emphasize the need for using multiple price specifications in assessing the effects of world shocks.

The comparative results are reported in Table 5. I examine eight alternative single-price models. My focus is on the share of the variances in inflation that are explained by world shocks. I report the estimates that are corrected for the small-sample bias. For ease of comparison, the first row in Table 5 reproduces the results from the SVAR model with three factors of commodity price series included in the study and the world interest rate from section 4.5 (column 5 in Table 6).

I first estimate the SVAR models with one of the three factors for which I have commodity prices, obtained in section 1. The results in Table 5 show that single-factor models can explain only a small fraction of fluctuations in inflation. I next examine other measures of world prices (the three commodity price indices obtained in section 4.3), the world interest rate, and the country-specific terms of trade in the foreign block. The terms-of-trade series is the ratio of trade-weighted exports to imports, measured according to price indices. Schmitt-Grohé and Uribe (2016) indicate that country-specific terms-of-trade shocks represent a significant source of business cycles in emerging economies. The results for specifications 4 to 8, in Table 5, also indicate that when only one world price is included in the foreign block, world shocks explain on average less than 6% of the vari-

Table 5: Share of variances using one-price specifications

Model specification	Inflation
Four world prices, pc^1, pc^2, pc^3, r	0.34
1. First factor of commodity price series, pc^1	0.13
2. Second factor of commodity price series, pc^2	0.01
3. Third factor of commodity price series, pc^3	0.11
4. Agricultural price index, p^a	0.05
5. Fuel price index, p^f	0.04
6. Metal price index, p^m	0.06
7. World interest rate, r	0.02
8. Terms of trade, tot	0.03

Note: The reported variance shares are group-specific medians, using annual data. The domestic block includes only the inflation rate. Statistics are medians across 67 countries, corrected for the small-sample bias. The first row is reproduced from column 5 in Table 6. Here, r_t is measured by the real Treasury bill rate.

ances in the median country's rate of inflation. Overall, these results emphasize the need for using multiple price specifications in assessing the effects of world shocks on domestic inflation fluctuations.

4.5 Results with the extended foreign block

In this section, I extend the foreign block to include more channels to investigate the extent to which world shocks explain fluctuations in inflation. To answer the question posed in this section, I augment the price vector p_t in the foreign block (equation 3.1) to include the other global indicator, g_t, when I re-estimate the SVAR model for each country.

$$p_t = \begin{bmatrix} {p_t}^a \\ {p_t}^f \\ {p_t}^m \\ g_t \end{bmatrix} \tag{4.1}$$

First, I consider the global economic index, which can be viewed as another mechanism through which world shocks can cause fluctuations in domestic inflation. This estimation is based on the suggestions of Kamber and Wong (2020), who consider that global economic indicators can proxy for world shocks. Here, I use a global economic index obtained from Baumeister, Korobilis, and Lee (2020) to consider this mechanism.

I provide another estimation to discuss the relation between the world interest rate and domestic inflation. These results echo the conclusions of Fernández et al. (2017) who demonstrate the importance of using multiple prices for output fluctuations. These results highlight the importance of the world interest rate as an additional transmission channel for world shocks to affect domestic inflation. Changes in world prices can be viewed as the key mechanism through which world shocks are transmitted to small open economies (Lubik & Teo, 2005). While real commodity prices represent the relative prices of goods in the same period, the real interest rate represents the relative prices of goods dated in different periods. A possible link from the world interest rate to domestic inflation is its impact on the availability of intermediate goods and production costs (Auer et al., 2017; Kaldor, 1976; Neely & Rapach, 2011).

Several papers suggest that U.S. monetary policy generates sizable macroeconomic spillovers to the rest of the world (see e.g., Chen, Filardo, He, and Zhu (2016); Georgiadis (2016)). In addition, it has been argued that each country's economic growth may be driven by a global financial cycle which, in turn, appears to be determined to a large extent by U.S. monetary policy (Habib, Venditti, et al., 2018). To control for the impact of U.S. monetary policy on each country's monetary policy, I extend the domestic block and consider country-specific real interest rates with inflation in the domestic block (see equation 3.2). This analysis includes 38 countries due to the data availability.

Table 6: Share of inflation fluctuations explained by world shocks—extended foreign block

	Extended foreign block				Extended both blocks
	Four factors	Commodity indices	Global Economic index	Commodity prices & r	Commodity prices & r
Non-corrected estimate	0.52	0.25	0.51	0.46	0.56
Small-sample bias	0.10	0.12	0.13	0.13	0.13
Corrected estimate	0.42	0.14	0.38	0.34	0.43
MAD of corrected estimate	0.09	0.10	0.10	0.09	0.12
Number of countries	67	67	67	67	38

Note: Each column represents the estimation results for inflation for an extended foreign block. Column 1 shows the results using four factors of commodity prices. Column 2 reports the results using commodity price indices replicated from the model. The source of these commodity price indices is the WDI. The data covers the period 1970-2014. Column 3 reports the results using a global economic index and three factors of commodity prices. In columns 4 and 5, r_t is measured according to the real Treasury bill rate, to proxy for the world interest rate. Column 5 includes the real interest rate as a control variable for the estimation (extended domestic block) over the period 1970-2014.

Data. The data for the global economic index is available quarterly for the period

1973-2015. I compute the annual data by taking the average of the quarterly samples in the index over the period 1973-2014. I take the real three-month U.S. Treasury bill rate to proxy for the world interest rate. I subtract the monthly U.S. CPI from the monthly Treasury bill rate and then average the monthly data into the annual frequencies to obtain this measure. I later use this indicator in the price vector in equation 3.1 to include the world interest rate r_t.

Results with the global economic index. Column 3 in Table 6 shows the estimation results that are explained by world shocks, mediated by commodity price factors and the global economic index. The statistics point to the increased importance of world shocks in explaining the inflation movements in the model. The non-corrected estimates show that commodity price shocks explain, on average, 51% of the variation in the fluctuations in inflation. Based on the corrected estimates, the shares of the fluctuations in inflation explained by world shocks now account for 38% of the variation in the median country's inflation rate. These shares are about twelve percentage points higher relative to the benchmark SVAR model with the commodity prices (see section 4.1). This result is consistent with what Fernández et al. (2017) suggests about other mechanisms used to explain domestic business cycles: using multiple world prices provides more statistical characteristics with which to capture the impact of the world shocks on inflation fluctuations in advanced and emerging countries. If I consider the same countries included in Kamber and Wong (2020), factors characterizing the co-movement in commodity prices and the global economic index, in my paper, explain 38% of the inflation fluctuations after correcting for the small-sample bias (the other 53% are non-corrected estimates). However, Kamber and Wong (2020) consider the common factors of the macroeconomic indicators of five advanced economies as proxies for global economic indicators. To this, they add the commodity price indices for agriculture, fuel, and metals in the foreign block to proxy for world shocks that explain 25% of the inflation gap.

Results with annual world interest rate. The resulting shares of the variances that are explained by worlds shocks, mediated by commodity price factors and the world interest rate, are reported in column 4 of Table 6 for annual data. The statistics in column 4 in Table 6 point to the increased importance of world shocks for explaining the variations of output and inflation in all estimations. Based on the corrected estimates, the shares of inflation fluctuations explained by world shocks now account for 34% of the median country's inflation rate variation. These shares are about ten percentage points higher relative to the benchmark SVAR model with the commodity prices, shown in section 4.1.

Results with world and real interest rate. The last column in Table 6 shows the estimates for this analysis. The non-corrected estimates in Table 6 show that commodity price shocks explain, on average, 56% of the fluctuations in inflation in the extended model estimations for 38 countries. Furthermore, after correcting for the small-sample bias, I find that world shocks explain 43% of the median country's inflation fluctuations.

Results with quarterly world interest rate. I re-estimate the SVAR model with three factors of commodity prices and the world interest rate, using quarterly data. Due to data limitations, the number of countries in the sample decrease to 29. These countries and the available sample periods are listed in the last column of Table A6, in the appendix. Table 7 reports the results for the estimation in which only inflation is included in the domestic block. The findings using quarterly data show that world shocks explain 30% of the variance in inflation, and when using annual data, I find that world shocks explain 35% of the variance in inflation. The estimate using annual data for the sample is 34%. These estimates indicate that the results are consistent using quarterly data, compared to the baseline result.

Table 7: World shocks mediated by commodity prices and world interest rate—quarterly data

	Cross-country median variance share of inflation		
	Quarterly data	Annual data	Annual data
Non-corrected estimate	0.43	0.47	0.46
Small-sample bias	0.13	0.13	0.13
Corrected estimate	0.30	0.35	0.34
MAD of corrected estimate	0.19	0.17	0.09
Number of countries	29	29	67

Note: Variance decompositions are based on country-by-country estimates of the SVAR system over the period 1970-2014, using both quarterly and annual data. MAD stands for the cross-country median absolute deviation. Statistics are computed across 29 countries. The domestic block contains only one country-specific indicator, the inflation rate. The small-sample bias in the variance decomposition is almost 13 percentage points. Here, r_t is measured by the real U.S. interest rate.

5 Alternative specifications

This section demonstrates that the results on the importance of world shocks for explaining fluctuations in inflation are robust to different dimensions. I report the estimates that have been corrected for the small-sample bias. For ease of comparison, the first row in Table 8 reproduces the results from the SVAR model with commodity price factors obtained from Table 2—the baseline result. For each exercise, the names of the countries included in the estimations are listed in a separate table in the appendix.

Excluding large commodity exporters. These countries' market power might violate the identification assumption of the exogeneity of each country's commodity prices. To address this concern, I exclude large commodity exporters from the sample. I identify the top 20% largest exporters for each of the three commodity groups, using annual average exports of the fuel, agricultural, and metals commodities obtained from the WDI database (1970-2014). This exercise excludes 22 countries that are large exporters of commodities. Panel A in Table 8 reports the results for the remaining 45 countries. World shocks appear to explain 31% of the variations in inflation in the countries included in this modified sample. These statistics are almost similar to the baseline results. I conclude that market power in commodity production does not affect an economy's susceptibility to world shocks. Table A12, in the appendix, lists the countries included in this estimation.

Table 8: Heterogeneity among countries in response to world shocks

	Share of variances explained by world shocks	
Model specification	Number of countries	Inflation
Baseline estimation	67	0.26
A. Excluding large commodity exporters	45	0.31
B. Oil		
Exporters	14	0.18
Importers	53	0.28
C. Net commodity traders		
Exporters	23	0.31
Importers	42	0.35
D. Level of development		
High income	40	0.28
Low income	24	0.31

Note: The reported variance shares are group-specific medians, using annual data. The foreign block consists of three factors of commodity price series. The domestic block includes only inflation and the variance shares are corrected for the small-sample bias.

Oil exporters and oil importers. I compute the country-specific median of net exports of fuel beginning in 1970, using annual data on exports and imports of fuel commodities obtained from the WDI database. A country is defined as an oil exporter (importer) if its median net fuel export share in GDP is positive (negative). Based on this specification, the analysis consists of 14 oil exporters and 53 oil importers (see Panel B of Table 8). The effects of commodity price shocks on inflation fluctuations in oil-importing countries (28%) are much stronger than in oil-exporting countries (18%). This result indicates that higher oil prices may increase industry costs and, hence, inflation rates in oil-importing countries. This result is in line with the discussion in Barsky and Kilian (2004), which notes that world shocks appear to be more important in explaining business cycles in oil importers than in oil exporter countries. Table A13, in the appendix, lists the countries included in this estimation.

Net commodity traders. World shocks appear to be more important for explaining fluctuations in macroeconomic indicators in countries that are net commodity importers, compared to countries that are net commodity exporters (Barsky & Kilian, 2004). In my analysis, I consider a country is a commodity exporter (importer) if it has had a positive (negative) trade balance, on average, in the three commodities in my study (agricultural products, fuel, and metals) since 1970. I use annual data on agricultural, fuel, and metals commodities to calculate the net trade for each category. This classification yields 23 commodity exporters and 42 commodity importers. Panel C of Table 8 indicates that commodity importers experience higher fluctuations in inflation in response to world shocks compared to commodity exporters, which is consistent with the literature. Table A14, in the appendix, lists the countries included in this estimation.

Level of development. Adler and Mora (2012) discuss how the level of development affects the importance of world shocks as drivers of domestic business cycles. They indicate that advanced countries have more service-oriented economies and, hence, larger shares of non-tradables, which means they are less exposed to world shocks. In contrast, Fernández et al. (2017) argue that advanced countries, especially those with relatively small economies, tend to be more integrated with the rest of the world. These tighter links could imply larger exposures to world shocks. I divide countries into high-income (40 countries) and low-income (26 countries). This categorization is based on per capita gross national incomes, published in WDI 2015.[5] Panel D of Table 8 shows the results

[5]The results are robust to establishing the categorization on income levels in 1990.

of this estimation. The share of the inflation variance explained by world shocks in the high-income group is three percentage points higher than the low-income group. These results are fairly robust across income groups. There are no apparent differences in the share of the inflation variance explained by world shocks across income groups. Table A15, in the appendix, shows the list of countries included in this estimation.

6 Conclusion

This research evaluates the historical importance of world shocks for explaining changes in domestic inflation. This result sheds light on the origin of inflation fluctuations in advanced and emerging economies. My paper's key innovation is the use of commodity price factors to proxy for world shocks. Previous studies typically rely on a single commodity price. However, this underestimates the importance of world shocks for domestic inflation. My findings show that 26% of fluctuations in inflation can be explained by world shocks mediated through factors characterizing the co-movement in commodity prices after correcting for the small-sample bias. I find an increased contribution of world shocks to changes in domestic inflation rates relative to previous studies.

Knowledge of the drivers of domestic inflation is critical for determining the optimal policy for controlling inflation. Most modern central banks aim to achieve low, stable, predictable inflation, creating favorable economic conditions for economic decisions. Yet, central banks may not always successfully mitigate the effects of world shocks. This information can also be used to find better institutional arrangements to shelter domestic inflation from world shocks.

One limitation of my analysis is the absence of explicit identification of a structural world shocks. For example, these types of shocks can be driven by productivity shocks, monetary or fiscal policy, or global uncertainty. Further, the method used in this paper is incapable of differentiating the origins of specific world shocks. Further analysis in this regard would be helpful.

Appendices

Table A1: The Bai & Ng test result for the number of commodity factors

	common factor
According to IC(1) criteria	3
According to IC(2) criteria	1
According to IC(3) criteria	10
According to PC(1) criteria	9
According to PC(2) criteria	3
According to PC(3) criteria	10
According to BIC(3) criteria	3
According to AIC(3) criteria	3

Note: IC(1) is most commonly used. BIC(1) is not recommended for small N relative to T (where N is the cross-section dimension and T is the time dimension, and in my paper it is 67 to 45.) AIC(3) and BIC(3) take into account the panel structure of the data. AIC(3) performs consistently across configurations of the data, while BIC(3) performs better on large N data sets.

Table A2: World prices: second moments of cyclical components

	pc^1	pc^2	pc^3	r
Standard Deviation, $\sigma(x)$	3.69	2.12	2.36	0.02
Serial Correlation, $\rho(x)$	0.31	0.23	0.41	0.70
Relative Standard Deviation, $\sigma(p)/\sigma(gdp)$	0.93	0.53	0.59	0.56

Note: Annual data from 1970-2014. The variables pc^1, pc^2, and pc^3 denote co-factors of 43 real commodity prices (agricultural, metal, and fuel), respectively. The variable r denotes the real three-month Treasury bill rate (same specification used in section 4.5). The relative standard deviation with respect to GDP is the median over the 67 country-specific relative standard deviations in the sample.

Table A3: List of commodity price series

List of commodity price series			
Agricultural		Metal	Fuel
Urea	Coconut oil	Tin	Crude oil, average
Maize	Soybeans	Gold	Coal, Australian
Rice, Thai 5%	Groundnut oil	Silver	Gas
DAP	Sugar, world	Copper	
TSP	Cotton, A Index	Lead	
Sorghum	Potassium chloride	Zinc	
Soybean oil	Phosphate rock	Iron ore, CFR spot	
Barley	Sawnwood, Malaysian	Nickel	
coffee	Banana, US	Aluminum	
Logs	Cocoa	Platinum	
Palm oil	Tea		
Wheat	Orange		
Rubber, SGP/MYS	Beef		
Copra	Tobacco, U.S. import u.v.		
	Meat, chicken		
	Shrimps, Mexican		

Note: List of commodities included in equation 3.1 to obtain the foreign block. The data is annual prices available in real terms, in 2010 U.S. dollars, for 1970 to 2014. Source: the World Bank Pink Sheet data.

Table A4: The R^2 of common factors—over the period 1970 to 2014

	1^{st} factor	three factors	six factors	ten factors
Aluminum	0.06	0.35	0.57	0.70
Banana, U.S.	0.01	0.30	0.49	0.57
Barley	0.55	0.58	0.63	0.76
Beef	0.01	0.16	0.20	0.59
Coal, Australian	0.35	0.83	0.87	0.94
Cocoa	0.01	0.36	0.50	0.70
Coconut oil	0.40	0.75	0.84	0.87
coffee	0.50	0.89	0.91	0.96
Copper	0.41	0.72	0.86	0.90
Copra	0.42	0.78	0.85	0.88
Cotton, A Index	0.26	0.35	0.40	0.68
Crude oil, average	0.37	0.43	0.44	0.49
DAP	0.58	0.59	0.71	0.79
Gas	0.04	0.13	0.18	0.77
Gold	0.44	0.60	0.88	0.90
Groundnut oil	0.33	0.55	0.58	0.64
Iron ore, cfr spot	0.18	0.43	0.66	0.66
Lead	0.29	0.50	0.63	0.74
Logs	0.50	0.89	0.92	0.96
Maize	0.60	0.74	0.76	0.89
Meat, chicken	0.12	0.55	0.60	0.64
Nickel	0.12	0.34	0.75	0.81
Orange	0.002	0.12	0.29	0.67
Palm oil	0.50	0.81	0.84	0.89
Phosphate rock	0.14	0.50	0.70	0.82
Platinum	0.06	0.59	0.67	0.75
Potassium chloride	0.26	0.48	0.64	0.65
Rice, Thai 5%	0.58	0.59	0.75	0.81
Rubber, SGP/MYS	0.44	0.65	0.71	0.86
Sawnwood, Malaysian	0.13	0.21	0.23	0.32
Shrimps, Mexican	0.15	0.26	0.31	0.56
Silver	0.42	0.56	0.90	0.95
Sorghum	0.55	0.65	0.69	0.89
Soybean oil	0.55	0.86	0.86	0.90
Soybeans	0.33	0.63	0.67	0.76
Sugar, world	0.27	0.41	0.70	0.82
Tea	0.01	0.37	0.60	0.82
Tin	0.51	0.53	0.77	0.80
Tobacco, U.S. import u.v.	0.03	0.49	0.60	0.82
TSP	0.56	0.57	0.74	0.80
Urea	0.61	0.82	0.87	0.88
Wheat	0.49	0.89	0.93	0.96
Zinc	0.2	0.28	0.58	0.86
Average	0.32	0.54	0.66	0.78

Note: I regress the normalized commodity price series on the common factors of the factor model. Then, I list the R^2 of the OLS analysis in this table.

Table A5: List of countries excluded from the estimation

Country	Data	Average	Standard deviation
Algeria	Highly volatile data	9.20	7.87
Angola	High standard deviation	456.46	988.32
Bahrain	High standard deviation	4.04	16.43
Botswana	Highly volatile data	9.85	22.70
Bulgaria	High standard deviation	68.17	202.05
Burkina Faso	High standard deviation	4.73	17.19
Central African Republic	High standard deviation	4.18	17.54
Chad	High standard deviation	4.02	10.66
Cote d'Ivoire	High standard deviation	6.33	16.50
Croatia	High standard deviation	161.62	386.13
Guinea-Bissau	High standard deviation	20.61	26.24
Honduras	Highly volatile data	9.96	27.15
India	Highly volatile data	9.06	15.11
Indonesia	Highly volatile data	9.62	19.98
Iran, Islamic Rep.	Highly volatile data	7.99	19.23
Malawi	Highly volatile data	20.33	14.84
Mali	High standard deviation	2.98	10.77
Mongolia	High standard deviation	27.58	57.13
Niger	High standard deviation	4.79	8.62
Romania	High standard deviation	56.18	78.69
Russian Federation	High standard deviation	78.64	192.10
Slovak Republic	highly volatile	6.53	15.19
Slovenia	High standard deviation	87.84	235.08
Sudan	High standard deviation	34.37	34.76
Tanzania	Highly volatile data	16.86	28.82
Togo	High standard deviation	5.72	10.57
Tunisia	Highly volatile data	4.75	22.00

Note: List of countries excluded from the sample.

Table A6: List of countries — baseline results

	Annual data set				Quarterly data set	
Country name	Real GDP	Inflation	Data source	Balanced sample	Time period	Data source
Australia	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Austria	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Bangladesh	1970-2014	1987-2014	WDI	1987-2014		
Barbados	1970-2014	1986-2014	WDI	1986-2014		
Belgium	1970-2014	1977-2014	WDI	1977-2014	1970Q3-2014Q4	OECD
Benin	1970-2014	1993-2014	WDI	1993-2014		
Bolivia	1970-2014	1980-2014	WDI	1980-2014		
Burundi	1970-2014	1980-2014	WDI	1980-2014		
Cabo Verde	1970-2014	1984-2014	WDI	1984-2014		
Cameroon	1970-2014	1980-2014	WDI	1980-2014		
Canada	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Chile	1970-2014	1971-2014	WDI	1971-2014	1980Q3-2014Q4	OECD
China	1970-2014	1987-2014	WDI	1987-2014		
Congo, Rep.	1970-2014	1986-2014	WDI	1986-2014		
Cyprus	1970-2014	1977-2014	WDI	1977-2014		
Czech Republic	1970-2014	1992-2014	WDI	1992-2014	1995Q3-2014Q4	OECD
Denmark	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Dominican Republic	1970-2014	1978-2014	WDI	1978-2014		
El Salvador	1970-2014	1979-2014	WDI	1979-2014		
Equatorial Guinea	1980-2014	1986-2014	WDI	1986-2014		
Ethiopia	1970-2014	1981-2014	WDI	1981-2014		
Finland	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
France	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Gambia, The	1970-2014	1970-2014	WDI	1970-2014		
Germany	1978-2014	1978-2014	WDI	1978-2014	1970Q3-2014Q4	OECD
Greece	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Haiti	1970-2014	1974-2014	WDI	1974-2014		
Hong Kong SAR, China	1970-2014	1982-2014	WDI	1982-2014		
Iceland	1970-2014	1977-2014	WDI	1977-2014	1976Q2-2014Q4	OECD
Ireland	1970-2014	1970-2014	WDI	1970-2014	1976Q2-2014Q4	OECD
Italy	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Japan	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Jordan	1975-2014	1974-2014	WDI	1974-2014		
Kenya	1970-2014	1979-2014	WDI	1979-2014		
Korea, Rep.	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Kuwait	1970-2014	1979-2014	WDI	1979-2014		
Lesotho	1970-2014	1980-2014	WDI	1980-2014		
Libya	1970-2014	1990-2014	WDI	1990-2014		
Luxembourg	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Malaysia	1970-2014	1970-2014	WDI	1970-2014		
Malta	1970-2014	1983-2014	WDI	1983-2014		
Mauritania	1970-2014	1986-2014	WDI	1986-2014		
Mauritius	1970-2014	1978-2014	WDI	1978-2014		

Continue on the next page

Table A6: List of countries — baseline results (cont.).

	Annual data set				Quarterly data set	
Country name	Real GDP	Inflation	Data source	Balanced sample	Time period	Data source
Mexico	1970-2014	1980-2014	WDI	1980-2014	1970Q3-2014Q4	OECD
Myanmar	1970-2014	1982-2014	WDI	1982-2014		
Netherlands	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
New Zealand	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Nigeria	1970-2014	1980-2014	WDI	1980-2014		
Norway	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Pakistan	1970-2014	1980-2014	WDI	1980-2014		
Panama	1970-2014	1980-2014	WDI	1980-2014		
Poland	1970-2014	1984-2014	WDI	1984-2014	1995Q3-2014Q4	OECD
Rwanda	1970-2014	1980-2014	WDI	1980-2014		
Saudi Arabia	1970-2014	1981-2014	WDI	1981-2014		
Seychelles	1970-2014	1983-2014	WDI	1983-2014		
Singapore	1970-2014	1978-2014	WDI	1978-2014		
South Africa	1970-2014	1980-2014	WDI	1980-2014	1970Q3-2014Q4	OECD
Spain	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Sri Lanka	1970-2014	1980-2014	WDI	1980-2014		
Sweden	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Switzerland	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Thailand	1975-2014	1970-2014	WDI	1970-2014		
Turkey	1970-2014	1977-2014	WDI	1977-2014	1970Q3-2014Q4	OECD
United Kingdom	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
United States	1970-2014	1970-2014	WDI	1970-2014	1970Q3-2014Q4	OECD
Yemen, Rep.	1970-2014	1990-2014	WDI	1990-2014		
Zambia	1970-2014	1986-2014	WDI	1986-2014		

Table A7: List of countries—baseline results with confidence intervals at 95% level

	Confidence interval at 95\% level				
Country	$\hat{\sigma^{\pi}}$	Confidence interval	Country	$\hat{\sigma^{\pi}}$	Confidence interval
Australia	0.21	[0.21, 0.22]	Kenya	0.30	[0.24, 0.25]
Austria	0.40	[0.38, 0.39]	Korea, Rep.	0.41	[0.40, 0.41]
Bangladesh	0.33	[0.32, 0.34]	Kuwait	0.26	[0.27, 0.28]
Barbados	0.19	[0.19, 0.20]	Lesotho	0.16	[0.15, 0.17]
Belgium	0.52	[0.51, 0.53]	Libya	0.18	[0.17, 0.19]
Benin	0.03	[0.03, 0.05]	Luxembourg	0.49	[0.48, 0.49]
Bolivia	0.10	[0.08, 0.10]	Malaysia	0.37	[0.37, 0.38]
Burundi	0.03	[0.05, 0.06]	Malta	0.33	[0.33, 0.35]
Cabo Verde	0.14	[0.11, 0.12]	Mauritania	0.06	[0.06, 0.07]
Cameroon	0.02	[0.04, 0.05]	Mauritius	0.30	[0.29, 0.30]
Canada	0.03	[0.07, 0.08]	Mexico	0.21	[0.21, 0.23]
Chile	0.27	[0.24, 0.25]	Myanmar	0.18	[0.17, 0.18]
China	0.24	[0.23, 0.24]	Netherlands	0.46	[0.46, 0.47]
Congo, Rep.	0.40	[0.37, 0.38]	New Zealand	0.25	[0.25, 0.26]
Cyprus	0.14	[0.22, 0.23]	Nigeria	0.00	[0.00, 0.02]
Czech Republic	0.48	[0.40, 0.41]	Norway	0.18	[0.17, 0.18]
Denmark	0.33	[0.41, 0.43]	Pakistan	0.42	[0.42, 0.43]
Dominican Republic	0.37	[0.35, 0.37]	Panama	0.42	[0.42, 0.43]
El Salvador	0.36	[0.31, 0.32]	Poland	0.12	[0.12, 0.13]
Equatorial Guinea	0.19	[0.17, 0.21]	Rwanda	0.13	[0.13, 0.15]
Ethiopia	0.14	[0.13, 0.15]	Saudi Arabia	0.28	[0.28, 0.29]
Finland	0.30	[0.30, 0.32]	Seychelles	0.26	[0.24, 0.25]
France	0.66	[0.64, 0.66]	Singapore	0.62	[0.62, 0.63]
Gambia, The	0.54	[0.54, 0.55]	South Africa	0.03	[0.03, 0.04]
Germany	0.10	[0.11, 0.12]	Spain	0.14	[0.13, 0.14]
Greece	0.41	[0.39, 0.41]	Sri Lanka	0.27	[0.26, 0.27]
Haiti	0.16	[0.15, 0.16]	Sweden	0.15	[0.14, 0.15]
Hong Kong SAR, China	0.07	[0.10, 0.11]	Switzerland	0.35	[0.34, 0.35]
Iceland	0.42	[0.37, 0.39]	Thailand	0.44	[0.44, 0.45]
Ireland	0.01	[0.08, 0.09]	Turkey	0.20	[0.18, 0.20]
Italy	0.48	[0.46, 0.47]	United Kingdom	0.42	[0.41, 0.42]
Japan	0.44	[0.45, 0.46]	United States	0.74	[0.73, 0.74]
Jordan	0.42	[0.38, 0.39]	Yemen, Rep.	0.12	[0.12, 0.13]

Note: List of countries included in the baseline estimation with the results. The sample used in this paper is unbalanced, and the number of observations for the domestic block is different across countries (20 to 45 across 67 countries). The confidence interval is also mentioned here to show the uncertainty of the results.

Table A8: List of countries in the estimation using core inflation

Australia	France	Japan	Norway
Austria	Germany	Korea, Rep.	Spain
Belgium	Greece	Luxembourg	Sweden
Canada	Iceland	Mexico	Switzerland
Denmark	Ireland	Netherlands	United Kingdom
Finland	Italy	New Zealand	United States

Note: List of countries that included core inflation in the estimation. The sample used in this paper is unbalanced, and the number of observations for the domestic block is different across countries (20 to 45 across 24 countries).

Table A9: List of countries in the estimation with real interest rate

Albania	Gambia, The	Myanmar
Australia	Honduras	Panama
Bahrain	Hong Kong SAR, China	Seychelles
Bangladesh	Iceland	Singapore
Barbados	Indonesia	Solomon Islands
Bolivia	Italy	South Africa
Burundi	Japan	Sweden
Canada	Kenya	Tanzania
Chile	Kuwait	Thailand
China	Lesotho	United Kingdom
Czech Republic	Malaysia	United States
Dominican Republic	Mauritania	Zambia
Ethiopia	Mauritius	

Note: List of countries that included real interest rate in the estimation. The sample used in this paper is unbalanced, and the number of observations for the domestic block is different across countries (20 to 45 across 38 countries).

Table A10: List of countries in the estimation with exchange rates

Australia	Congo, Rep.	Haiti	Netherlands
Austria	Cyprus	Hong Kong SAR, China	New Zealand
Bangladesh	Czech Republic	Iceland	Norway
Belgium	Denmark	Ireland	Panama
Benin	Dominican Republic	Italy	Poland
Bolivia	El Salvador	Japan	Rwanda
Burkina Faso	Equatorial Guinea	Jordan	Saudi Arabia
Burundi	Ethiopia	Lesotho	Seychelles
Cabo Verde	Finland	Luxembourg	Spain
Cameroon	France	Malaysia	Sweden
Canada	Gambia, The	Mauritania	Switzerland
Chile	Germany	Mauritius	United States
China	Greece	Myanmar	Yemen, Rep.
			Zambia

Note: List of countries that included the exchange rate in the estimation. The sample used in this paper is unbalanced, and the number of observations for the domestic block is different across countries (20 to 45 across 53 countries).

Table A11: Correlation between commodity factors and indices

	1^{st} factor	2^{nd} factor	3^{rd} factor
Agricultural index	0.35	-0.02	-0.08
Fuel index	0.36	0.10	0.20
Metal index	0.43	0.36	-0.10

Note: This table shows the correlation between the factors of commodity prices with commodity price indices.

Table A12: List of countries—Excluding large commodity exporters

Countries included in the estimation			Large commodity exporters	
Angola	Hong Kong SAR, China	Seychelles	Australia	Sweden
Bahamas, The	Iceland	Singapore	Austria	Switzerland
Bangladesh	Ireland	Spain	Belgium	Thailand
Barbados	Japan	Sri Lanka	Canada	United Kingdom
Benin	Jordan	Turkey	Chile	United States
Bolivia	Kuwait	Yemen, Rep.	China	
Burundi	Lesotho	Zambia	Denmark	
Cabo Verde	Libya		Ethiopia	
Cameroon	Luxembourg		Finland	
Congo, Rep.	Malta		Gambia, The	
Cyprus	Mauritania		Italy	
Czech Republic	Mexico		Kenya	
Dominican Republic	Myanmar		Korea, Rep.	
El Salvador	New Zealand		Malaysia	
Equatorial Guinea	Pakistan		Mauritius	
France	Panama		Netherlands	
Germany	Poland		Nigeria	
Greece	Rwanda		Norway	
Haiti	Saudi Arabia		South Africa	

I exclude large commodity exporters from the sample. I identify the top 20% largest exporters for each of the three commodity groups. Then I exclude the union of these large exporters from the panel. This yields the exclusion of 22 countries from the sample which results in 45 countries used in the estimation.

Table A13: List of countries—Oil exporters vs oil importers

Oil importers			Oil exporters
Bahrain	Guatemala	Papua New Guinea	Australia
Bangladesh	Haiti	Poland	Bolivia
Benin	Hong Kong SAR, China	Saudi Arabia	Cameroon
Botswana	Iceland	Seychelles	Canada
Bulgaria	Iran, Islamic Rep.	Singapore	Congo, Rep.
Burkina Faso	Ireland	Slovak Republic	Egypt, Arab Rep.
Burundi	Italy	Slovenia	France
Chad	Japan	South Africa	India
Chile	Kuwait	Spain	Korea, Rep.
China	Luxembourg	Sri Lanka	Lesotho
Cote d'Ivoire	Madagascar	Sweden	Mauritius
Croatia	Malta	Switzerland	Nigeria
Denmark	Mauritania	Tanzania	Norway
Dominican Republic	Mexico	Thailand	Yemen, Rep.
El Salvador	Mongolia	Turkey	
Ethiopia	Myanmar	Zambia	
Finland	New Zealand		
Gambia, The	Pakistan		
Germany	Panama		

I compute the net trade in fuel oil for each country. I compute the country-specific median of net exports of fuels since 1970, using annual information on exports and imports of fuel commodities from the WDI. A country is an oil exporter (importer) if the median net share of fuel exports in GDP is positive (negative).

Table A14: List of countries—Net commodity traders

Net commodity importers			Net commodity exporters	
Austria	Iceland	Thailand	Bahrain	Sri Lanka
Bangladesh	Ireland	Turkey	Benin	Togo
Barbados	Italy	United Kingdom	Bolivia	Yemen, Rep.
Belgium	Japan	United States	Burkina Faso	Zambia
Burundi	Jordan		Cameroon	
Cabo Verde	Kuwait		Canada	
China	Libya		Chile	
Cyprus	Luxembourg		Congo, Rep.	
Czech Republic	Malaysia		Equatorial Guinea	
Denmark	Mauritania		France	
Dominican Republic	Pakistan		Korea, Rep.	
El Salvador	Rwanda		Lesotho	
Ethiopia	Saudi Arabia		Malta	
Finland	Senegal		Mauritius	
Gambia, The	Singapore		Mexico	
Germany	South Africa		Nigeria	
Greece	Spain		Norway	
Haiti	Sweden		Panama	
Hong Kong SAR, China	Switzerland		Seychelles	

I consider a country as a commodity exporter (importer) if there is a positive (negative) trade balance on average in the group of three commodities (agricultural, fuel, and metals) since 1970. To do so, I use annual data on agricultural, fuel, and metals commodities from the WDI. Then, I calculate the net trade in each category. This classification yields 39 commodity exporters and 64 commodity importers.

Table A15: List of countries—Income level

High income countries			Low income countries	
Australia	Japan	Sweden	Bangladesh	Spain
Austria	Kenya	Switzerland	Benin	Sri Lanka
Barbados	Korea, Rep.	Thailand	Bolivia	Yemen, Rep.
Belgium	Kuwait	Turkey	Burundi	Zambia
Canada	Lesotho	United Kingdom	Cabo Verde	
Chile	Libya	United States	Cameroon	
China	Malaysia		Congo, Rep.	
Cyprus	Malta		El Salvador	
Czech Republic	Mauritania		Germany	
Denmark	Mauritius		Greece	
Dominican Republic	Mexico		Haiti	
Equatorial Guinea	Myanmar		Iceland	
Ethiopia	Netherlands		Jordan	
Finland	Nigeria		Luxembourg	
France	Norway		New Zealand	
Gambia, The	Pakistan		Panama	
Hong Kong SAR, China	Poland		Rwanda	
Ireland	Singapore		Saudi Arabia	
Italy	South Africa		Seychelles	

Note: I divide countries into two categories: The high income (59 countries) and the low income (24 countries). The categorization is based on the WDI and the per capita gross national incomes for 2015. The results are robust to basing the categorization on income levels in 1990.

.1 The small-sample bias procedure

I apply a Monte Carlo procedure as suggested by Fernández et al. (2017) to correct for the small-sample bias in this paper. The procedure consists of the following steps:

1. For a given country, let $\hat{F}$, $\hat{G}$, and $\hat{\Sigma}$ denote the estimates of F, G, and Σ obtained using actual data. Let $\hat{\sigma}$ denote the associated estimate of the share of the variance of Y_t explained by μ_t. Use $\hat{F}$, $\hat{G}$, and $\hat{\Sigma}$ to generate artificial time series for Y_t and p_t of the desired length from the SVAR model given in equation 3.1. I generate artificial time series for 250 years.

2. Let T^p denote the sample size of commodity prices. I set $T^p = 45$, the sample size of commodity prices in the data set. Let T^y denote the sample size of Y_t. I consider T^y equal to the number of observations of Y_t in the data set for the particular country. Then I use the last T^p observations of the artificial time series to re-estimate the foreign block of the SVAR. Next, I use the last T^y observations of the artificial series to re-estimate the domestic bloc.

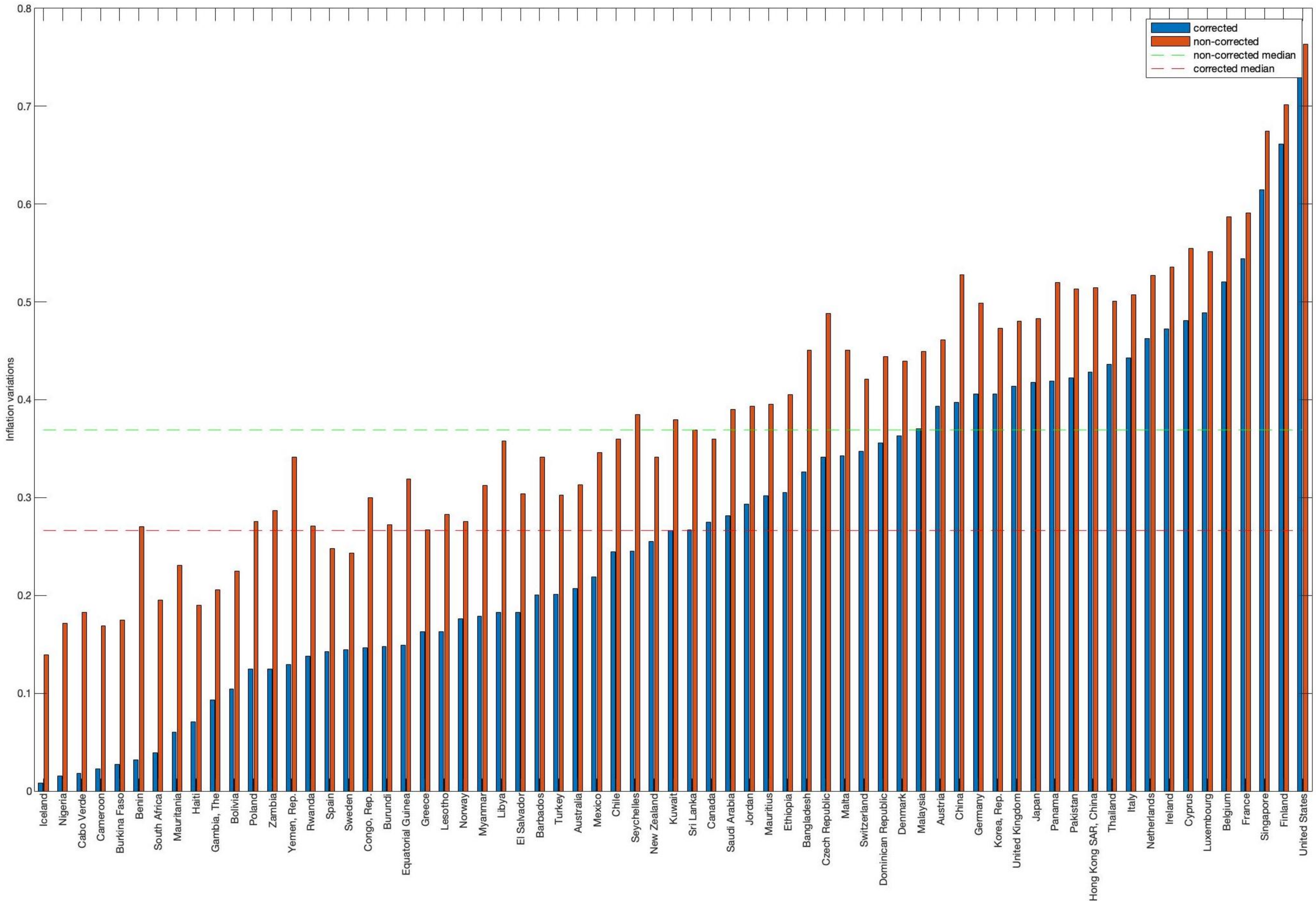
3. Steps 1 and 2 yield an estimate of the matrices F, G, and Σ from the simulated data. I use these estimates to compute the share of the variance of Y_t explained by μ_t shocks, which is denoted by σ.

4. I repeat steps 1–3 N times. I set $N = 1000$. Then I compute averages of the resulting estimate of σ and denote it by $\bar{\sigma}$.

5. I define the small-sample bias as $\bar{\sigma} - \hat{\sigma}$. The corrected estimate of the share of the variance of Y_t explained by μ_t is then given by $2\hat{\sigma} - \bar{\sigma}$.

6. I perform steps 1 through 5 for each of the 67 countries in the panel.

Fig. 5: Inflation fluctuations to commodity price shocks – Baseline result.



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