Australian National University

Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Global Factors and Trend Inflation

CAMA Working Paper 62/2019
August 2019

Güneş Kamber
International Monetary Fund
Centre for Applied Macroeconomic Analysis, ANU

Benjamin Wong
Monash University
Centre for Applied Macroeconomic Analysis, ANU

Abstract

We develop an empirical model to study the influence of global factors in driving trend inflation and the inflation gap. We apply our model to 7 developed economies and 21 emerging market economies. Our results suggest that while global factors can have a sizeable influence on the inflation gap, they play only a marginal role in driving trend inflation. Much of the influence of global factors in the inflation gap may be reflecting commodity price shocks. Finally, we find that the effect of global factors to be greater in our sample of emerging market economies relative to the developed economies. There is some evidence which suggest propagation mechanisms, which may reflect institutional structures or policy choices, can explain the greater role for global factors in driving trend inflation in emerging market economies.

Keywords

Trend inflation, foreign shocks, Beveridge-Nelson decomposition

JEL Classification

C32, E31, F41

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Global Factors and Trend Inflation *†

Güneş Kamber[1,3] and Benjamin Wong[2,3]

[1]International Monetary Fund
[2]Monash University, Australia
[3]Centre for Applied Macroeconomic Analysis, The Australian National University

Abstract

We develop an empirical model to study the influence of global factors in driving trend inflation and the inflation gap. We apply our model to 7 developed economies and 21 emerging market economies. Our results suggest that while global factors can have a sizeable influence on the inflation gap, they play only a marginal role in driving trend inflation. Much of the influence of global factors in the inflation gap may be reflecting commodity price shocks. Finally, we find that the effect of global factors to be greater in our sample of emerging market economies relative to the developed economies. There is some evidence which suggest propagation mechanisms, which may reflect institutional structures or policy choices, can explain the greater role for global factors in driving trend inflation in emerging market economies.

JEL Classification: C32, E31, F41

Keywords: Trend inflation, foreign shocks, Beveridge-Nelson decomposition

*Kamber: gkamber@imf.org Wong: benjamin.wong@monash.edu

†We thank the Editor, Martín Uribe, two anonymous referees, Joshua Chan, Peter Hoerdahl, Enrique Martínez-García, Madhusudan Mohanty, Elmar Mertens, Benoit Mojon, James Morley, Matteo Luciani, James Yetman, participants at various conferences and seminars for comments and suggestions. We also thank Anamaria Illes, Abby Nguyen, and Jimmy Shek for excellent research assistance. We are grateful to Jongrim Ha from the World Bank who provided the inflation data. Benjamin Wong acknowledges funding support from the Australian Research Council (DP190100202). Part of the work underpinning this paper was completed when Benjamin Wong visited the Bank for International Settlements Representative Office for Asia and the Pacific as a Central Bank Research Fellow. The office's hospitality is gratefully acknowledged. The views expressed in this paper are those of the authors and do not necessarily represent the views of the International Monetary Fund, its Executive Board, IMF management or the Bank for International Settlements. The online appendix can be found on our websites https://sites.google.com/site/guneskamber/ and https://sites.google.com/site/benjaminwongshijie/research

1 Introduction

> *... are central banks still masters of their domestic monetary destinies? Or have they become slaves to global factors?* – Carney (2015)

Figure 1 presents year-on-year inflation in a number of industrialized countries to provide a flavor of global co-movement in inflation. Casual observation suggests inflation co-moves globally: a feature of the data that has been extensively statistically verified (e.g., see Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012). The stylized fact that inflation co-moves globally has led to interest in quantifying the role of global determinants of inflation (e.g., see Borio and Filardo, 2007; Neely and Rapach, 2011; Bianchi and Civelli, 2015; Auer, Levchenko, and Sauré, 2017) and examining the implications for monetary policy (Carney, 2015).

Our paper contributes to the debate on the role of global factors in driving inflation. Specifically, the main contribution of our paper is to develop a unified framework to study the role of foreign shocks in driving the permanent and transitory components of inflation, which we interpret as trend inflation and the inflation gap respectively. To answer whether global factors have monetary policy implications, we view distinguishing between trend inflation and the inflation gap as key. For example, Draghi (2015) states *"central banks typically choose to 'look through' such global forces until their effect on inflation fades out or until prices reverse"*. We interpret this statement as typical central banking doctrine that one should "look through" transitory or one-off changes in prices. Correspondingly, the degree of importance one should attach to the foreign determinants of domestic inflation from a policy perspective depends on how much foreign shocks feed into the trend, or the permanent component of, inflation. If the influence of foreign shocks is shown to be one-off or transitory, then the standard doctrine would be to "look through" or not respond to them. Our paper tackles this issue head-on by developing a model which quantifies the role of foreign shocks in the determination of trend inflation and the inflation gap.

We apply our model to a sample of 28 countries; 7 developed economies and 21 emerging market economies. We highlight three main findings. First, a key result of our empirical exercise is that while they can have a sizeable influence on the inflation gap, foreign shocks play a smaller role in driving trend inflation. This result is consistent with the idea that inflation in the long-run appears to be a monetary phenomenon largely determined by domestic monetary policy, despite foreign shocks driving its short to medium run fluctuations. Second, we find that commodity price shocks account for a large share of the identified role of foreign shocks in driving inflation gap. Third, we find that foreign shocks have a larger impact on trend inflation in emerging market economies relative to developed economies. In fact, in our sample of developed economies, we sometimes find foreign shocks have a negligible to no role in determining trend inflation. We also uncover evidence that these differences in how foreign shocks affect emerging market and developed economies respectively may not just be due to emerging market economies experiencing larger shocks. In other words, it appears that there is some evidence that there are propagation mechanisms at work in emerging market relative to developed economies which accentuate the role of foreign shocks in driving trend inflation in the former group.

Our empirical model can, at a broad level, be viewed as a Factor-Augmented Vector Autoregression (FAVAR). Using the FAVAR model, we construct trend inflation and the inflation gap consistent with the Beveridge and Nelson (1981)(BN) decomposition. By utilizing the BN decomposition, we adopt a similar concept of trend inflation and the inflation gap which is consistent with the wider trend inflation literature (see, e.g. Stock and Watson, 2007). Taking guidance from the well-established Structural Vector Autoregression (SVAR) literature, the small open economy structure we adopt provides a straightforward identification of foreign and domestic shocks. Our empirical strategy then consists of decomposing trend inflation and the inflation gap into the identified foreign and domestic shocks, thus providing an account of the role of foreign and domestic shocks in driving both trend inflation and the inflation gap.

While Unobserved Components (UC) models have featured prominently in trend inflation literature (e.g., see Stock and Watson, 2007; Mertens, 2016; Chan, Clark, and Koop, 2017), we make a deliberate deviation from the UC literature in one important dimension; by allowing for multivariate information through the FAVAR framework. Our choice allows us to draw on the SVAR literature to identify foreign shocks, and thus tease out causality within our framework. Even so, we stress that the concept of trend inflation is identical to the UC framework, providing a natural link to this body of work. Our work is also related to the literature on the foreign determinants of inflation. In particular, much of the work on the globalization of inflation has looked at the influence of foreign *vis-a-vis* domestic slack in driving inflation (e.g. Borio and Filardo, 2007; Ihrig, Kamin, Lindner, and Marquez, 2010; Martínez-García and Wynne, 2013; Kabukçuoğlu and Martínez-García, 2018). Indeed, we concur, similar to others (e.g Milani, 2010; Eickmeier and Pijnenburg, 2013), that a regression against a foreign slack measure, such as a foreign output gap, is not sufficiently rich to tell apart the effect of domestic shocks from that of foreign shocks. If an economy is sufficiently open, then foreign shocks drive *both* the foreign and domestic slack, which means one cannot tell the influence of foreign shocks without a formal identification exercise, which is why we view our identification exercise as crucial. In this regard, we take a much broader perspective relative to the extant work of foreign determinants of inflation, which largely focus attention to only a measure of foreign slack.

The rest of the paper is organized as follows. In Section 2, we provide a description and justification of our empirical methodology. In Section 3, we present the results. In particular, we use our decomposition to understand the role of foreign shocks in driving trend inflation and the inflation gap. We then offer some concluding remarks.

2 Empirical Specification

We conduct our empirical analysis on a group of 7 developed and 21 emerging market small open economies. We list our group of developed and emerging market economies in Table 1.[1] Broadly, our empirical approach involves first estimating trend inflation and the inflation gap for each country by appealing to the Beveridge and Nelson (1981) decomposition. Subsequently, for each country, we decompose the estimated trend inflation and inflation gap into foreign and domestic shocks appealing to multivariate extensions to the BN decomposition developed by Morley and Wong (forthcoming). The second part of our empirical exercise enables us to understand the role of foreign shocks on both trend inflation and the inflation gap. In the subsections that follow, we first introduce our trend-cycle decomposition. We then present our empirical model and briefly discuss our estimation strategy.

2.1 Permanent-Transitory Decomposition

This subsection outlines the concepts of trend and gap which we use in this paper. We work with the Beveridge and Nelson (1981) (BN) decomposition to perform a trend-cycle decomposition on inflation. The BN decomposition has proven a useful approach to separate trend from cycle in a wide variety of settings (e.g. Evans and Reichlin, 1994; Morley and Piger, 2012; Kamber, Morley, and Wong, 2018). Moreover, the equating of trend inflation as the BN permanent component of inflation is widespread within the empirical literature (e.g. Stock and Watson, 2007; Cogley, Primiceri, and Sargent, 2010), providing a natural link of our work to the wider literature.

Let π_t represent the (annualized quarter on quarter) inflation rate. Denoting trend inflation, τ_t, as the BN permanent component of inflation, which corresponds to the long-horizon forecast of the level of inflation given the information at time t and a suitably specified time series model to form this expectation:

$$\tau_t = \lim_{j \to \infty} \mathbb{E}_t \pi_{t+j}. \tag{1}$$

The transitory component, $\tilde{\pi}_t$, is the inflation gap, where $\tilde{\pi}_t = \pi_t - \tau_t$. Let $\mathbf{X_t}$ be a vector of variables with $\Delta\pi_t$, the first difference of inflation, its k^{th} element. We can write

[1] Our definition of developed and emerging market economies is from the Bank for International Settlements. For example, see page vii of https://www.bis.org/publ/arpdf/ar2018e.pdf. From this group of countries, we choose our small open economies by omitting large economies (i.e. United Kingdom, United States) and countries in the Euro Area as it is unclear how to model the Euro Area countries as individual small open economies.

the law of motion of the state equation in $\mathbf{X_t}$ as a first order autoregressive process,

$$\mathbf{X_t} = \mathbf{B}\mathbf{X_{t-1}} + \mathbf{H}\boldsymbol{\nu_t} \tag{2}$$

where $\mathbf{B}$ is a companion matrix whose eigenvalues are all within the unit circle. $\boldsymbol{\nu_t}$ is a vector of serially uncorrelated forecast errors with covariance matrix, $\mathbf{\Sigma}_{\boldsymbol{\nu}}$, and $\mathbf{H}$ is a matrix which maps the forecast errors to the companion form. Defining $\mathbf{e_k}$ as a selector row vector with 1 as its k^{th} element and zero otherwise, the trend inflation and the inflation gap consistent with the BN decomposition can be written as (see, e.g. Morley, 2002)

$$\begin{aligned}
\tau_t &= \pi_t + \mathbf{e_k}\mathbf{B}(\mathbf{I}-\mathbf{B})^{-\mathbf{1}}\mathbf{X_t} && (3)\\
\tilde{\pi}_t &= -\mathbf{e_k}\mathbf{B}(\mathbf{I}-\mathbf{B})^{-\mathbf{1}}\mathbf{X_t}. && (4)
\end{aligned}$$

Equations (3) and (4) state that with an empirical model cast into a form like Equation (2), inflation can be decomposed into its trend and gap components consistent with the BN decomposition. In our empirical implementation, we work with what can broadly be described as a Factor-Augmented VAR (FAVAR), which can readily be cast into the form suggested by Equation (2).

To see how we can decompose the inflation gap and trend inflation into foreign and domestic shocks, suppose we had a matrix $\boldsymbol{C}$ which maps the forecast errors, $\boldsymbol{\nu}_t$ to the foreign and domestic shocks, $\boldsymbol{\vartheta}_t$, where $\boldsymbol{C\vartheta_t = \nu_t}$. Using this mapping, and recursively substituting Equation (2) into Equations (3) and (4), we can express trend inflation and inflation gap as (see Morley and Wong, forthcoming):

$$\begin{aligned}
\Delta\tau_t &= \mathbf{e_k}(\mathbf{I}-\mathbf{B})^{-\mathbf{1}}\mathbf{HC}\boldsymbol{\vartheta_t} && (5)\\
\tilde{\pi}_t &= -\mathbf{e_k}\left\{\sum_{\mathbf{i=0}}^{\mathbf{t-1}} \boldsymbol{B}^{\boldsymbol{i+1}}(\mathbf{I}-\mathbf{B})^{-\mathbf{1}}\mathbf{HC}\boldsymbol{\vartheta_t}\right\} - \mathbf{e_k}\boldsymbol{B}^{\boldsymbol{t+1}}(\mathbf{I}-\mathbf{B})^{-\mathbf{1}}\mathbf{e_k}'\boldsymbol{\Delta}\pi_{\mathbf{0}}. && (6)
\end{aligned}$$

The final term in Equation (6) contains an initial condition, $\Delta\pi_0$, but the influence of the initial condition is expected to vanish over time, due to the coefficient, $\mathbf{B^{t+1}}$, as all the eigenvalues of $\mathbf{B}$ are assumed to be within the unit circle. Equations (5) and (6) show that the change of trend inflation and the inflation gap are just linear functions of the history of foreign and domestic shocks. Therefore, Equations (5) and (6) provide the basis for our subsequent analysis, as they enable us to quantify the effects of foreign shocks on trend inflation and the inflation gap.

While our modeling choice deviates from Unobserved Components (UC) models of trend inflation (e.g. Stock and Watson, 2007; Mertens, 2016), our concept of trend is identical. This stems from the facts that the (filtered) trend from a UC model is equivalent to the BN permanent component (see Morley, Nelson, and Zivot, 2003). By appealing to the BN decomposition, it is clear that our estimate of trend is conceptually identical to that of UC models. We now turn our attention to specifying our empirical model.

2.2 FAVAR Model

At a broad level, our empirical specification can be described as a standard FAVAR model (e.g., see Bernanke, Boivin, and Eliasz, 2005). Our key motivation of using a FAVAR is because we require all relevant information for modeling trend inflation without necessarily imposing the same time series on all 28 countries. More precisely, a practical challenge we face when estimating the model across 28 economies is that consistent coverage of series may not be available. As an example, long time series of the unemployment rate or capacity utilization exist for some countries, but not for others. Nonetheless, we know from Morley and Wong (forthcoming) that in using the multivariate BN decomposition, if the goal of including a variable is to include relevant information that is important for forecasting inflation, the precise variable one includes does not matter, as long as the information is being spanned by either another variable, or a set of other variables. Therefore, rather than estimating 28 individual VARs whose precise variable coverage might differ, we include relevant information in the form of factors in a FAVAR. Using the reduced form FAVAR model, we apply identification restrictions to identify domestic and foreign shocks in a small open economy setting (e.g. Zha, 1999; Fernández, Schmitt-Grohé, and Uribe, 2017).

Let $\boldsymbol{Y}_t^*$ and $\boldsymbol{Y}_t$ represent vectors of variables from the foreign sector and the domestic small open economy, respectively. Modelling both vectors jointly as a VAR, we obtain:

$$\begin{aligned}
\begin{bmatrix} \boldsymbol{Y}_t^* \\ \boldsymbol{Y}_t \end{bmatrix} &= \begin{bmatrix} \boldsymbol{\beta}_{11}(L) & \boldsymbol{\beta}_{12}(L) \\ \boldsymbol{\beta}_{21}(L) & \boldsymbol{\beta}_{22}(L) \end{bmatrix} \begin{bmatrix} \boldsymbol{Y}_{t-1}^* \\ \boldsymbol{Y}_{t-1} \end{bmatrix} + \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon}_t^* \\ \boldsymbol{\epsilon}_t \end{bmatrix} \\
&= \begin{bmatrix} \boldsymbol{\beta}_{11}(L) & \boldsymbol{0} \\ \boldsymbol{\beta}_{21}(L) & \boldsymbol{\beta}_{22}(L) \end{bmatrix} \begin{bmatrix} \boldsymbol{Y}_{t-1}^* \\ \boldsymbol{Y}_{t-1} \end{bmatrix} + \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{0} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon}_t^* \\ \boldsymbol{\epsilon}_t. \end{bmatrix} \qquad (7)
\end{aligned}$$

$\boldsymbol{\beta}_{ij}(L)$ is conformable lag polynomial where $\boldsymbol{\beta}_{ij}(L) = \sum_{k=0}^{p-1} \boldsymbol{\beta}_{ij}^k L^k$. $\boldsymbol{\epsilon}_t^*$ and $\boldsymbol{\epsilon}_t$ are respectively the identified domestic and foreign shocks, where $\mathbb{E}\left[\boldsymbol{\epsilon}_t^{*\prime}\boldsymbol{\epsilon}_t^{\prime}\right]^{\prime}\left[\boldsymbol{\epsilon}_t^{*\prime}\boldsymbol{\epsilon}_t^{\prime}\right] = \boldsymbol{I}$. Equation (7) follows from the previous line after applying the standard small open economy block exogeneity identification restriction. The block exogeneity identification restriction imposes that the domestic economy is too small to affect the foreign economy. This restriction has roots in the traditional small open economy SVAR literature (e.g. Zha, 1999; Justiniano and Preston, 2010; Fernández, Schmitt-Grohé, and Uribe, 2017), and implies that $\boldsymbol{\beta}_{12}(L) = \boldsymbol{A}_{12} = 0$. Note that because we do not attempt to separately identify individual foreign and domestic shocks, our identification restriction is sufficient to identify all aggregate foreign and domestic shocks in our model.[2] Further disaggregation of foreign and domestic shocks requires stronger identification assumptions, which may be less tenable than the looser restriction we currently present. While we present stronger identification restrictions later in the paper to attempt to gain finer interpretation of the foreign shocks, we keep the foreign and domestic shocks dichotomy unless we explicitly state so.

Specification of Foreign Block, $\boldsymbol{Y}_t^*$ We use Fernández, Schmitt-Grohé, and Uribe (2017) as our starting point for modeling the foreign block. They use three aggregate commodity price series to model the foreign sector in their work; namely energy, agricultural commodities, and metals and minerals from the World Bank. We augment the foreign sector by also considering data from a large international dataset including economic indicators such as real GDP, industrial production, capacity utilization etc., from five large economies; the U.S., U.K., Germany, France and Japan.[3] In order to consider the large international dataset, we extract factors using principal components, in the spirit of Bernanke, Boivin, and Eliasz (2005). Let p_t^E, p_t^A and p_t^M represent the real commodity prices for energy, agricultural commodities, and metals and minerals and $f_{i,t}^*$ represent the i^{th} factor extracted from the international dataset. The foreign sector is thus modeled as

$$\boldsymbol{Y}_t^* = \begin{bmatrix} \boldsymbol{P}_t^C \\ \boldsymbol{F}_t^* \end{bmatrix}, \quad \text{where} \quad \boldsymbol{F}_t^* = \begin{bmatrix} f_{1,t}^* \\ f_{2,t}^* \\ \vdots \\ f_{\eta^*,t}^* \end{bmatrix}, \boldsymbol{P}_t^C = \begin{bmatrix} p_t^E \\ p_t^A \\ p_t^M \end{bmatrix} \tag{8}$$

Specification of Domestic Block, $\boldsymbol{Y}_t$ To model the domestic block, we first include the first difference of (quarter on quarter) headline CPI inflation and the real exchange rate, which we denote $\Delta\pi_t$ and q_t respectively. The inclusion of $\Delta\pi_t$ is obvious given our objective is to decompose headline inflation into its trend and gap components. We include real exchange rates, as they are often seen to be a relevant factor in shaping short-run inflation dynamics. Consistent with our block exogeneity restrictions, we include the

[2]To see this, suppose we had an orthonormal matrix $\boldsymbol{Q}$ where $\boldsymbol{Q} = \begin{pmatrix} \boldsymbol{Q_{11}} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{Q_{22}} \end{pmatrix}$ with $\boldsymbol{Q_{11}}$ and $\boldsymbol{Q_{22}}$ are similarly orthonormal. Then it is straightforward to show that starting from a matrix $\boldsymbol{C}$ which maps the reduced form forecast errors to the domestic and foreign shocks, a new set of rotated shocks, $\tilde{\boldsymbol{C}} = \boldsymbol{CQ}$, will still retain the relative shares of the aggregate foreign and domestic shocks.

[3]We did not include data from China mainly for practical reasons as we do not have enough data covering all our sample. While this may be a potential concern given China's growing role in the global economy, because we are using factors from five major economies to form an indicator of the global economic environment, as well as including commodity prices in our foreign block, this should provide a reasonable guard against misspecifying the state of the global economic environment despite the omission of China. In particular, the fluctuations in the commodity price will also provide information about the state of the Chinese economy.

real exchange rate for each individual country in the domestic block. Similar to our specification of the foreign block, we augment the domestic sector by also considering datasets including a range of macroeconomic variables, such as real GDP, industrial production, capacity utilization, and represent the macroeconomic dynamics in the domestic block via factors extracted through principal components from these datasets. Let $f_{i,t}$ represent the i^{th} factor extracted from the dataset of the domestic small open economy. We therefore model the domestic sector as

$$\boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{F}_t \\ q_t \\ \Delta\pi_t \end{bmatrix}, \quad \text{where} \quad \boldsymbol{F}_t = \begin{bmatrix} f_{1,t} \\ f_{2,t} \\ \vdots \\ f_{\eta,t} \end{bmatrix} \tag{9}$$

Selection of the number of Factors in $\boldsymbol{F}_t^*$ and $\boldsymbol{F}_t$ To close the specification of our empirical model, we need to determine the number of foreign and domestic factors, η^* and η, to be included in the estimation.

Our main objective with the modeling of the factors is to ensure that our modeling approach spans, as much as possible, the information set of the shocks which drive inflation, or to ensure the so-called informational sufficiency. As shown by Forni and Gambetti (2014), it is known that one requires information sufficiency to properly identify shocks in VAR models. Moreover, in the context of a trend-cycle decomposition, Morley and Wong (forthcoming) show that obtaining reliable estimates of trend and cycle with a multivariate BN decomposition also requires information sufficiency. We therefore use the informational sufficiency test as proposed by Forni and Gambetti (2014) to guide the selection of the number of factors for our model.

To do so, we start with a baseline specification only using the first principal component from the international and the domestic dataset. That is, in Equations (8) and (9), we specify $\boldsymbol{Y}_t^*$ and $\boldsymbol{Y}_t$ with $\eta^* = \eta = 1$. We first pin down the domestic block by sequentially adding principal components from the domestic dataset for the equations in the domestic block until they no longer Granger cause any of the other variables at the 1% level of significance.[4] This specifies η. We next specify the number of retained factors from the international dataset, η^*, by similarly sequentially adding principal components from the foreign block until the included factor no longer Granger causes any of the

[4]We experimented with both 5% and 10%, but found this approach retained too many factors. In small samples such as ours, this implies a considerable risk of overfitting. At the same time, in-sample Granger Causality tests may be oversized, consistent with our experience of retaining too many factors when we tested at 5% and 10%. For this reason, Forni and Gambetti (2014) use out-of-sample Granger Causality tests. However, they use a long out-of-sample evaluation sample (20 years), a luxury that we do not enjoy in our small sample setting. We therefore view our choice of doing an in-sample test at 1% level of significance as striking an appropriate balance in mitigating many of these aforementioned concerns.

other variables at the 1% level of significance. In doing so, we retain block exogeneity restriction throughout the procedure. That is, we test for Granger Causality from the principal components in the domestic dataset to only variables in the domestic block, but test for Granger causality from the principal components in the international dataset to all the variables in the model. Therefore we allow the number of domestic and foreign factors to differ between countries. As the number of foreign factors can vary across countries, this implies that we do not impose the same foreign shocks in all individual countries. In subsection 3.3, we consider an alternative specification in which foreign block is the same for all countries.

Dealing with Structural Breaks A practical issue which arises in our context is the transformation of the data. This is an especially key concern because our approach requires the VAR to be stationary. Morley and Wong (forthcoming) also show that the multivariate BN can be extremely sensitive to non-stationarity or highly persistent series. Moreover, variables entering a factor model also need to be stationary, as the conventional method of extracting factors requires an unconditional mean. While convention provides a sensible guide on the starting point, (e.g. unemployment in its percent levels, industrial production and GDP growth in percent change, interest rate in levels etc.) (e.g., see Stock and Watson, 2002; Bernanke, Boivin, and Eliasz, 2005), these conventions are often established within the context of U.S. data. With non-U.S., and especially emerging market economies, data, these established conventions might not be entirely appropriate. While first differencing is an established method of dealing with non-stationary data, we noticed many instances in our dataset where a variable should be stationary in its levels appealing to both theory and convention, but tests non-stationary. There is a known issue in macroeconomics literature where breaks in the unconditional mean can result in a time series testing non-stationary (e.g., see Perron, 1989). Certainly, we would like to retain the information in levels if a series was indeed stationary around a break in mean, and would only difference as a last resort as over-differencing can throw out a lot of useful information.[5] We therefore proceed as follows. We use convention and theory as a starting point for the transformation of all the time series in question (including variables not used to construct the factors such as the commodity prices and the real exchange rate). We then run a conventional Dickey Fuller test. If the series tests non-stationary, we use a

[5] To just cite one example in the interest of providing some intuition, the unemployment rate should be stationary by theory and convention. However, we find that the unemployment rate tests non-stationary in countries such Australia and New Zealand. We find the unemployment rate becomes stationary after we adjust for a break in the mean unemployment rate. Further, we can reconcile these breaks with structural reforms in the labour market in these countries in the mid-late 1980s. Therefore, treating the unemployment rate as being stationary around a break in the mean is probably a better characterization of the unemployment rate in these countries, both from a conventional and theoretical perspective. Differencing the unemployment rate in these settings would be throwing out a lot of useful information about the business cycle.

sup-F test (see Andrews, 1993) to locate a break in the mean at an unknown breakpoint. We first test for whether adjusting for one break renders the series stationary, otherwise, we adjust for two breaks. If a series still tests non-stationary after adjusting for two breaks, only then do we conclude the conventional transformation as being insufficient, and then difference the data. We view our approach as an appropriate compromise to retain as much of the useful information (especially that is contained in the levels of time series such as unemployment rate or the interest rate), and also allows us to consider long time series that contain possible structural breaks. Setting up an automated procedure that we have described for data processing is also more transparent, given we will treat a large number of series equally through the same data processing rules.[6]

Estimation Given that a number of the specifications we estimate contain four or five retained factors and that we work with relatively short data samples for some countries, the possibility of overfitting becomes non-trivial. We opt for Bayesian estimation of the remaining VAR parameters, using the natural conjugate Normal-Inverse Wishart prior in conjunction with the Minnesota Prior, so as to utilize standard methods to apply shrinkage to mitigate possible overfitting. We note that our approach of using principal components to extract factors as the first step, and subsequently treating the factors as observed data where which we subsequently fit a standard Bayesian VAR techniques is similar to the approach by Mumtaz and Surico (2012). The FAVAR is estimated with four lags, as typical for quarterly data. We impose a restriction that trend inflation evolves as a random walk without drift, as opposed to random walk with drift, as the former is consistent with the wider trend inflation literature (e.g. Stock and Watson, 2007), and the latter is also economically implausible.[7] Post-estimation, we take the posterior mode (which is analogous to the posterior mean in our class of models) and cast the model described by Equation (7) into a form implied by Equation (2).[8] We can then use Equation (3) and (4) to apply the BN decomposition to get an estimate of trend inflation and the inflation gap and subsequently Equations (5) and (6) to understand the role of foreign shocks in driving both the inflation gap and trend inflation. We relegate details on the estimation to Section A1 of the online appendix.

[6]We also found that if we do not adjust the data, the factors also appeared to contained a drift, and the Granger Causality test started retaining too many factors. There is reason to expect that the drift in the factors probably causes the Granger Causality test to conclude that the factors are fitting the data better, which is possibly spurious. Adjusting for breaks also stabilizes the number of retained factors across different countries, and this is likely due to the factors now being stationary by construction.

[7]Imposing trend inflation evolves as random walk without drift requires a restriction that the mean of the first difference of headline inflation is zero. This can be achieved by not including a constant in the equation for $\Delta\pi_t$.

[8]Hamilton (1994), Chapter 10, provides details on how to cast the VAR post-estimation into state-space form implied by Equation (2).

Data Our inflation data is provided by the World Bank and is associated with Ha, Kose, and Ohnsorge (2019). In order to provide comparability of the results across countries, we seasonally adjust all the inflation data using the X12 procedure. Our commodity price data is from the World Bank's pinksheet, which is the same source used by Fernández, Schmitt-Grohé, and Uribe (2017). We adjust these commodity price aggregates by the U.S. CPI in order to work with the real prices. All other data is sourced from Datastream. The sample period used for our analysis is reported in Table 1. As much as possible, we use the longest possible sample for each country. This means that for some countries, the analysis begins in 1980Q1. The sample in general ends in 2018, depending on data availability. We list the data series used, and the associated sample in section A3 of the online appendix. We also select the sample to ensure that headline inflation on a seasonally adjusted annualized quarter on quarter basis, never exceeds 30% in any part of the sample. While our empirical model can deal, to some extent, with large swings in inflation, extremely high inflation, or hyper-inflation episodes, could affect the precise estimates of trend inflation. In regimes such as this, the use of a standard linear VAR also becomes more questionable, and one will need to tailor specific features to model such observations. Given we largely focus on making comparisons across countries, and comparison is likely to be more appropriate whilst keeping the empirical model constant across different countries, we omit such episodes from our sample.

3 Results

3.1 Trend Inflation Estimates

To offer a flavour of the estimated trend inflation we obtain from our model, Figure 2 presents estimates of trend inflation with quarter on quarter annualized inflation rates for two developed economies (Canada and New Zealand) and two emerging market economies (Colombia and Korea).[9]. While the trend inflation estimates appear to be more volatile than what one would extract from methods such as applying a bandpass or HP filter, several features stand out. First, for the developed economies with an inflation target, the estimates of trend inflation lie close to their inflation target, as in the cases of Canada and New Zealand. That said, any comparison relative to an inflation target, or inflation target band, is only suggestive because the target is often couched in language that does not necessarily correspond to the concept of an infinite horizon forecast.[10] However, given the two example countries are what many regard as successful inflation targeters, one's *a priori* expectation would be that trend inflation estimates should not deviate too much from their

[9]We present all the estimated trend inflation in Section A2 of the online appendix.

[10]For example, Australia has an inflation target of *"2-3 percent over the business cycle"* while the Reserve Bank of New Zealand is charged to *"keep inflation within a range of 1 to 3 percent on average over the medium term"*.

inflation targets. That our trend inflation estimates are close to official inflation targets provides some confidence about their plausibility. Second, the trend inflation estimate essentially "goes through" the headline inflation rate. Recall that our estimates of trend inflation are derived on the basis of a BN decomposition obtained from a Bayesian VAR, and there is no guarantee that these estimates will go through headline inflation. That our model can handle both developed economies with low and stable inflation, but more importantly, emerging market economies with high and volatile inflation (like Colombia) is reassuring. Third, despite using quarter-on-quarter, as opposed to year-on-year, inflation, which by construction is noisier, there are certainly periods where headline inflation has persistently deviated from trend inflation. For example, a persistent inflation gap opened up in Korea between 2010 and 2012 and in New Zealand from 2013 to 2016. The latter example is interesting as this was a period where New Zealand's inflation outcomes were persistently below the target. Our trend inflation estimate lies within the inflation target band during this period, suggesting that persistently low inflation outcome have had a limited effect on trend inflation. Recall that the widely used trend inflation model such as Stock and Watson (2007) essentially models the inflation gap as an i.i.d process, which by construction means a persistent inflation gap can never open up in such a setup. Contributions by Chan, Koop, and Potter (2013), Kim, Manopimoke, and Nelson (2014) and Chan, Clark, and Koop (2017) are essentially attempts to refine these trend inflation models to allow for persistence in the gap. The multivariate BN decomposition naturally allows for persistence in the gap as long as the multivariate information contains relevant forecasting information for inflation, a point first recognized by Evans and Reichlin (1994). Observing that there are periods where a gap does open up in the inflation gap also implies that that the multivariate information contained within the BN decomposition helps to pin down trend inflation and the inflation gap. It also suggests our approach is a reasonable alternative to introduce persistence into the estimates of inflation gap.

3.2 How Important Are Foreign Shocks?

Variance Decomposition

We now turn to the central point of the paper: How important are foreign shocks for trend inflation and the inflation gap? A natural starting point for quantifying the relative importance of foreign shocks is to compute the share of domestic and foreign shocks in the variance decomposition of trend inflation and the inflation gap.

Let N^* be the number of foreign variables in the FAVAR system.[11] The first difference of headline inflation is in the k^{th} position in the system, with $k > N^*$. To calculate a variance decomposition, we use Equations (5) and (6) to obtain (see also Morley and

[11] Recall $N^* = \eta^* + 3$ as the foreign block contains η^* retained principal components from the international dataset and three commodity prices.

Wong, forthcoming)

$$
\Psi_F^{\tau} = \frac{\sum_{j=1}^{N*}\left\{\mathbf{e_k}(\mathbf{I}-\mathbf{B})^{-1}\mathbf{HCe_j'}\right\}^2}{\mathbf{e_k}(\mathbf{I}-\mathbf{B})^{-1}\mathbf{H}\boldsymbol{\Sigma}_{\nu}\mathbf{H}'(\mathbf{I}-\mathbf{B})^{-1\prime}\mathbf{e_k}'} \tag{10}
$$

$$
\Psi_F^{\tilde{\pi}} = \frac{\sum_{j=1}^{N*}\left[\mathbf{e_k}\sum_{\mathbf{i=0}}^{\infty}\left\{\boldsymbol{B}^{\boldsymbol{i+1}}(\mathbf{I}-\mathbf{B})^{-1}\mathbf{HCe_j'}\right\}\right]^2}{\mathbf{e_k}\left\{\sum_{\mathbf{i=0}}^{\infty}\left[\boldsymbol{B}^{\boldsymbol{i+1}}(\mathbf{I}-\mathbf{B})^{-1}\mathbf{H}\boldsymbol{\Sigma}_{\nu}\mathbf{H}'\left\{\boldsymbol{B}^{\boldsymbol{i+1}}(\mathbf{I}-\mathbf{B})^{-1}\right\}'\right]\right\}\mathbf{e_k}'}, \tag{11}
$$

where Ψ_F^{τ} and $\Psi_F^{\tilde{\pi}}$ are the shares of foreign shocks in the variance decomposition of trend inflation and the inflation gap, respectively.

Figures 3 and 4 present the relative shares of foreign shocks in the variance decomposition of inflation gap and trend inflation for the sample of developed economies and emerging market economies, respectively. An immediate observation for both the developed and emerging market economies is that foreign shocks have a larger impact on the gap relative to the trend. For developed economies (see Figure 3), we see a clear pattern where the share of foreign shocks is more pronounced when comparing the variance decomposition of the inflation gap relative to trend inflation. In particular, the share of foreign shocks in the variance decomposition of trend inflation for the developed economies is either negligible (less than 10%) or very small (slightly over 10%). The corresponding share of foreign shocks in the variance decomposition of inflation gap is, with the exception of Norway, over 50%. For emerging market economies, we also generally observe a larger share of the inflation gap explained by foreign shocks then trend inflation. The differences are, however, less stark when compared to the patterns we observe in developed economies. In particular, while foreign shocks explain a similarly small share in trend inflation for some of these emerging market economies (like Colombia and Korea), they explain a much larger share in countries such as Indonesia, Malaysia and the Philippines (over 20% to about a third). Moreover, unlike developed economies where foreign shocks account for a large share of fluctuations in the inflation gap, there is a wider dispersion of the degree of influence foreign shocks on inflation gap within the sample of emerging market economies.

Commodity Price Shocks

Given our analysis that foreign shocks appear to drive much of the variation in the inflation gap, and to some extent trend inflation in emerging market economies, we next explore what these foreign shocks could represent. This requires imposing more stringent identifying assumptions within the foreign block of our model. While our structure may make it challenging to identify and interpret shocks such as foreign monetary policy or foreign productivity shocks, a natural possibility within our framework is to consider commodity price shocks given our model also has a subblock of commodity prices. Moreover, given Fernández, Schmitt-Grohé, and Uribe (2017) only use commodity prices to identify foreign shocks, it is also worthwhile to investigate whether such an approach is sufficiently informative within our setup.

In order to separately identify commodity price shocks, we assume that the block of three commodity prices are pre-determined to the rest of the foreign block. This identifying assumptions about commodity prices are defensible to the extent that much of commodity supply is pre-determined from futures markets and thus producers take at least some time to adjust supply to price incentives. This additional identifying assumption is in line, with the empirical work identifying oil or commodity price shocks (see, e.g. Bachmeier and Cha, 2011; Kilian and Lewis, 2011; Wong, 2015), and has been shown to be tenable within oil markets (see Kilian and Vega, 2011). We also note that the identification of the effects of foreign shocks as a whole is not affected by the particular identification assumptions on commodity block of the model as long as we keep the small open economy structure by imposing the block exogeneity of the foreign block.

Figures 5 and 6 present the variance decomposition of commodity price shocks and the remaining foreign shocks in driving the inflation gap and trend inflation, respectively. As the identification between domestic and foreign shocks is left unaltered, the sum of the shares of commodity price shocks and other foreign shocks is equal to the shares reported in Figures 3 and 4. In Figure 5, it is clear that most of the influence of foreign shocks on the inflation gap represents commodity price shocks. This observation seems to hold both for developed and emerging market economies. For trend inflation, the results are more mixed. Nonetheless, it appears that for a number of emerging market economies where we find a large role for foreign shocks in driving trend inflation (Brazil, Indonesia and Malaysia), commodity price shocks account for most of the influence of foreign shocks. This observation is interesting to the extent that Brazil, Indonesia, and Malaysia are commodity exporters. Finding a sizeable role for commodity price shocks in driving their trend inflation suggests that such shocks may have been systematically accommodated in the conduct of their monetary policy.

We corroborate our results with existing empirical evidence that the inclusion of global variables, such as global inflation, can help improve forecast of either deviations from average inflation or notions of the inflation gap (e.g., see Kabukçuoğlu and Martínez-García, 2016, 2018; Gillitzer and McCarthy, forthcoming). To the extent that commodity price shocks affect measures of global inflation given almost all countries experience such shocks, it is conceivable that documented improvements in using measures of global inflation to improve forecast of the inflation gap may be due to approximating information related to commodity price shocks. Our finding that commodity price shocks explain most of the effects of foreign shocks in the inflation gap is also consistent with Kearns (2016), who finds that much of the correlated forecast errors of inflation globally can be explained by commodity prices, and specifically food and oil prices. We also contrast our results with Fernández, Schmitt-Grohé, and Uribe (2017) who identify foreign shocks by only considering three real commodity prices and find that foreign shocks explain about one third of the business cycle fluctuations.[12] While we have a narrowly defined focus on modeling inflation, the main difference between our foreign block and theirs is the presence of foreign factors extracted from the large FAVAR dataset in our case. We can interpret our finding that, at least for the modeling of the inflation gap, Fernández, Schmitt-Grohé, and Uribe (2017)'s strategy of using the three commodity prices alone may be sufficient to account for most of the effects of foreign shocks.

Interpretation of Variance Decompositions A key conclusion we draw from the variance decompositions is that foreign shocks appear to matter more for fluctuations in the inflation gap relative to those in trend inflation. This finding accords with the idea that if inflation is indeed a monetary phenomenon, then foreign shocks should not play a large role in explaining trend inflation unless these shocks are systematically accommodated by monetary policy. The finding that the share of foreign shocks in explaining trend inflation is low in the sample of developed economies is consistent with that explanation. In particular, the seven developed economies have very similar experiences of having low and stable inflation during the period we consider, at least, relative to the sample of emerging market economies. Therefore, if one was seeking to find a greater influence of foreign shocks in explaining trend inflation, this would probably be more likely in the emerging market economies where inflation has been generally higher and more volatile. For example, in our sample, the average standard deviation of inflation of the emerging market economies sample is nearly twice that of our developed economies sample. This may somewhat explain why we document a larger role for foreign shocks in explaining these economies' trend inflation outcomes.

Nonetheless, while the variance decompositions are informative and useful in understanding the influence of foreign shocks, they do not tell the whole story. More importantly, because inflation volatility is in general much higher in emerging market economies, we might expect trend inflation volatility to be similarly higher in these economies. The left subplot of Figure 7 presents a boxplot of the volatility of trend inflation estimates for developed and emerging market economies. Indeed we observe more volatile trend inflation estimates in our sample of emerging market economies and there is also a larger spread, or dispersion, of trend inflation volatility estimates. These results are not entirely surprising, as we expect greater inflation volatility to result in more volatile trend inflation estimates. Nonetheless, the greater trend inflation volatility in emerging market economies could potentially complicate the comparison of the variance decompositions.

[12] Fernández, Schmitt-Grohé, and Uribe (2017) have a much broader focus and consider the impact of foreign shocks on trade balance, terms of trade, GDP, consumption and investment.

More precisely, even if the share of foreign shocks is similar across both samples, foreign shocks would contribute to higher trend inflation volatility in the emerging market economies given their absolute trend inflation volatility is higher. To show this, the right subplot of Figure 7 presents the absolute trend inflation volatility induced by foreign shocks which is calculated as

$$var(\Delta\tau_t \mid \epsilon_t^*) = \Psi_f^\tau \times var(\Delta\tau_t)$$

Unsurprisingly, the absolute trend inflation volatility induced by foreign shocks is much larger in emerging market relative to the developed economies.[13] In fact, given that trend inflation volatility is much larger in the emerging market economies, the share of foreign shocks in the variance decomposition of trend inflation would need to be almost negligible in emerging market economies for the absolute inflation volatility induced by foreign shocks to be lower in emerging market compared to developed economies. Given that foreign shocks have a small to negligible influence in trend inflation fluctuations of developed economies, and that the developed economies have less volatile trend inflation, we conclude that foreign shocks matter very little for developed economies, and most of the effect of foreign shocks manifests themselves in the dynamics of inflation gap. However, while we may gain insights from the variance decompositions, the fact that trend inflation volatility is much higher in emerging market economies means it is difficult to make more substantive conclusions. This leads us to exploring an alternative metric: the signal-to-noise ratio.

Signal-to-Noise Ratios

The fact that inflation and estimates of trend inflation are more volatile in the sample of emerging market economies means that the variance decomposition analysis that we conduct, while informative, may not reveal the whole picture. In particular, we establish in Figure 7 that foreign shocks contribute partly to the larger *absolute* trend inflation volatility in emerging market economies. One straightforward explanation is that the larger trend inflation volatility in emerging market economies is due to these economies being hit by larger shocks. An alternative explanation is that particular features of emerging market economies could result in a different propagation and amplification of foreign shocks.[14] These mechanisms may relate to monetary policy, especially the systematic

[13]This difference is statistically significant as we can reject a one sided t-test for equality of means (allowing for unequal variances across groups) with a p-value of less than 0.01.

[14]There is a related strand in the emerging market economies' business cycle literature which mimics some of the discussion we are alluding to. For example, Aguiar and Gopinath (2007) argue that larger permanent productivity shocks can explain the higher volatility in output growth in emerging market economies, while Garcia-Cicco, Pancrazi, and Uribe (2010) demonstrate how considering additional propagation mechanisms like financial frictions can alter conclusions about larger permanent shocks driving the dynamics in emerging market economies.

component which responds to foreign shocks, or institutional characteristics such as financial frictions or rigidities in the goods and labour markets.

While our empirical model is silent about what these precise propagation mechanisms are, given that we do not explicitly model them, however, if present, such features should also be reflected in the reduced form we estimate. In our empirical setup, we can get some idea of the balance between an explanation based on larger shocks and based on the propagation mechanism by considering the signal-to-noise ratio of inflation. In a univariate BN setting, Kamber, Morley, and Wong (2018) define the signal-to-noise ratio, δ, as the fraction of the change in a variable as being permanent. We therefore define:

$$\delta = \frac{var(\Delta\tau_t)}{var(\nu_t^\pi)} \tag{12}$$

where ν_t^π is the forecast error of the inflation equation.[15] As an example to interpret the signal-to-noise ratio, $\delta = 0.1$ implies that 10% of the variation of inflation is permanent.

The rationale for using the signal-to-noise ratio is as follows. If the reason emerging market economies experience higher trend inflation is because they experience larger shocks, then we would expect the signal-to-noise ratio in developed and emerging market economies to be similar. Instead, if the higher volatility of trend inflation in emerging market economies is due to different propagation mechanisms, then for a similarly sized shock, more of the variation in inflation would be permanent in emerging market economies, resulting in a higher signal-to-noise ratio.

Equation (12) is an unconditional signal-to-noise ratio since it considers all shocks, and does not require the identification of any of the underlying shocks. We can adapt Equation (12) to calculate the signal-to-noise ratio *conditional* on foreign shocks, δ^F, in a straightforward manner:

$$\delta^F = \frac{var(\Delta\tau_t \mid \epsilon_t^*)}{var(\nu_t^\pi \mid \epsilon_t^*)} \tag{13}$$

Figure 8 presents boxplots comparing the signal-to-noise ratios in developed and emerging market economies. In the left subplot, we can see the distribution of the estimates of δ to be larger in emerging market relative to developed economies. This implies

[15] In the univariate context of Kamber, Morley, and Wong (2018), the signal-to-noise ratio is obtained from the Wold form where $\delta = \left[\frac{\partial \pi_t}{\partial \nu_t^\pi}\right]^2$. We can either plug in the estimated variance of the obtained trend inflation and forecast error, or obtain δ in our multivariate setting using the Wold form like Kamber, Morley, and Wong (2018). We opt for the latter approach, but note that one would get very similar answers using either approach. Note that if shocks to the trend and cycle are orthogonal, in the sense of a UC model, the signal-to-noise ratio is bounded from above by 1. However, our framework is fully unrestricted, so this ratio is not necessarily bounded by 1 from above, as trend and cycle are allowed to correlate (see, e.g. Morley, Nelson, and Zivot, 2003). While orthogonality between trend and cycle is still a controversial issue, Morley, Nelson, and Zivot (2003) and Hwu and Kim (forthcoming), at least in univariate frameworks, have both shown allowing for correlation is probably a better characterization of the data with U.S. output growth and inflation respectively.

that facing shocks of same volatilities, emerging market economies would experience a higher trend inflation volatility, which suggests a role for differences in propagation mechanisms.

The right subplot compares δ^F which conditions on foreign shocks. The difference in signal-to-noise ratios are much larger between the two groups of economies in this case. The median δ^F is about twice larger in emerging market economies compared to developed economies.[16] This result suggests propagation mechanisms of foreign shocks on trend inflation can explain some of the differences between developed and emerging market economies.

The finding that differences in propagation mechanisms may be at work, especially when we condition on foreign shocks, is important. It would be natural that if differences in propagation mechanisms were at work in explaining higher trend inflation volatility in emerging market economies, domestic shocks would likely play a prominent role. The fact that we find larger differences in the propagation of foreign shocks suggests that one needs to account for the influence of foreign shocks to form a fuller understanding of why trend inflation is more volatile in emerging market economies.

As our empirical model does not feature microfoundations and explicit propagation mechanisms, we can only speculate why these differences in propagation mechanisms might arise. At least from our sample, one candidate possibility is monetary policy. As we have touched on from the introduction, given the conventional notion that inflation is a monetary phenomenon, we are unaware of any explanation according to which foreign shocks can feed into trend inflation unless they are continuously accommodated by the monetary policy.

Given our sample of developed economies have experienced lower inflation within their sample period, it is not surprising that their estimated trend inflation volatility is lower relative to the emerging market economies. Nonetheless, given foreign shocks start out with "less to explain" for trend inflation volatility for the developed economies, the finding of a much smaller share of the trend inflation volatility is driven by foreign shocks relative to the emerging market economies suggests that there is a negligible to no role for foreign shocks in understanding trend inflation in developed economies. Just given the anecdotal evidence that these are economies where inflation has been well behaved, and a number are explicit inflation targeters, which at least institutionally prohibits the accommodation of foreign shocks, this seems the greatest source of difference between the developed and emerging market economies sample. That we find evidence that there is a role for propagation mechanism for foreign shocks in the group of emerging market economies further reinforces our intuition.

[16] This difference is also statistically significant as we obtain a p-value of 0.01 for a one sided t-test of inequality of means across the two groups (allowing for unequal variance across the two groups).

3.3 Robustness

In this subsection, we consider a number of other issues which may be relevant to the robustness of our results. We provide a short discussion of each of these issues but present detailed results in Appendix B of the online appendix.

Prior We investigate the sensitivity of our conclusions with respect to the shrinkage hyperparameter that we use as a prior in the Bayesian estimation. We present these results in section B1 of the online appendix, and show that our conclusions are robust to the choice of the prior.

Common Trend Core inflation, defined as CPI excluding food and energy, is often used to filter out transitory components of headline inflation. It is possible that core inflation may contain useful information which may help sharpen the identification of the permanent component of inflation. To consider a specification which can incorporate such information, we assume core inflation shares a common (BN) trend with headline inflation. Allowing a common trend adds an error correction term into the baseline model in the inflation equations. Let π_t^c denote core inflation, and ξ^{π^c} and ξ^{π} the respective error correction term in the core inflation and inflation equations, the baseline model becomes:

$$\begin{bmatrix} \boldsymbol{Y}_t^* \\ \boldsymbol{Y}_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\beta}_{11}(L) & \mathbf{0} \\ \boldsymbol{\beta}_{21}(L) & \boldsymbol{\beta}_{22}(L) \end{bmatrix} \begin{bmatrix} \boldsymbol{Y}_{t-1}^* \\ \boldsymbol{Y}_{t-1} \end{bmatrix} + \boldsymbol{\Gamma} \left[\pi_{t-1} - \pi_{t-1}^c \right] + \begin{bmatrix} \boldsymbol{A}_{11} & \mathbf{0} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon}_t^* \\ \boldsymbol{\epsilon}_t . \end{bmatrix} \tag{14}$$

where

$$\boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{F}_t \\ q_t \\ \Delta\pi_t^c \\ \Delta\pi_t \end{bmatrix}, \quad \boldsymbol{\Gamma} = \begin{bmatrix} \mathbf{0} \\ \xi^{\pi^c} \\ \xi^{\pi} \end{bmatrix}$$

It is an open question whether this is a more appropriate specification to estimate trend inflation. In particular, assuming cointegration between core inflation and headline inflation implies that both are driven by only one stochastic trend. We note that if this assumption is true, then core inflation shares a common (BN) trend with headline inflation and such an approach will sharpen the identification of the permanent component of inflation. There is of course the possibility that this model may also be misspecified, if the assumption of common trend fails to hold for some reason, for example because the gap between headline and core inflation is not stationary or there are trending relative prices (e.g., see Wolman, 2011).

We also note that the unavailability of core inflation measures implies that, we can only conduct the analysis for the 7 developed economies and only 10 of the 21 emerging market economies. We leave the detailed results to Section B2 in the online appendix, but highlight some key results. Even though considering a common trend smooths out the trend inflation estimates by significantly lowering the signal-to-noise ratio in most cases, our qualitative results remain unaltered. That is, (i) foreign shocks still appear to be more important for the inflation gap relative to trend inflation, (ii) many of these foreign shocks in the inflation gap appear to still reflect commodity price shocks and (iii) we still find an overall higher signal-to-noise ratio conditional on foreign shocks in the emerging market economies, suggesting propagation mechanisms in the emerging market economies can reconcile why foreign shocks appear to matter more for trend inflation in emerging market economies.

Keeping the number of Factors Constant Across Blocks In our baseline analysis, the estimated foreign shocks across countries may differ because for each country the foreign block is specified differently on the basis of the Granger Causality test introduced by Forni and Gambetti (2014). This may affect our inference when conducting our analysis on the signal-to-noise ratio conditional of foreign shocks, or δ^F, as we might be omitting foreign shocks for some specifications, but not for others.

We therefore checked our results keeping the number of foreign factors the same across all 28 countries. More specifically, we set $\eta^* = \eta = 3$ for each country. The left panel of Figure 9 shows that our conclusion that emerging market economies have a higher signal-to-noise ratio when conditioned on foreign shocks still holds. We also note that under this specification, the difference in signal-to-noise ratios is statistically significant with a p-value of less than 0.01 on a one sided t-test of equality of means. We therefore conclude our finding based on the signal-to-noise ratio conditional on the foreign shocks is not driven by the differences in the specification of the factor structure of the foreign block across countries. It is also worth noting that the difference in η^* across the different countries should not conceptually matter. Because we are choosing the number of factors on the basis of Granger Causality test, the exclusion of a factor in the international block of a country means that this additional factor does not contain information when added in the foreign block of that particular country. Nonetheless, it is reassuring that our conclusions are robust to this particular technical point.

Omitting the BRIC countries One potential concern with our identification approach is that some countries in our sample may not satisfy the small open economy restriction. This could be potentially relevant for the BRIC (i.e. Brazil, Russia, India and China) countries in our sample. We first note that in our results presented in Figures 4 and 5 on the variance decompositions there is nothing unusual about the BRIC countries relative to the rest of the emerging market economies. So our conclusions about (i) foreign shocks still appear to be more important for the inflation gap relative to trend inflation,

(ii) many of these foreign shocks in the inflation gap appear to still reflect commodity price shocks are robust to the omission of the BRIC countries. Given our third conclusion about the role of propagation mechanisms is on the basis of the estimated signal-to-noise ratio conditional on the foreign shocks, or δ^F, we recalculated this statistic omitting the BRIC countries. This is presented in the right panel of Figure 9. Removing the BRIC countries does not alter our results as we still find an overall higher signal-to-noise ratio conditional on foreign shocks in the emerging market economies, with a p-value of 0.04 on a one sided t-test of equality of means. We therefore conclude that all our results are robust to omitting the BRIC countries.

Relaxing Elements of the Small Open Economy Assumption We also check the robustness of our results to relaxing small open economy identification restrictions that impose the block exogeneity of the foreign block to the domestic block. One straightforward check is to allow the lags of the domestic variables to enter the equations of the foreign variables, effectively relaxing $\boldsymbol{\beta}_{12}(L) = 0$ in Equation (7). In this variant, foreign shocks are identified via standard recursive identification that only imposes that foreign variables do not respond to domestic shocks contemporaneously. We find that this has a very marginal effect on our results. These results are detailed in Appendix B3 of the online appendix.

We also consider whether the presence of asset prices in our dataset affects our main conclusions. For example, it may be possible that, as fast-moving financial variables, stock prices in the foreign block may react to shocks in our set of small open economies. If that is the case, this would then violate our block exogeneity restriction and could affect the accurate identification of domestic and foreign shocks. We deal with this possibility in two alternative ways. As a first check, we drop all stock prices from the foreign and domestic economy datasets, and re-run our model. Second, we split all international factors into two orthogonalized components through

$$\begin{aligned} f^*_{i,t} &= \sum_{j=1}^{k} \lambda_j SP_{j,t} + \tilde{f}^*_{i,t} \\ &= f^*_{A,it} + \tilde{f}^*_{i,t} \end{aligned}$$

where $SP_{j,t}$ is the percent change in the stock index for the j^{th} international economy, $f^*_{i,t}$ is i^{th} factor described in Equation (8). We run a regression between the k stock prices in order to get two orthogonal components where $f^*_{A,it}$ is the component of the i^{th} factor that loads on the stock prices, and $\tilde{f}^*_{i,t}$ is the i^{th} factor, but does not load on the stock price. Clearly, the fit of the regression is $f^*_{A,it}$ and the residual is $\tilde{f}^*_{i,t}$. We then respecify the model as a BVAR between $\boldsymbol{Y}^*_t$, $\boldsymbol{F}^*_{A,t}$ and $\boldsymbol{Y}_t$ where we respecify $\boldsymbol{Y}^*_t$ is now block exogenous and thus identifies the foreign shocks where

$$\boldsymbol{Y}_t^* = \begin{bmatrix} \boldsymbol{P}_t^C \\ \tilde{\boldsymbol{F}}_t^* \end{bmatrix} \text{ where } \tilde{\boldsymbol{F}}_t^* = \begin{bmatrix} \tilde{f}_{1,t}^* \\ \tilde{f}_{2,t}^* \\ \vdots \\ \tilde{f}_{\eta^*,t}^* \end{bmatrix} \boldsymbol{F}_{A,t}^* = \begin{bmatrix} f_{A,1t}^* \\ f_{A,2t}^* \\ \vdots \\ f_{A,\eta^* t}^* \end{bmatrix}$$

The two approaches have their distinct advantages and disadvantages. In the first approach, the advantage is that, by omitting asset prices and re-running the model, the issue of international asset prices responding to domestic shocks becomes moot. The drawback is that we still assume that, even without the asset prices, the BVAR still spans the same set of shocks as the baseline analysis. In approach two, we retain all the information, and so the shocks span the same space as the baseline analysis, given that we are just breaking the factors up into two parts. The drawback is that we lose the neat dichotomy between foreign and domestic shocks, given the $\boldsymbol{Y}_t^*$ block identifies part of the foreign shocks, the $\boldsymbol{F}_{A,t}^*$ and $\boldsymbol{Y}_t$ blocks may have a mix of foreign and domestic shocks. In this regard, the estimated effect of foreign shocks is a lower bound given the $\boldsymbol{F}_{A,t}^*$ block may also contain foreign shocks.

We leave the presentation of detailed results in Section B3 of the online appendix but we obtain very similar results to the baseline using either approach. The similarity of the results suggests that the use of block exogeneity and the inclusion of international asset prices is not a concern for the identification of the foreign shocks.

4 Conclusion and Discussion

In this paper, we develop an open economy model to estimate trend inflation, which allows us to quantify the role of foreign shocks in driving both trend inflation and the inflation gap. We estimate the model on 28 economies, 7 developed economies and 21 emerging market economies.

We highlight three key findings. First, we find that foreign shocks appear to be more important for the inflation gap, relative to trend inflation. Second, commodity price shocks account for much of the reported shares of foreign shocks in the inflation gap. Third, trend inflation in emerging market economies appear to be more affected by foreign shocks relative to developed economies. Our results provide suggestive evidence that propagation mechanisms, which could range from institutional features or policy setting, may play a role in reconciling the differences in results between emerging market and developed economies. We reach this conclusion by documenting foreign shocks have played a negligible to no role for trend inflation for our sample of developed economies whereas foreign shocks can play a larger role in driving trend inflation. While larger shocks are a natural candidate explanation for why foreign shocks have a much larger impact in our sample of emerging market economies, we also find a role for propagation mechanisms in the emerging market economies sample, which altogether suggest policy as a natural candidate for reconciling these results.

It is important to stress that the literature on the increased globalization of inflation argues that domestic inflation has become *more* sensitive to global slack over time, which is subtly different from our work, as we only measure the average share of foreign shocks in trend inflation and the inflation gap over the entire sample. However, we do propose an empirical setup which allows for a broader view of global determinants (i.e. foreign shocks) that tackles a first order policy issue of whether the influence of foreign shocks is transitory or permanent. This may provide a good starting point to model time variation in future work in order to investigate whether inflation has become increasingly globalized. However, we note that Bianchi and Civelli (2015) do explicitly model time variation in studying the effect of the increased globalization of inflation, albeit with a narrower focus on global slack, and find no evidence of time variation.

The overall conclusion from our findings is that even if foreign shocks matter for inflation, inflation in the long run is ultimately a domestic phenomenon. That is, without any accommodation by domestic monetary policy, the effects foreign shocks on inflation are transitory. Our results are therefore supportive of Woodford (2007) who argues that, despite greater globalization, it should remain possible for central banks with clear inflation targets to achieve their goals.

References

Aguiar, M., and G. Gopinath (2007): "Emerging Market Business Cycles: The Cycle Is the Trend," *Journal of Political Economy*, 115, 69–102.

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

Auer, R., A. A. Levchenko, and P. Sauré (2017): "International Inflation Spillovers Through Input Linkages," BIS Working Papers 623, Bank for International Settlements.

Bachmeier, L. J., and I. Cha (2011): "Why Don't Oil Shocks Cause Inflation?," *Journal of Money, Credit, and Banking*, 43(6), 1165–1183.

Bernanke, B. S., J. Boivin, and P. Eliasz (2005): "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach," *Quarterly Journal of Economics*, 120(1), 387–422.

Beveridge, S., and C. R. Nelson (1981): "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'," *Journal of Monetary Economics*, 7(2), 151–174.

Bianchi, F., and A. Civelli (2015): "Globalization and Inflation: Evidence from a Time Varying VAR," *Review of Economic Dynamics*, 18(2), 406–433.

Borio, C. E. V., and A. Filardo (2007): "Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation," BIS Working Papers 227, Bank for International Settlements.

Carney, M. (2015): "Inflation in a globalised world," *Remarks at Economic Policy Symposium hosted by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming, 29 August 2015.*

Chan, J. C., G. Koop, and S. M. Potter (2013): "A New Model of Trend Inflation," *Journal of Business and Economic Statistics*, 31(1), 94–106.

Chan, J. C. C., T. E. Clark, and G. Koop (2017): "A New Model of Inflation, Trend Inflation, and Long-Run Inflation Expectations," *Journal of Money, Credit and Banking*, forthcoming.

Ciccarelli, M., and B. Mojon (2010): "Global Inflation," *The Review of Economics and Statistics*, 92(3), 524–535.

Cogley, T., G. E. Primiceri, and T. J. Sargent (2010): "Inflation-Gap Persistence in the U.S.," *American Economic Journal: Macroeconomics*, 2(1), 43–69.

Draghi, M. (2015): "Global and domestic inflation," *Speech at Economic Club of New York, 4 December 2015.*

Eickmeier, S., and K. Pijnenburg (2013): "The Global Dimension of Inflation ? Evidence from Factor-Augmented Phillips Curves," *Oxford Bulletin of Economics and Statistics*, 75(1), 103–122.

Evans, G., and L. Reichlin (1994): "Information, forecasts, and measurement of the business cycle," *Journal of Monetary Economics*, 33(2), 233–254.

Fernández, A., S. Schmitt-Grohé, and M. Uribe (2017): "World shocks, world prices, and business cycles: An empirical investigation," *Journal of International Economics*, 108(S1), 2–14.

Forni, M., and L. Gambetti (2014): "Sufficient information in structural VARs," *Journal of Monetary Economics*, 66(C), 124–136.

Garcia-Cicco, J., R. Pancrazi, and M. Uribe (2010): "Real Business Cycles in Emerging Countries?," *American Economic Review*, 100(5), 2510–2531.

Gillitzer, C., and M. McCarthy (forthcoming): "Does global inflation help forecast inflation in industrialized countries?," *Journal of Applied Econometrics*.

Ha, J., A. Kose, and F. L. Ohnsorge (2019): *Inflation in Emerging and Developing Economies : Evolution, Drivers, and Policies*. World Bank Group, Washington D.C.

Hamilton, J. (1994): *Time series analysis*. Princeton Univ. Press, Princeton, NJ.

Hwu, S.-T., and C.-J. Kim (forthcoming): "Estimating Trend Inflation Based on Unobserved Components Model: Is It Correlated with the Inflation Gap?," *Journal of Money, Credit and Banking*.

Ihrig, J., S. B. Kamin, D. Lindner, and J. Marquez (2010): "Some Simple Tests of the Globalization and Inflation Hypothesis," *International Finance*, 13(3), 343–375.

Justiniano, A., and B. Preston (2010): "Can structural small open-economy models account for the influence of foreign disturbances?," *Journal of International Economics*, 81(1), 61–74.

Kabukçuoğlu, A., and E. Martínez-García (2016): "What helps forecast U.S. inflation? - Mind the gap!," Koç University Working Paper 1615.

——— (2018): "Inflation as a global phenomenon Some implications for inflation modeling and forecasting," *Journal of Economic Dynamics and Control*, 87(C), 46–73.

Kamber, G., J. Morley, and B. Wong (2018): "Intuitive and reliable estimates of the output gap from a Beveridge-Nelson filter," *Review of Economics and Statistics*, 100, 550–566.

Kearns, J. (2016): "Global inflation forecasts," BIS Working Papers 582, Bank for International Settlements.

Kilian, L., and L. T. Lewis (2011): "Does the FED Respond to Oil Price Shocks?," *Economic Journal*, 121(September), 1047–1072.

Kilian, L., and C. Vega (2011): "Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices," *The Review of Economics and Statistics*, 93(2), 660–671.

Kim, C., P. Manopimoke, and C. R. Nelson (2014): "Trend Inflation and the Nature of Structural Breaks in the New Keynesian Phillips Curve," *Journal of Money, Credit and Banking*, 46(2-3), 253–266.

Martínez-García, E., and M. A. Wynne (2013): "Global slack as a determinant of US inflation," in *Globalisation and inflation dynamics in Asia and the Pacific*, ed. by B. for International Settlements, vol. 70 of *BIS Papers chapters*, pp. 93–98. Bank for International Settlements.

Mertens, E. (2016): "Measuring the Level and Uncertainty of Trend Inflation," *The Review of Economics and Statistics*, 98(5), 950–967.

Milani, F. (2010): "Global slack and domestic inflation rates: A structural investigation for G-7 countries," *Journal of Macroeconomics*, 32(4), 968–981.

Morley, J., and J. Piger (2012): "The Asymmetric Business Cycle," *The Review of Economics and Statistics*, 94(1), 208–221.

Morley, J., and B. Wong (forthcoming): "Estimating and accounting for the output gap with large Bayesian vector autoregressions," *Journal of Applied Econometrics*.

Morley, J. C. (2002): "A state-space approach to calculating the Beveridge-Nelson decomposition," *Economics Letters*, 75(1), 123–127.

Morley, J. C., C. R. Nelson, and E. Zivot (2003): "Why Are the Beveridge-Nelson and Unobserved-Components Decompositions of GDP So Different?," *The Review of Economics and Statistics*, 85(2), 235–243.

Mumtaz, H., and P. Surico (2012): "Evolving International Inflation Dynamics: World And Country-Specific Factors," *Journal of the European Economic Association*, 10(4), 716–734.

Neely, C. J., and D. E. Rapach (2011): "International comovements in inflation rates and country characteristics," *Journal of International Money and Finance*, 30(7), 1471–1490.

Perron, P. (1989): "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis," *Econometrica*, 57(6), 1361–1401.

Stock, J. H., and M. W. Watson (2002): "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, 20(2), 147–162.

Stock, J. H., and M. W. Watson (2007): "Why Has U.S. Inflation Become Harder to Forecast?," *Journal of Money, Credit and Banking*, 39(s1), 3–33.

Wolman, A. L. (2011): "The Optimal Rate of Inflation with Trending Relative Prices," *Journal of Money, Credit and Banking*, 43, 355–384.

Wong, B. (2015): "Do Inflation Expectations Propagate the Inflationary Impact of Real Oil Price Shocks?: Evidence from the Michigan Survey," *Journal of Money, Credit and Banking*, 47(8), 1673–1689.

Woodford, M. (2007): "Globalization and Monetary Control," NBER Working Papers 13329, National Bureau of Economic Research, Inc.

Zha, T. (1999): "Block recursion and structural vector autoregressions," *Journal of Econometrics*, 90(2), 291–316.

Table 1: Sample of Countries and Coverage

Developed Economies		**Emerging Market Economies**	
Australia	1985Q2-2018Q1	Brazil	1999Q2-2018Q1
Canada	1985Q2-2018Q1	Chile	1991Q2-2018Q1
Denmark	1987Q2-2018Q1	China	1997Q3-2018Q1
Norway	1985Q2-2018Q1	Colombia	1992Q2-2018Q1
New Zealand	1987Q4-2018Q1	Czechia	1996Q3-2018Q1
Switzerland	1985Q2-2017Q4	Hong Kong	1991Q4-2018Q1
Sweden	1987Q3-2018Q1	Hungary	1995Q4-2018Q1
		India	1997Q1-2018Q1
		Indonesia	2006Q2-2018Q1
		Israel	1995Q3-2018Q1
		Korea	1985Q2-2018Q1
		Malaysia	1994Q1-2018Q1
		Mexico	1996Q3-2018Q1
		Peru	2001Q3-2018Q1
		Philippines	1999Q2-2018Q1
		Poland	1995Q3-2018Q1
		Russia	2000Q2-2018Q1
		Singapore	1994Q4-2018Q1
		South Africa	1990Q3-2018Q1
		Thailand	1985Q2-2018Q1
		Turkey	2003Q2-2018Q1

Figure 1: Year on Year CPI Inflation for Selected Industrialized Countries

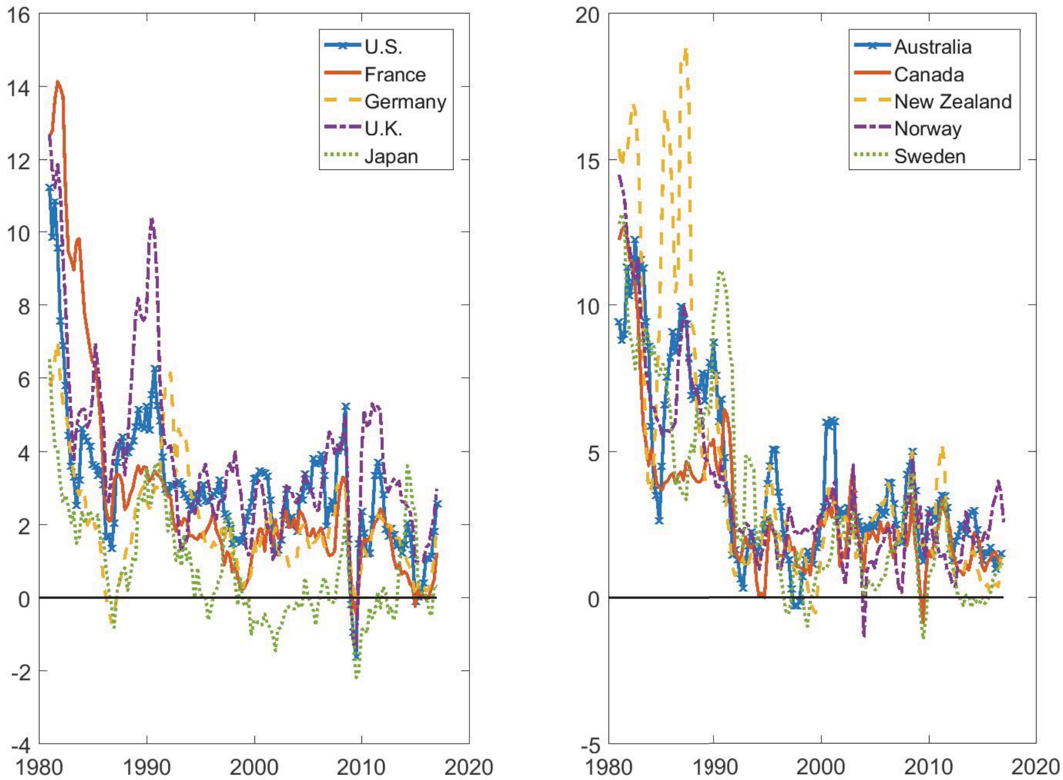
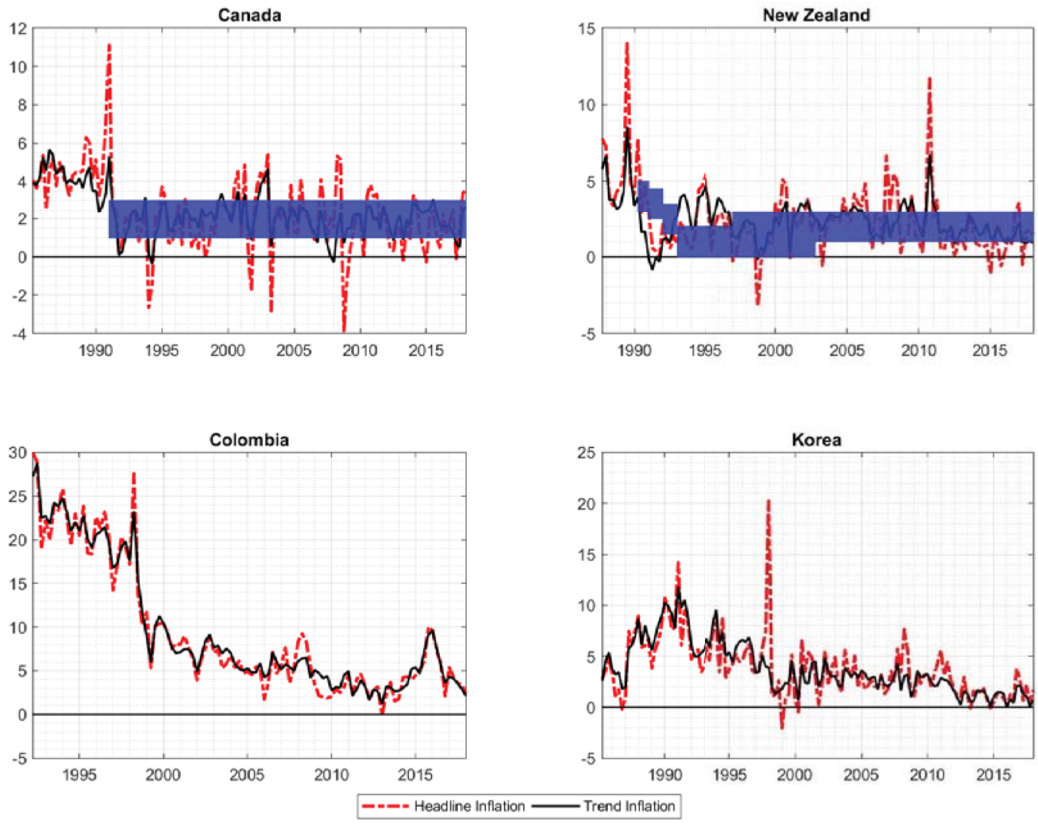
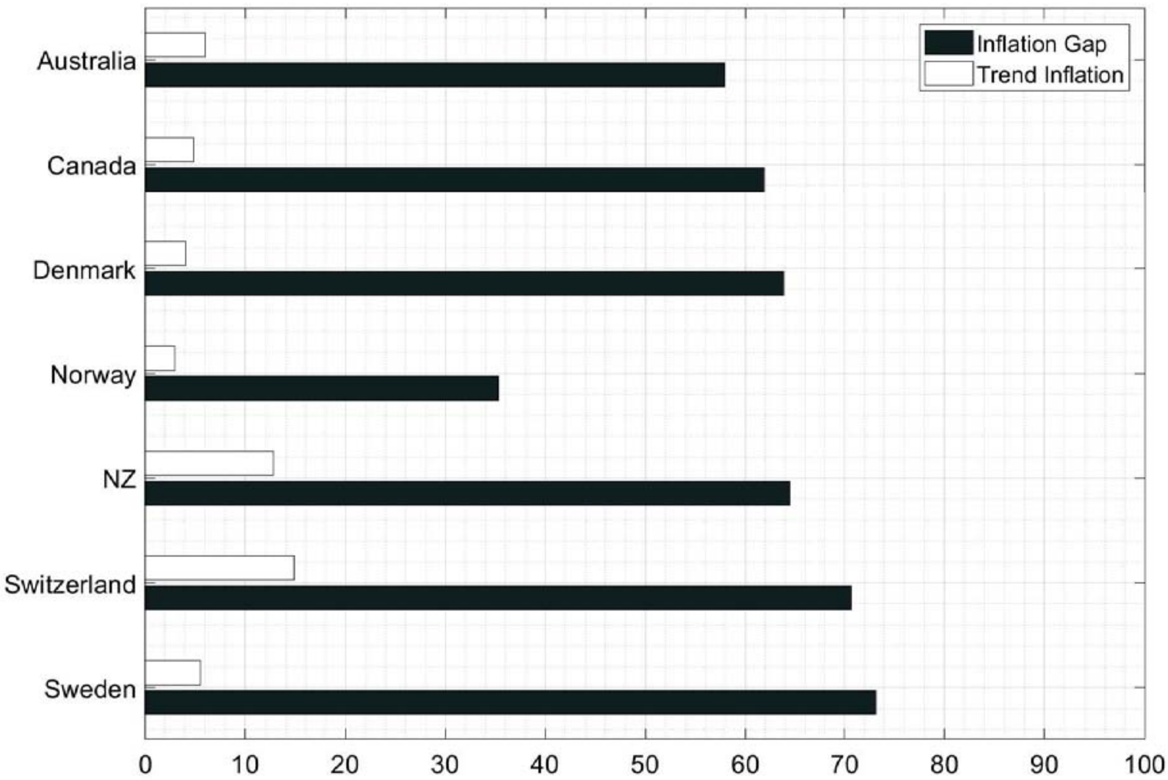


Figure 2: Trend Inflation Estimates



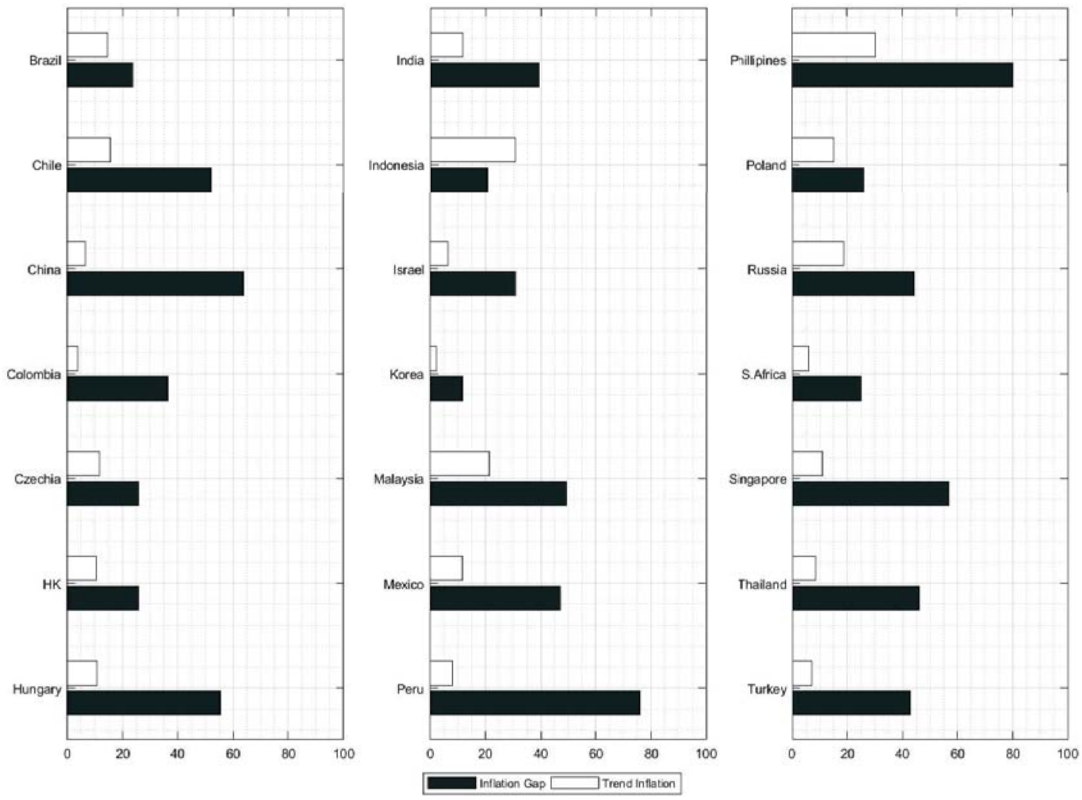
Notes: Trend inflation and headline inflation in annualized percentage terms. The shaded area represents the inflation target.

Figure 3: Share of Foreign Shocks - Developed Economies Sample



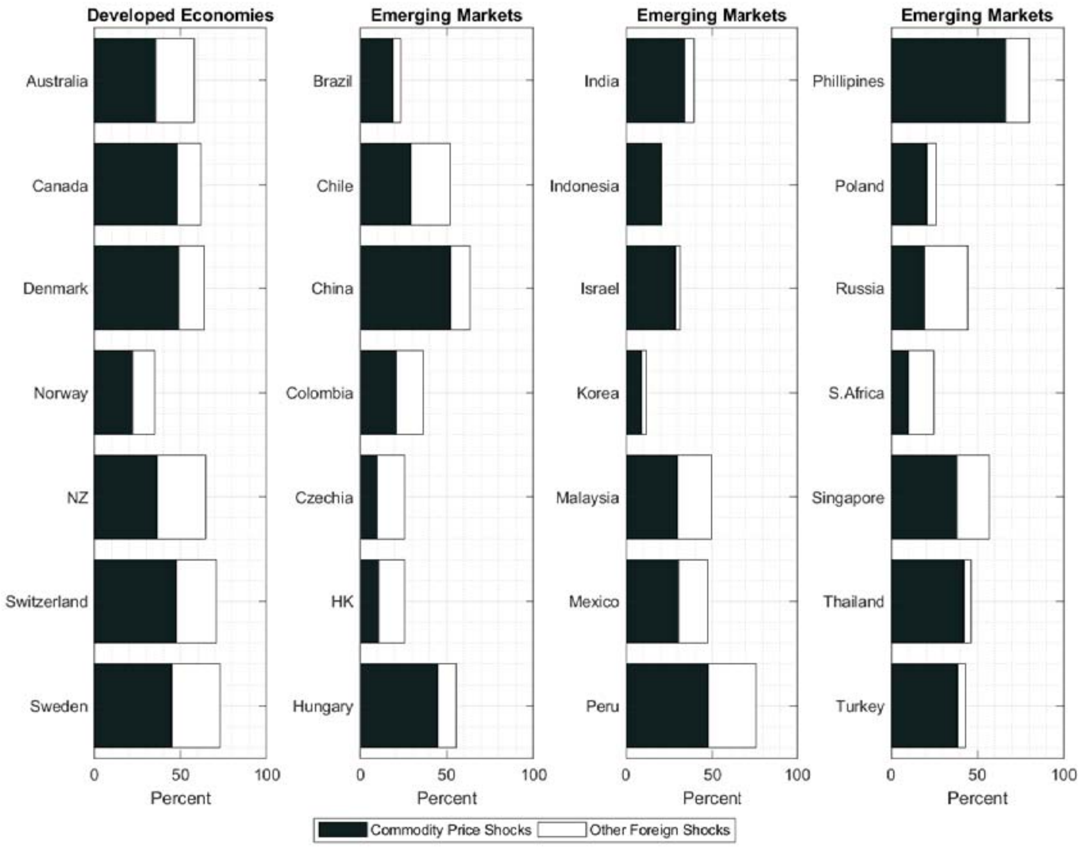
Notes: Both the shares of foreign and domestic shocks sum up to 100.

Figure 4: Share of Foreign Shocks - Emerging Market Economies Sample



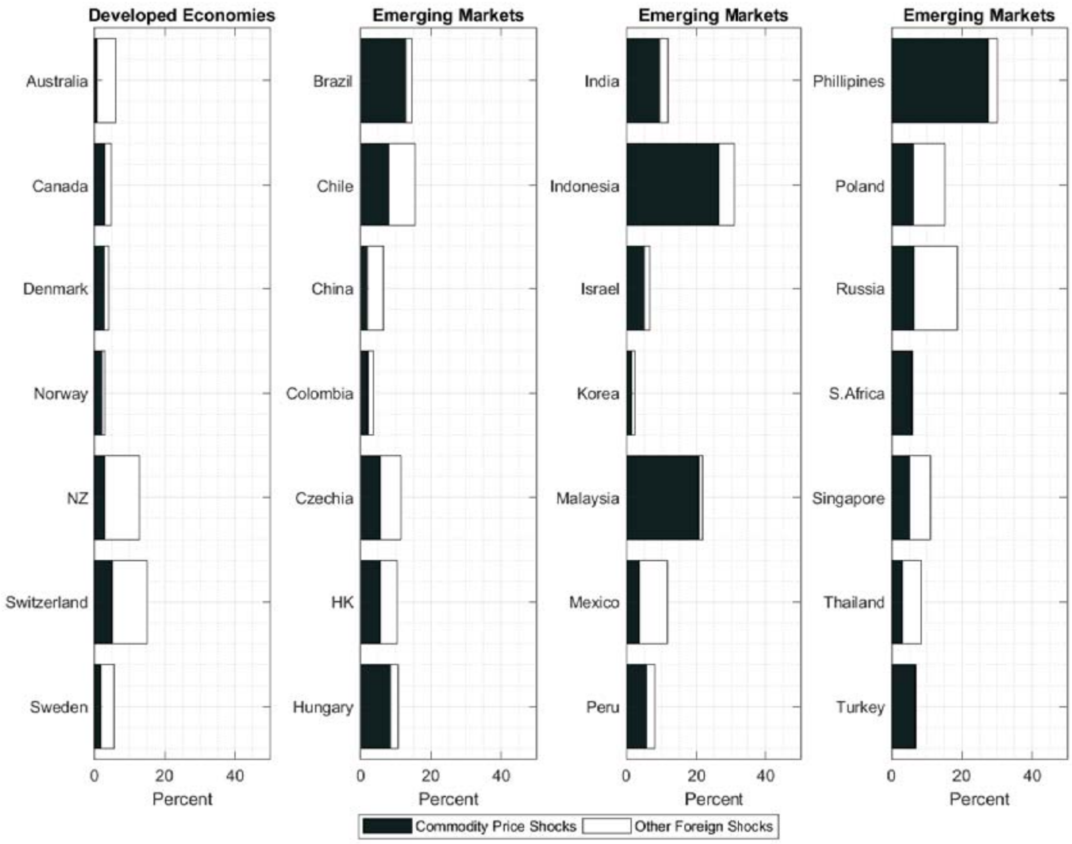
Notes: Both the shares of foreign and domestic shocks sum up to 100.

Figure 5: Share of Commodity Price Shocks for the Inflation Gap



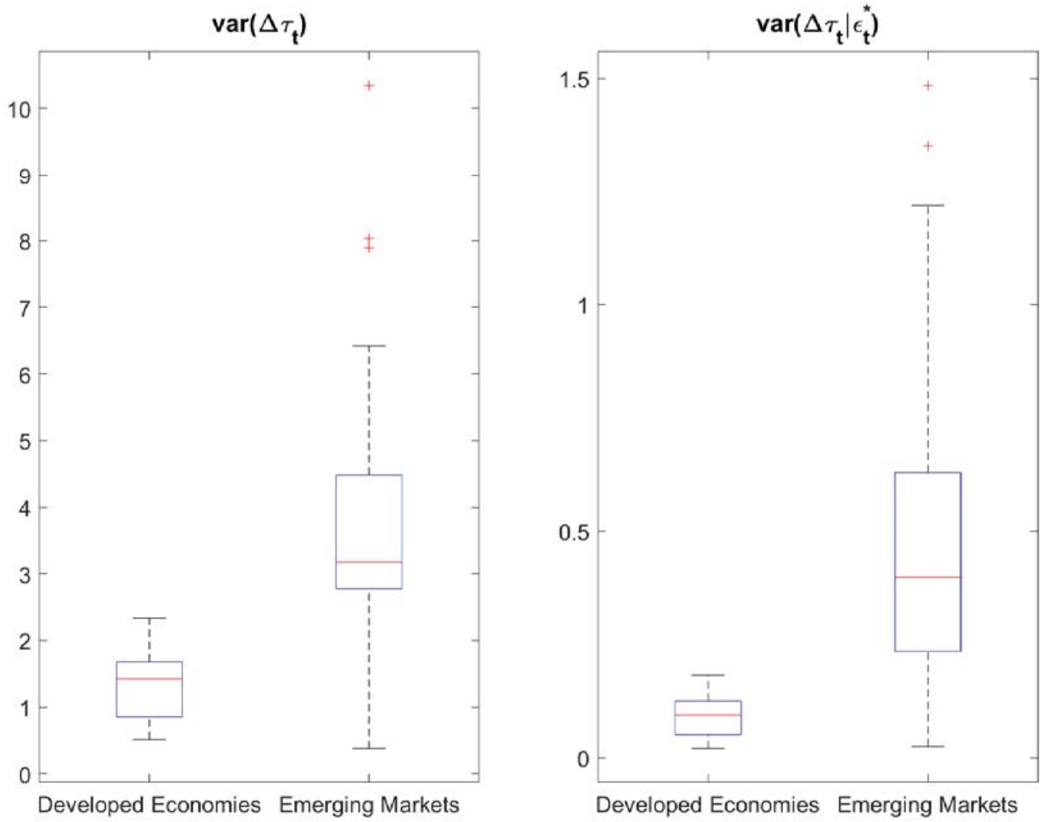
Notes: Both the shares of foreign and domestic shocks sum up to 100.

Figure 6: Share of Commodity Price Shocks for Trend Inflation



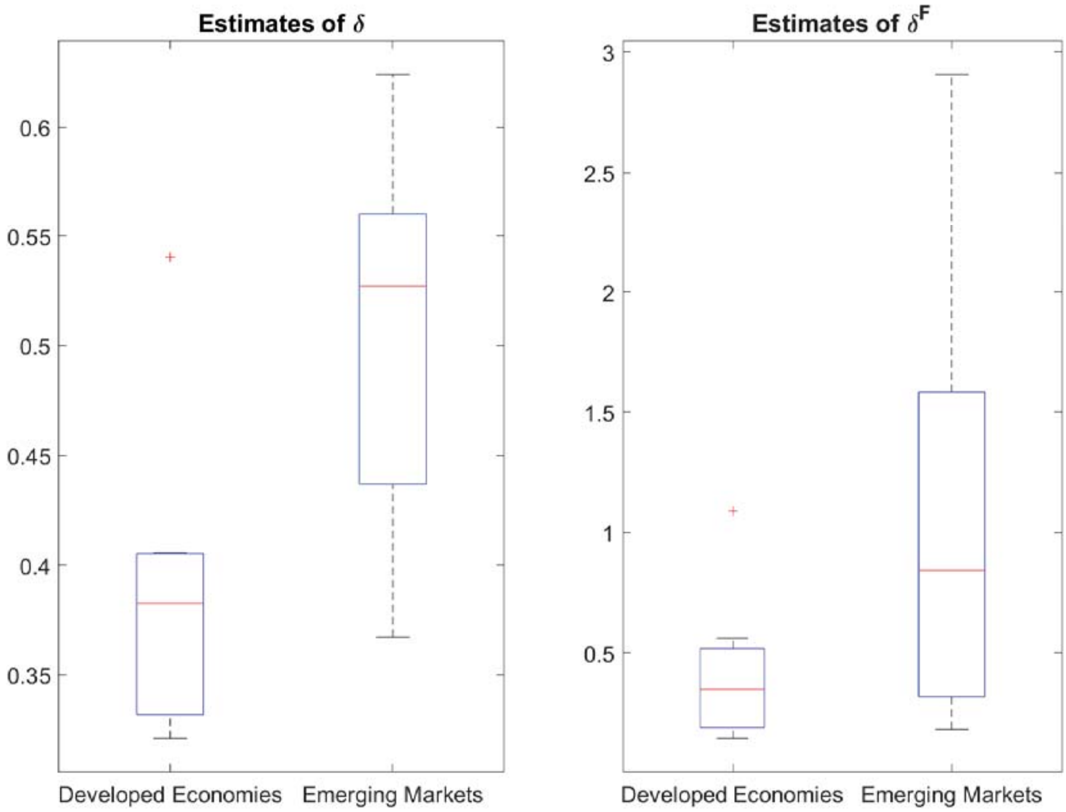
Notes: Both the shares of foreign and domestic shocks sum up to 100.

Figure 7: Estimated Trend Inflation Volatility



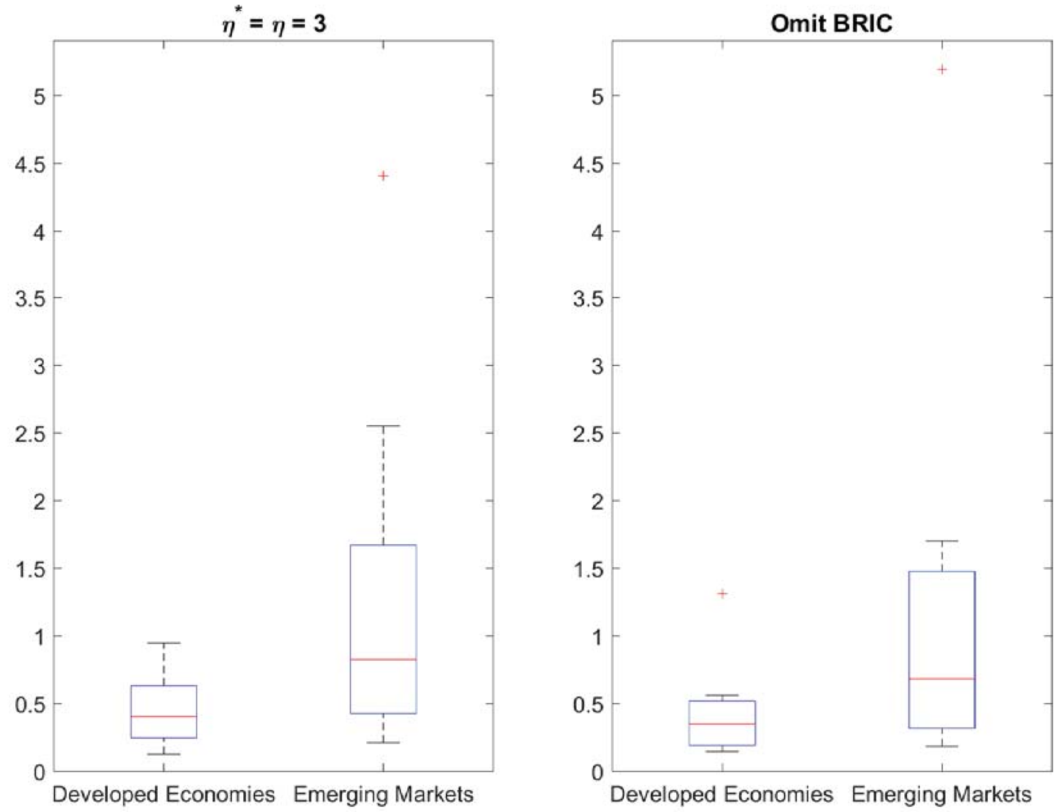
Notes: δ is the estimated unconditional signal-to-noise ratio based on the reduced form VAR. δ^F is the signal-to-noise ratio conditional on foreign shocks. The boxplot presents the minimum, maximum, together with the 25^{th}, 50^{th}, and 75^{th} percentiles (excluding of outliers). Outliers are defined as being three standard deviations from the mean and marked with a +.

Figure 8: Estimated Signal-to-Noise Ratio of Inflation



Notes: δ is the estimated unconditional signal-to-noise ratio based on the reduced form VAR. δ^F is the signal-to-noise ratio conditional on foreign shocks. The boxplot presents the minimum, maximum, together with the 25^{th}, 50^{th}, and 75^{th} percentiles (excluding outliers). Outliers are defined as being three standard deviations from the mean and marked with a +.

Figure 9: Estimated δ^F (Various Specifications)



Notes: δ^F is the estimated signal-to-noise ratio conditional on foreign shocks. $\eta^* = \eta = 3$ fixes the number of foreign and domestic and foreign factors at 3. The boxplot presents the minimum, maximum, together with the 25^{th}, 50^{th}, and 75^{th} percentiles (excluding outliers). Outliers are defined as being three standard deviations from the mean and marked with a +.