Do Commodity Prices Matter for Estimating the Output Gap?

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Abstract

This paper evaluates the importance of commodity price shocks in estimating the output gap. I use the Beveridge and Nelson decomposition method and compute the share of domestic and foreign shocks in the variance decomposition of the output gap. I devise a VAR model in which world shocks affect the output trend and the output gap through changes in commodity prices and global economic factors. I report the results for five advanced and ten emerging economies, over the 1980-2018 period. My results suggest that foreign shocks appear to be more important for the output gap, relative to the output trend, and emerging economies' output trends appear to be more affected by foreign shocks compared to advanced economies. Also, commodity price shocks account for much of the reported shares of foreign shocks in the output trend for both advanced and emerging economies. I also assess the reliability of estimated output gaps in predicting inflation, compared to the reliability of other output measures. I find that output gap estimates do relatively better in inflation forecasting compared to other specifications. This result highlights the need for using commodity price indices in assessing the effects of world shocks on the output gap.

Key words: world shocks, commodity prices, domestic inflation

JEL classification: E31, E32, F44, F62

1 Introduction

The output gap is the difference between potential and actual output. It is also one of the measures used to predict inflation (Smets, 2002; Svensson, 2003; Walsh, 2003).[1] The problem is that the output gap is not directly observable. Therefore, providing a reliable method to estimate the output gap is crucial to informing monetary policy. Economists can only observe actual output and can only infer what the potential output could be. Proposed estimates rely on economic indicators such as the unemployment rate, stock prices, or aggregate consumption (Morley & Wong, 2020). Still, more can be done to improve this estimate by considering other useful indicators. Fernández, Schmitt-Grohe, and Uribe (2017) suggest that multiple commodity prices should be considered to investigate the impact of world shocks on output fluctuations. However, no studies on the output gap incorporate commodity price changes in their estimates. This study investigates whether commodity price indices matter for estimating the output gap.

In this paper, I add to the existing literature on estimating the output gap by utilizing multiple commodity indicators, whereas previous papers use a single indicator: oil prices (Kilian, 2008). As pointed out by Morley and Wong (2020), using univariate models poses challenges to interpretations of estimated output gaps and this approach often needs to be corroborated with other sources of information outside of these models. Since fluctuations in commodity prices can have large impacts on production in world markets, all commodity prices are informative for output fluctuations (Jiménez-Rodríguez & Sánchez, 2005). The commodity prices that are particularly informative include the three indices of fuel, agricultural, and metals prices, calculated by the World Bank.[2] Thus, I include all commodity price indices as a proxy for world shocks to investigate whether they provide more precise estimations of the output gap.

I build on the empirical model suggested by **?** as I use multiple commodity price indices to estimate the output gap. I construct the potential output, known as the *"output trend"*, and the output gap consistent with the method of Beveridge and Nelson (1981). The BN decomposition allows multivariate information in a structural vector autoregression (SVAR) model used to investigate the role of world shocks in driving both the output

[1]The output gap is an indicator of measuring the economic activity. As such, the output gap measures the degree of inflation pressure in the economy and is an essential link between the economy's real side– which produces goods and services– and inflation.

[2]The data is publicly available at http://www.worldbank.org/en/research/commodity-markets.

trend and the output gap. This paper considers global and country-specific indicators jointly in a structural VAR model that provides a straightforward identification of foreign and domestic shocks. The empirical strategy decomposes the output trend and the output gap into identified foreign and domestic shocks, thereby providing an account of the role of foreign and domestic shocks in driving both the output trend and gap.

The model proposed in this paper identifies world shocks by using a foreign block according to the approach of Fernández et al. (2017). In my paper, the foreign block includes two parts (**?**). The first part includes three commodity price indices (agricultural, fuel, and metals products). Since the prices of internationally traded commodities, such as food, metal, and fuel, reflect changes in world markets' supply (Jiménez-Rodríguez & Sánchez, 2005; Kilian, 2008), I apply the commodity price indices to proxy for the world shocks as suggested by Fernández et al. (2017). A commodity price index is a weighted average of selected commodity prices based on spot or futures prices. Thanks to the data used, enough of the variation in commodity price changes is captured. This means that I do not need to compute the factors as I did in chapter 2. This makes both the calculations and estimations much easier. The second part uses a factor model to obtain common factors of macroeconomic indicators. Finally, these macroeconomic indicators are used in empirical studies on the output gap. For instance, Morley and Wong (2020) use data on the U.S. economy to capture the impact of global indicators on the output gap. I obtain data on six large economies with the most available indicators– the U.S., the U.K., Germany, France, Canada, and Japan– to proxy for global factors. The domestic block includes both the output and country-specific macroeconomic indicators.

There is no consensus on which method is the "best" for estimating output gaps. While Kamber, Morley, and Wong (2018) indicate that BN decomposition produces estimates that imply a high signal-to-noise ratio,[3] they state that this method is a relatively reliable way to estimate the output gap in an autoregressive model. They compare it to other methods such as the Hodrick-Prescott (HP) filter and the Band-Pass (BP) filter. The BN decomposition assumes that the expected growth rate of potential output is a constant, while the HP-filter assumes that potential output follows a random walk with a unit root, a hypothesis that is usually easy to reject (St-Amant & van Norden, 1997). The HP-filter also suffers from obvious end-of-sample problems.[4] In a multivariate concept, Morley and

[3]This signal-to-noise ratio is in terms of the variance of the trend shocks as a fraction of the overall forecast error variance.

[4]When a transitory shock occurs, the filter is reluctant to change the trend since it implies raising it

Wong (2020) apply BN decomposition to estimate the output gap that is based on a VAR model that directly allows for multivariate information in conducting and interpreting trend-cycle decompositions.

The last section evaluates the reliability of estimated output gaps using commodity prices in forecasting inflation, compared to other measures of the output. Several strands of literature discuss the relationship between the inflation rate and a measure of real activity (see e.g., Calvo (1983); Taylor (1980)). Since Phillips Curve predicts the direction of change in inflation (Fisher, Liu, & Zhou, 2002), using such a model to forecast inflation would be a sensible way to account for the reliability of estimated output gaps (Bjornland, Brubakk, & Jore, 2008; Clark & McCracken, 2006; Garratt, Mitchell, & Vahey, 2014). In this regard, I consider various specifications for forecasting inflation and use the mean-squared forecast error to compare the quality of inflation forecasts, as suggested by Diebold and Mariano (2002). The results indicate that including the impact of commodity price shocks when estimating output gaps allows for more accurate inflation forecasts compared to other output measures such as an estimated output gap with no commodity indices, HP-filtered output, or output growth.

I also study cross-country heterogeneity in the impact of the commodity prices on inflation. In this regard, I estimate a separate model for 15 countries to capture cross-country differences over the period 1980Q1-2018Q1. My results suggest that world shocks have a larger impact on the output gap, relative to the output trend, for almost every country in the sample. The impact of commodity price shocks on advanced economies represents most of the influence of world shocks on the output gap. Commodity price shocks for both advanced and emerging market economies represent most of the influence of considered world shocks on the output trend.

The rest of the paper is laid out as follows. Section 2 describes the empirical model and the data set. Section 3 presents the results. Section 4 examines the usefulness of output gap in predicting inflation. Section 5 concludes.

before the shock and lowering it afterward. However, the last penalty is absent at the end of the sample. Therefore, it implies that the optimal trend will be more responsive to transitory shocks at the end of the sample than in the mid-sample (St-Amant & van Norden, 1997).

2 Empirical strategy

2.1 Model and empirical strategy

I first use the *"BN decomposition,"* named for Beveridge and Nelson (1981), to estimate the output trend and gap for each country. This method turns non-stationary time series into permanent and transitory decompositions (output trend and output gap). The permanent component follows a random walk with a drift and the cyclical component is a stationary process with mean zero. Thus, the BN decomposition intuitively considers that the long-horizon conditional expectation of the time series only reflects its trend since the long-horizon conditional expectation of the cyclical component of a time series process is considered to be zero. Based on this assumption, to estimate the output trend, a forecasting model for the time series is needed (Morley & Wong, 2020), and to estimate the multivariate model, linear VARs are considered (e.g., Evans and Reichlin (1994)).

The BN decomposition. Let y_t represent the output and μ represent the constant drift. Equation 2.1 shows the time series for the output trend as its long-horizon conditional expectation minus any future deterministic drift as suggested by Morley and Wong (2020). The output trend, τ_t, at time t is

$$\tau_t = \lim_{j \to \infty} E_t[y_{t+j} - j.\mu], \tag{2.1}$$

and the output cycle, c_t, is computed as the difference between the observed time series and the output trend,

$$c_t = y_t - \tau_t. \tag{2.2}$$

For the multivariate setting, let X_t represent a vector of n stationary variables that includes the first difference of the output in log form as one of the elements which follows a first autoregressive process,

$$X_t = BX_{t-1} + H\nu_t, \tag{2.3}$$

where B represents a companion matrix whose eigenvalues are all within the unit circle, μ is a vector of unconditional means, ν_t is a vector of serially uncorrelated forecast errors with co-variance matrix Σ_μ, and H is a matrix that maps the forecast errors to the companion form. Considering an empirical model in the form of equation 2.3, the output trend and the output gap components obtained are consistent with the BN decomposition.

Following Morley (2002) in solving for this equation, the BN trend, τ_t, can be written as

$$\tau_t = y_t + e_i B(I - B)^{-1} X_t, \tag{2.4}$$

Defining e_i as a selector row vector with 1 as its i^{th} element and zero otherwise in equation 2.4, and the output gap can be written as

$$\tilde{y}_t = -e_i B(I - B)^{-1} X_t. \tag{2.5}$$

I now demonstrate how the changes in the output gap and the output trend are decomposed into foreign and domestic shocks. Let $\vartheta_t = \begin{bmatrix} \epsilon_t^* \\ \epsilon_t \end{bmatrix}$ represent the foreign and domestic shocks which are identified using the FAVAR model in the next section. $B\vartheta_t = \nu_t$ describes how the forecast errors and foreign and domestic shocks are mapped by matrix C. Using this mapping and recursively substituting equation 2.3 into equation 2.4 and 2.5, the change of output trend and the output gap can be written as follows:

$$\Delta\tau_t = e_i(I - B)^{-1} HC\vartheta_t, \tag{2.6}$$

$$\tilde{y}_t = -e_i\{\sum_{k=0}^{t-1} B^{k+1}(I - B)^{-1} HC\vartheta_t\} - e_i B^{t+1}(I - B)^{-1} e_i' y_0. \tag{2.7}$$

Since the coefficient $B \in (0, 1)$, the second part of equation 2.7 is expected to disappear. Considering equations 2.6 and 2.7, both the output gap and output trend are linear functions of both the foreign and domestic shocks. Therefore, equations 2.6 and 2.7 provide the basis for the subsequent analysis because they quantify the impacts of foreign and domestic shocks on the output trend and output gap. In appendix B, I explain how the output gap is computed in this analysis.

VAR/FAVAR model. I use both foreign and domestic blocks to identify foreign and domestic shocks. I use a factor augmented vector autoregression (FAVAR) framework for each foreign and domestic block to study the role of world shocks in driving the output gap. As noted by Morley and Wong (2020), the BN decomposition includes the relevant information required to forecast the output trend, even if only one variable is included in the model, as long as the information spans over other variables. Thus, this paper contains the relevant information in the form of an FAVAR model to estimate the output gap. Let

Γ_t^* and Γ_t represent the vectors of the foreign and domestic blocks in the reduced form FAVAR model to represent world prices and country-specific indicators, respectively. Both the foreign and domestic blocks are considered jointly as a vector autoregressive model in the form

$$\begin{bmatrix} \Gamma_t^* \\ \Gamma_t \end{bmatrix} = \begin{bmatrix} \alpha_{11(L)} & \alpha_{12(L)} \\ \alpha_{21(L)} & \alpha_{22(L)} \end{bmatrix} \begin{bmatrix} \Gamma_{t-1}^* \\ \Gamma_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} \epsilon_t^* \\ \epsilon_t \end{bmatrix}.$$

The identification restrictions are applied to identify foreign and domestic shocks in a small open economy framework. This implies that $\alpha_{12(L)} = \beta_{12} = 0$ which is a conventional assumption for small open economies (Fernández et al., 2017; Justiniano & Preston, 2010; Zha, 1999). Thus, the VAR specification form is

$$\begin{bmatrix} \Gamma_t^* \\ \Gamma_t \end{bmatrix} = \begin{bmatrix} \alpha_{11(L)} & 0 \\ \alpha_{21(L)} & \alpha_{22(L)} \end{bmatrix} \begin{bmatrix} \Gamma_{t-1}^* \\ \Gamma_{t-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & 0 \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} \epsilon_t^* \\ \epsilon_t \end{bmatrix} \tag{2.8}$$

in which $\alpha_{ij}(L)$ represents the conformable lag polynomial where $\alpha_{ij}(L) = \sum_{k=0}^{p-1} \alpha_{ij}^k L^k$. The foreign and domestic shocks are denoted as ϵ_t^* and ϵ_t, where $\mathbb{E}\begin{bmatrix} \epsilon_t^{*'} & \epsilon_t^{'} \end{bmatrix}' \begin{bmatrix} \epsilon_t^{*'} & \epsilon_t^{'} \end{bmatrix} = I$. As quarterly data are used, the FAVAR model includes four lags to estimate the output gap. My paper casts the model described in equation 2.8 into a form implied by equation 2.3. Then, equations 2.4 and 2.5 are applied to the BN decomposition to estimate the output trend and output gap, followed by the use of equations 2.6 and 2.7 to investigate the role of world shocks here. In section 3.6, I check the robustness of the results from a specification that relaxes the block exogeneity assumption. I also consider a specification to allow for the possibility of international stock prices reacting contemporaneously to domestic shocks.

To estimate the output gap, I build on the model advanced by **?** and use a large data set to study the role of world shocks in driving the trend and cycle of output in two ways. First, whereas the authors use their model to estimate the role of world shocks in driving the trend of inflation and inflation gap, I mainly focus on the output because this constitutes a critical macroeconomic indicator. Second, to build the foreign block, **?** include data of five major economies (the U.S., the U.K., Germany, France, Canada, and Japan), while the data in their sample is not balanced in terms of time period and choice of macroeconomic indicators. In my paper, I include macroeconomic indicators for six of the G7 countries in a balanced sample for all countries.[5]

Foreign block (Γ_t^*). In the baseline specification, the foreign block contains two parts inspired by **?**. The first part includes a world price vector that consists of three real price indices of agricultural, fuel, and metals series. The second part includes a factor model that is applied to a group of global economic indicators. This approach follows Bernanke, Boivin, and Eliasz (2005), who suggest using principle component analysis to extract the common factor of economic indicators. Let Γ_t^* represents the foreign block and its two parts: P_t^*, which includes three real prices of fuel, metals, and agricultural indices, p^f, p^m, p^a, and F_t^*, which includes the common factors of six major economies. The equations representing the foreign block are given by 2.9:

$$\Gamma^* = \begin{bmatrix} P_t^* \\ F_t^* \end{bmatrix}, \ where \qquad P_t^* = \begin{bmatrix} p^f \\ p^m \\ p^a \end{bmatrix}, \qquad F_t^* = \begin{bmatrix} f_{1,t}^* \\ f_{2,t}^* \\ \vdots \\ f_{n,t}^* \end{bmatrix} \tag{2.9}$$

Later, in section 3.4, I report the estimated output gap while the commodity price indices are excluded from the foreign block, that is, the foreign block includes only a factor model applied to global economic indicators from six major economies. Then, for the sake of comparison, I use these global economic indicators to estimate the output gap.

Domestic block (Γ_t). To estimate the output gap and the output trend, the domestic block, Γ, includes the output in real terms, y_t, and a range of country-specific macroeconomic indicators. Again, common factors of country-specific macroeconomic indicators are obtained by using the factor model from the data set of the small open economy. The domestic block is characterized by

$$\Gamma = \begin{bmatrix} F_t \\ y_t \end{bmatrix}, \ where \qquad F_t = \begin{bmatrix} f_{1,t} \\ f_{2,t} \\ \vdots \\ f_{n,t} \end{bmatrix}. \tag{2.10}$$

Number of factors in Γ_t & Γ_t^*. Forni and Gambetti (2014) suggest that information sufficiency is required to identify shocks in VAR models correctly. Furthermore, in the context of a trend-cycle decomposition, Morley and Wong (2020) point that obtaining re-

[5]Italy is excluded because data is not available for the choice of economic indicators.

liable estimates of trend and cycle by using a multivariate BN decomposition also requires information sufficiency. Thus, to select the number of factors included in F_t^* (denoted as κ^*) and F_t (denoted as κ), I use the sufficiency test suggested by Forni and Gambetti (2014). Here, I estimate equation 2.8 with only one factor such that $\kappa^* = \kappa = 1$. I first pin down the domestic block by sequentially adding the 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. This specifies κ. Then, I specify the number of retained factors from the international dataset, κ^*, by similarly sequentially adding principal components from the foreign block until the included factor no longer Granger causes any of the other variables at the 1% level. Note that since the optimal number of factors can differ between the foreign and domestic blocks. Also, the model has different world shocks across countries.

To identify the commodity price shocks, the block of three commodity prices is considered pre-determined for the rest of the foreign block, as suggested by **?**. This is reasonable since much of the commodity supply is pre-determined from futures markets and, thus, producers take time to adjust their supply to the price incentives. This is consistent with previous empirical work that identifies oil or commodity price shocks (see, e.g., Bachmeier and Cha (2011); Kilian and Lewis (2011); Wong (2015)). The identification of the effects of world shocks as a whole is not affected by the particular identification assumptions on commodity block of the model as long as the model includes the small open economy structure.

2.2 Data

In this section, I consider a group of five advanced and ten emerging market economies in the domestic block that are potentially representative of small open economies. These countries correspond to OECD countries for which imports of goods and services constitute more than a 10% share of GDP, according to the World Bank Indicator (WDI). The index on imports as a share of GDP is obtained from the WDI. They are selected based on data availability for the output in real terms and other macroeconomic indicators. Table A1 in Appendix A provides information on imports as a share of GDP, averaged over the period 1980-2019 for all countries in this paper. As part of the foreign block, I include six of the G7 countries: the U.S., the U.K., Germany, France, Canada, and Japan.[6] Italy is dropped because multiple economic indicators are missing for the time period used.[7] Table 1 displays the list of countries included as part of the domestic and foreign blocks. For these countries, there is no missing observation for 1980Q1-2018Q1.

Table 1: List of countries included in the sample over 1980Q1-2018Q1

Global major economies	Emerging market economies	Advanced economies
United States	Brazil	Australia
United Kingdom	Chile	Denmark
Japan	Hong Kong	Norway
Canada	India	Switzerland
Germany	Korea, Rep.	Sweden
France	Malaysia	
	Mexico	
	Singapore	
	South Africa	
	Thailand	

Note: The empirical analysis includes six major global economies in the foreign block, a group of five advanced and ten emerging small open market economies in the domestic block, over the period from 1980Q1-2018Q1.

Foreign block Data for the foreign block commodity price indices (fuel, agriculture, and metals) are obtained from the World Bank Pink Sheet and quarterly.[8] Other macroeconomic indicators for the G7 countries include the natural logarithm of gross domestic product, final consumption expenditure and gross fixed capital formation (domestic investment) all in real terms, and industrial production, the consumer price index, and the stock price index come from Datastream.[9]

Domestic block This block includes quarterly data on country-specific natural logarithms of gross domestic product in real terms. This data set also includes country-specific final consumption expenditure, gross fixed capital formation (domestic investment), industrial production, the share price index in the second part of the domestic block. Information on these variables are also obtained from Datastream.

These variables were selected because they are important determinants of output

[6] The data used in this paper are from the World Bank Indicators, the World Bank Pink Sheet, and the Datastream database. The data is publicly available: see http://www.worldbank.org/en/research/commodity-markets and http://solutions.refinitiv.com.

[7] I did not include the data from China in the foreign block since there is not enough data for multiple variables covering all the years in the sample.

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

[9] The Datastream database is publicly available at http://solutions.refinitiv.com.

growth (e.g., Bernanke (1983); Collier, Van Der Ploeg, Spence, and Venables (2010); Ndikumana (2000)). I also include the stock price index to consider the relationship between stock returns and expected and unexpected output growth (Morley & Wong, 2020; Rodrik, 2008).

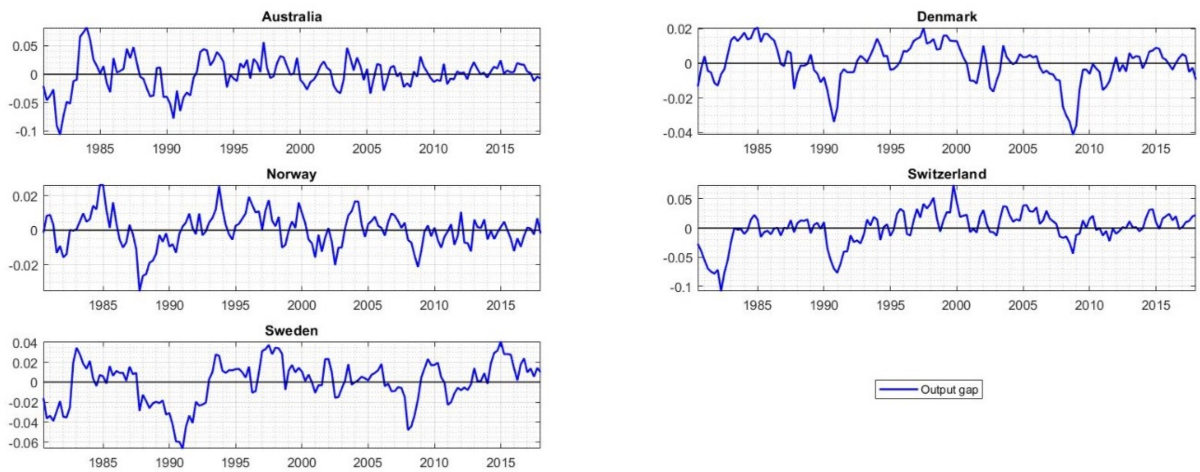
The data transformation Morley and Wong (2020) recommend normalizing the data before performing the factor models. I subtracted the mean from the data and divided them by the standard deviation of the variables to standardize the data of the macroeconomic indicators. The data for the factor models should be stationary. Using the Augmented Dickey Fuller test, I find that the real data in levels are not stationary. Therefore, I ensure stationarity by taking the first difference of the variables that are not in percentage points.

3 Results

3.1 Estimated output gap using BN decomposition

In this section, I use commodity price indices in the foreign block to estimate the output gap. Figures 1 to 3 show the estimated output gap when I use the baseline empirical model for the advanced and emerging market economies included in the sample for the period 1980Q1-2018Q1.

Fig. 1: Estimated output gap for advanced economies



Figures 5 and 6, in Appendix A, show the output trend and the output for the advanced and emerging market, included in the sample, over the period 1980Q1-2018Q1. These

Fig. 2: Estimated output gap for emerging market economies (1)

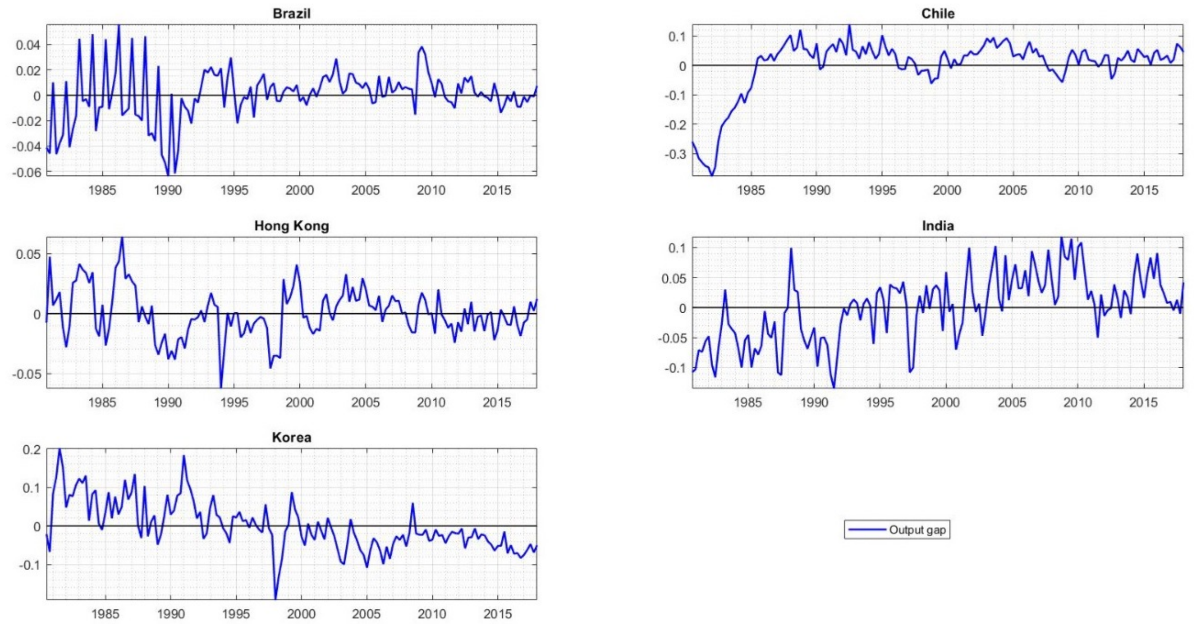
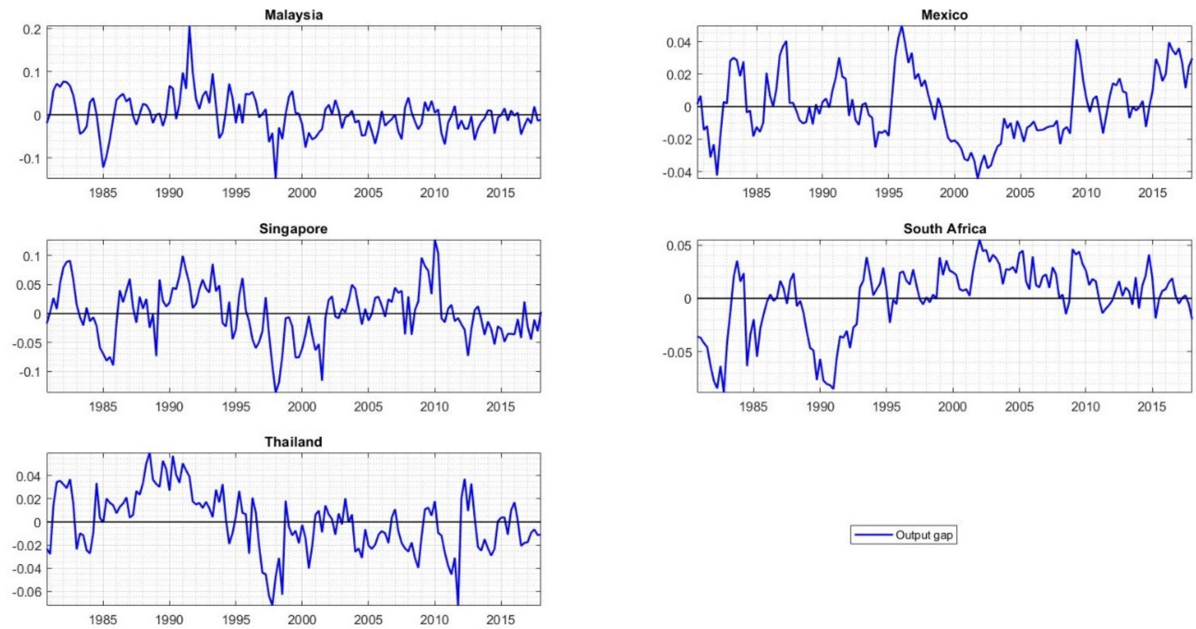


Fig. 3: Estimated output gap for emerging market economies (2)



figures show that the estimates of the output trends lie close to their actual outputs for both advanced and emerging market economies.

3.2 How important are world shocks?

Variance decomposition. A question that arose in this study is, how important are commodity price shocks for the output trend and output gap? One way of quantifying the relative importance of world shocks is to compute the share of domestic and world shocks in the variance decomposition of the output trend and output gap.

In an FAVAR system, let N^* be the number of foreign variables that is equal to the number of factors obtained from the factor model, κ^*, plus the three commodity price indices in the foreign block. The natural logarithm of output in real terms is in the k^{th} position in the FAVAR system, with $k > N^*$. To compute the variance decomposition, I use equations 2.6 and 2.7 to obtain the shares of world shocks in the variance decomposition of the output trend and the output gap, respectively, by using the following formula suggested by Morley and Wong (2020):

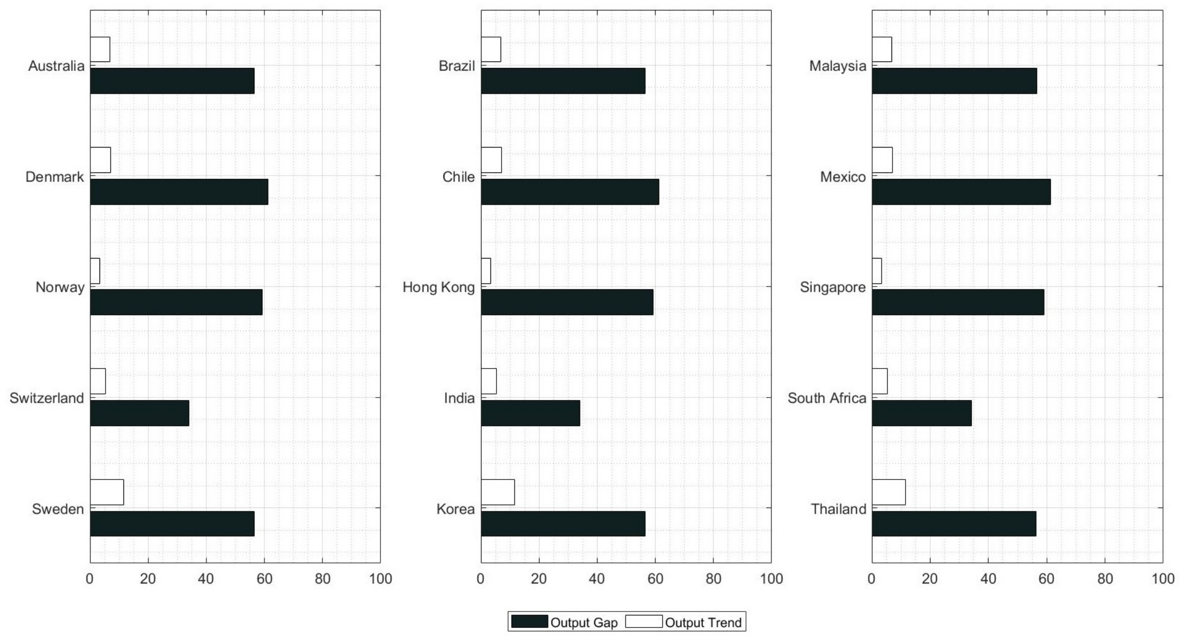
$$\psi_y^\tau = \frac{\sum_{j=1}^{N^*} \left\{ e_k (I - B)^{-1} H C e_j' \right\}^2}{e_k (I - B)^{-1} H \Sigma_\nu H' e_k (I - B)^{-1\prime} e_k'} \tag{3.1}$$

$$\psi_{\tilde{y}} = \frac{\sum_{j=1}^{N^*} (e_k \sum_{i=0}^{\infty} \left\{ B^{i+1} (I - B)^{-1} H C e_j' \right\})^2}{e_k \left\{ \sum_{i=0}^{\infty} \left[B^{i+1} (I - B)^{-1} H \Sigma_\nu H' \left\{ B^{i+1} (I - B)^{-1} \right\}' \right] \right\} e_k'}, \tag{3.2}$$

where ψ_y^τ and $\psi_{\tilde{y}}$ are the shares of the world shocks in the variance decomposition of the output trend and the output gap.

Figure 4 shows the relative shares of world shocks in the variance decomposition of the output gap and the output trend for advanced and emerging market economies. As can be seen from these figures, world shocks have a larger impact on the output gap relative to the output trend for almost all of the countries in the sample. To be more specific, the pattern in Figure 4 shows that the shares of world shocks in the variance decomposition of the output gap are more pronounced relative to the output trend for advanced economies such as Australia, Denmark, or Sweden. In particular, for almost all advanced economies, the corresponding share of world shocks in the variance decomposition of the output gap is over 50%, except for Switzerland; whereas the share of world shocks in the variance decomposition of the output trend is smaller (less than 15%) for all five advanced economies. World shocks can also explain the larger share of the output gap, compared to the output trend, for each emerging economy in my sample. The pattern in Figure 4 shows that while world shocks explain a similarly small share of the output trend for most of the emerging market economies, such as Thailand or Malaysia, some countries have very large shares of output gaps that are explained by world shocks, such as Mexico.

Fig. 4: Shares of world shocks for advanced and emerging market economies.



3.3 The role of commodity price shocks in estimating the output gap

The above results show that world shocks explain much of the variation in the output gap and, to some extent, the output trend in both advanced and emerging market economies. This section discusses the indicators that are included in world shocks. First, more identifying assumptions need to be imposed within the foreign block of the model. While it is challenging to identify and interpret shocks such as foreign monetary policy or foreign productivity shocks, a natural possibility within the empirical framework in this paper is to consider commodity price shocks. This is in line with what Fernández et al. (2017) suggest as world shocks. They use commodity price indices to identify world shocks and investigate their impact on domestic business cycles.

Figures 5 and 6 present the variance decomposition of commodity price shocks and the other foreign shocks that drive the output trend and output gap, respectively. Figure 5 shows that most of the influence of world shocks on the output gap for both advanced and emerging market economies comes from commodity price shocks. Figure 6 shows that,

Fig. 5: Share of commodity price shocks in the output gap.

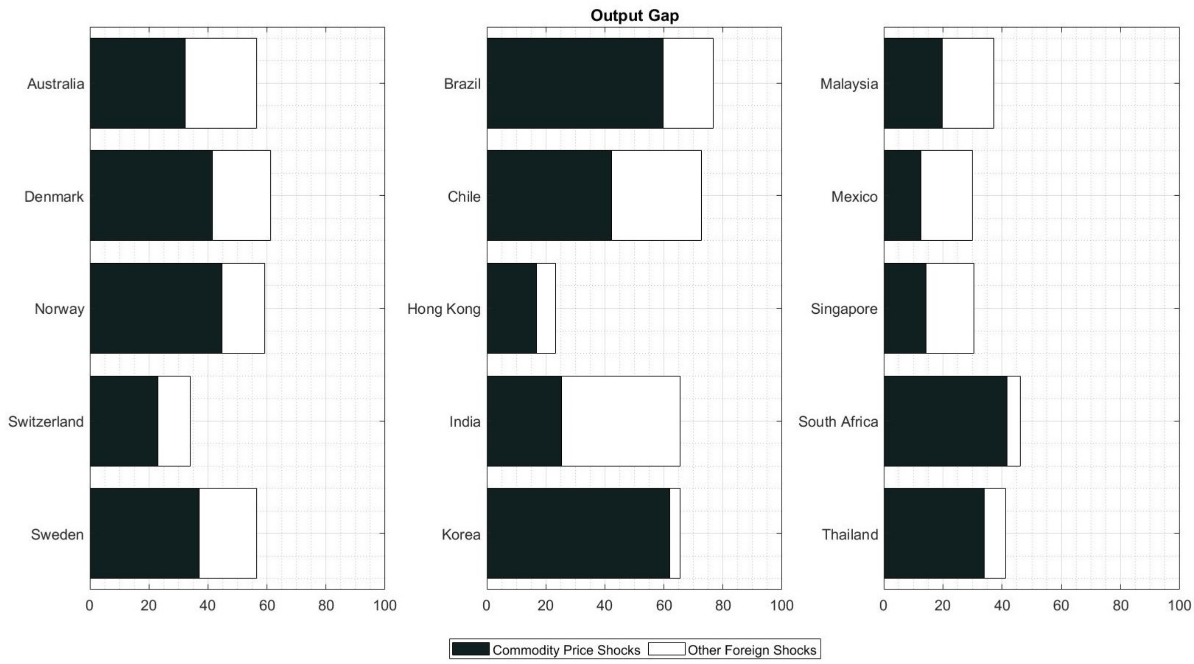
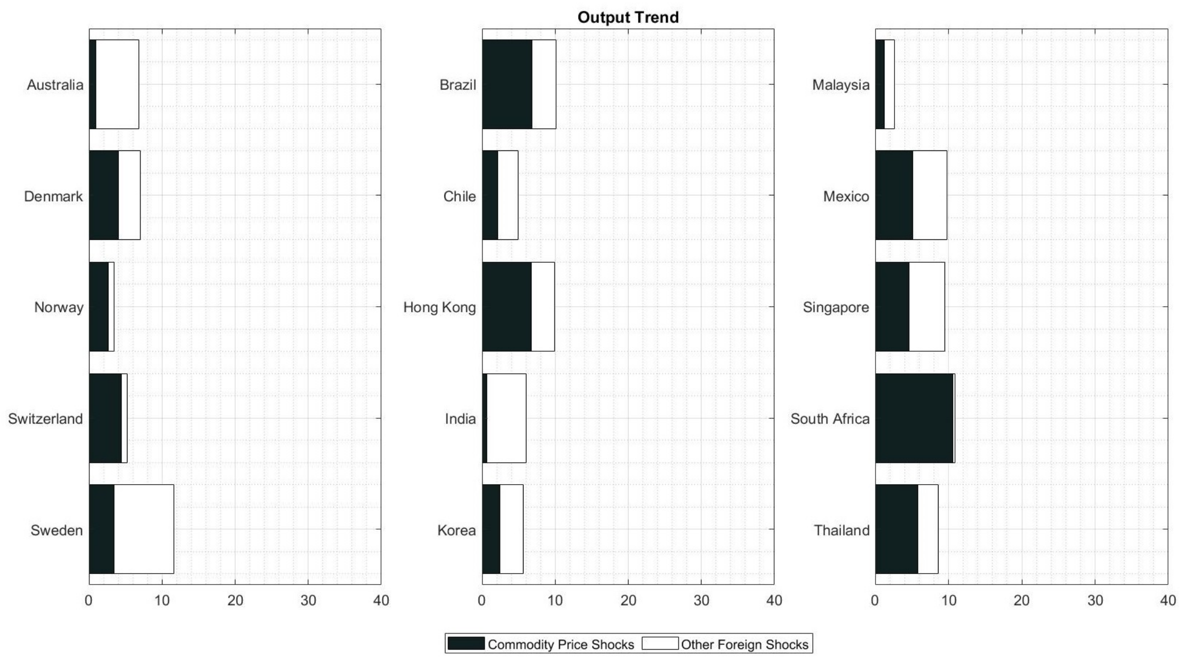


Fig. 6: Share of commodity price shocks in the output trend.



for emerging market economies, most of the influence of world shocks on the output trend comes from commodity price shocks. This shows that commodity price shocks explain most of the effects of world shocks on the output gap; this finding is also consistent with Fernández et al. (2017). These authors find that commodity price shocks explain much of domestic business cycles, or at least 30% of fluctuations in output. This result is also consistent with my findings in chapter 2. Commodity price shocks explain on average 26% of inflation fluctuations for the median country.

3.4 Estimated output gap with no commodity price shocks

In this section, I estimate the output gap without considering the commodity price indices in the foreign block. That is, the foreign block contains only a factor model that is applied to global economic indicators from six major economies: the U.S., the U.K., Germany, France, Canada, and Japan. I use the same method as in section 2.1 for the sample of countries in the study. The domestic block is the same as the baseline estimation, which includes the output in real terms, y_t, and a range of country-specific macroeconomic indicators whose common factors are obtained by using the factor model.

Figures 7 to 9 show the estimated output gap that is obtained without using commodity prices (red lines). The figures also show the estimates obtained in the baseline estimation (blue lines) for the advanced and emerging market economies included in the sample for the period 1980Q1-2018Q1. Based on these figures, there are some slight differences in the estimated output gaps for both specifications. To investigate whether commodity price shocks matter in estimating the output gap, in section 4, I evaluate whether alternative estimates of the output gap improve predictions for inflation, compared to other measures.

Fig. 7: Estimated output gap both with and without commodities for advanced economies

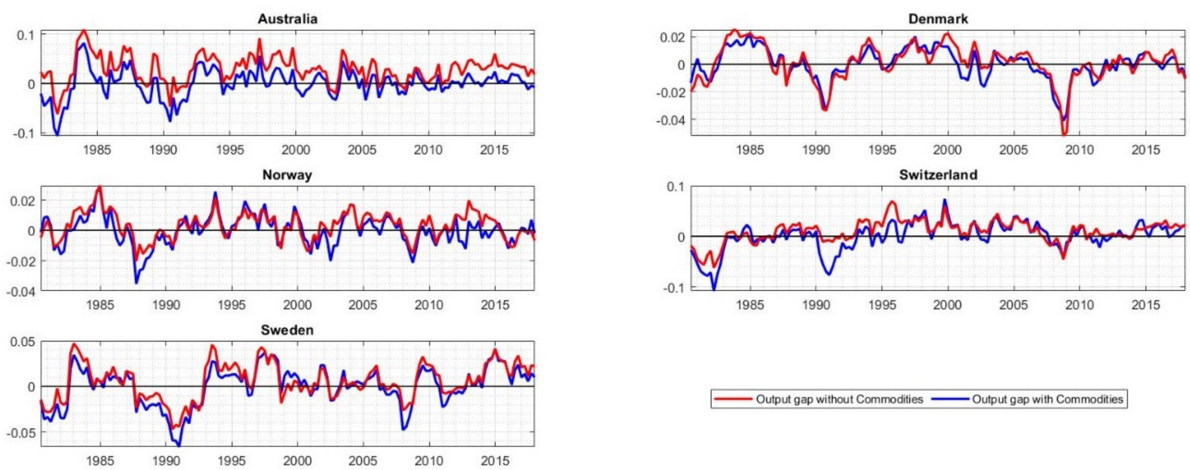


Fig. 8: Estimated output gap both with and without for emerging market economies (1)

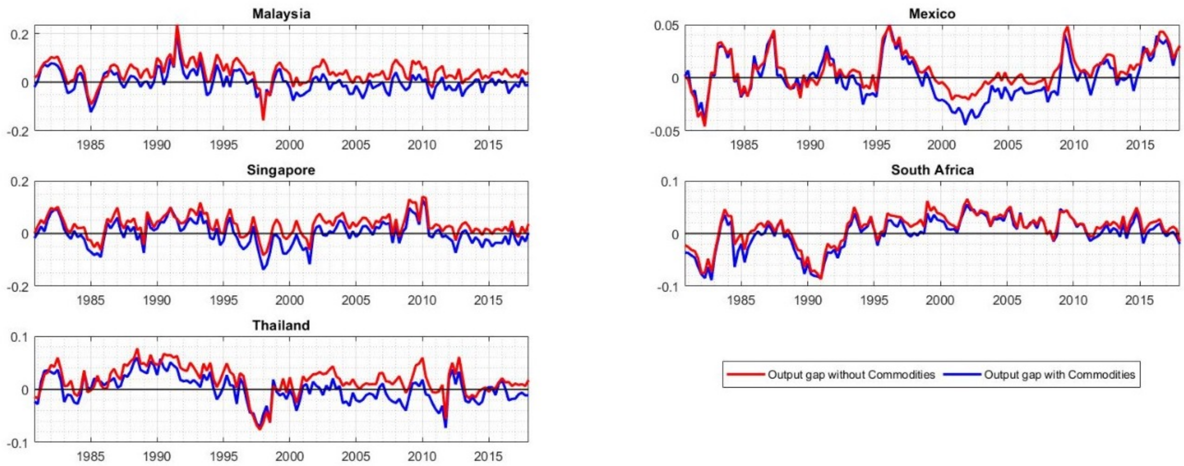
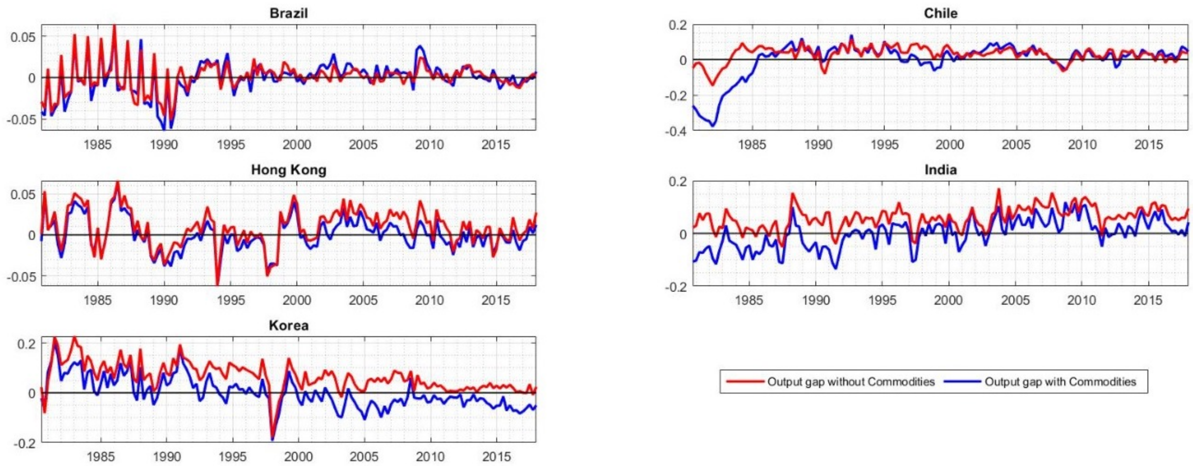


Fig. 9: Estimated output gap both with and without commodities for emerging market economies (2)



3.5 Estimated output gap with alternative measures

This section compares the output gap measures resulting from the multivariate BN decomposition used throughout this paper to a benchmark of models traditionally used in the literature. Figures 10 to 12 present the estimated output gap using these different estimates. Specifically, the figures show the estimates obtained in the baseline estimation (blue lines) for the advanced and emerging market economies included in the sample 1980Q1-2018Q1 and the alternative measures using the Hodrick-Prescott (HP) filter and the Hamilton filter on the log real GDP (De Brouwer et al., 1998), and the univariate Beverage-Nelson filter applied to the GDP data, as implemented in Kamber et al. (2018). I use the smoothing parameter of 100 for Hp-filter. To obtain the Hamilton filter, I use the default for quarterly data in which the number of lags is 8 (two-year horizon) and the default for the number of lags in regression in quarterly data (p=4). In the Univariate model, I use what Kamber et al. (2018) suggest for the lag order equal to 12 quarters or three years in quarterly data.

The comparison of the different estimates suggest that the baseline model is more volatile when compared to other measures. As is expected by the ability of multivariate BN decomposition method to capture the volatility of all commodity prices in the model, the baseline method is more volatile compared to alternative ones. To discuss the similarities and differences between these methods, Table 2 presents the correlation coefficients for these estimates. With a correlation of 0.55, the multivariate BN, on average, is closest to the HP filter, although the correlation coefficients are close to this number for the univariate BN decomposition (0.38) and the Hamilton filter (0.45).

Fig. 10: Estimated output gap compared with alternative methods for advanced economies

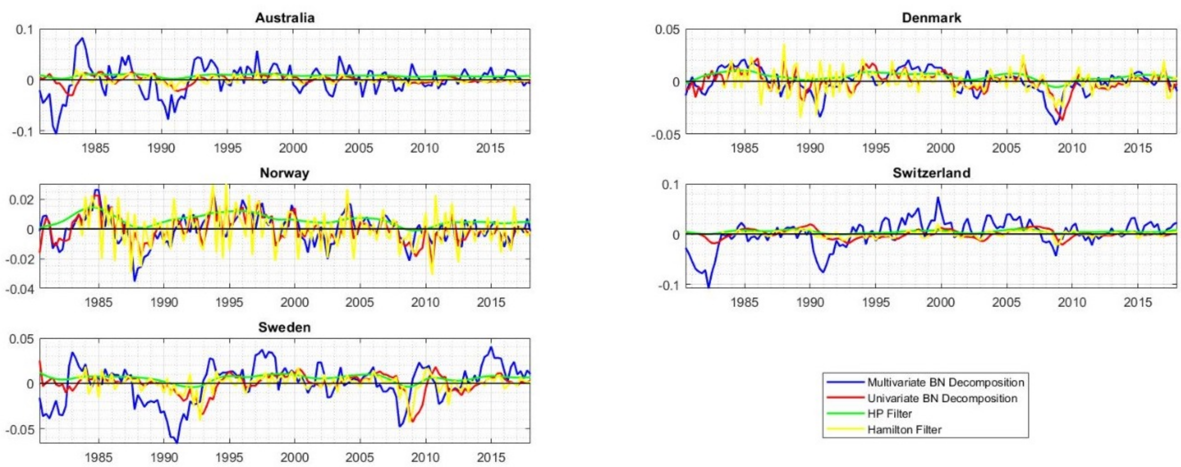


Table 2: Correlation coefficient between the baseline estimates and alternative methods

	Univariate model	Hamilton filter	HP filter
Australia	0.37	0.61	0.56
Denmark	0.56	0.33	0.77
Norway	0.63	0.30	0.61
Switzerland	0.30	0.58	0.54
Sweden	0.21	0.39	0.53
Brazil	-0.20	-0.01	0.43
Chile	0.50	0.28	0.70
Hong Kong	0.39	0.50	0.46
India	0.66	0.53	0.68
Korea	0.73	0.63	0.68
Malaysia	0.35	0.68	0.44
Mexico	-0.16	0.20	0.13
Singapore	0.39	0.59	0.51
South Africa	0.32	0.56	0.58
Thailand	0.69	0.53	0.69
Average	0.38	0.45	0.55

Note: This table shows the correlation coefficient between alternative measures for estimating the output gap with the baseline estimate - multivariate BN decomposition.

Fig. 11: Estimated output gap compared with alternative methods for emerging market economies (1)

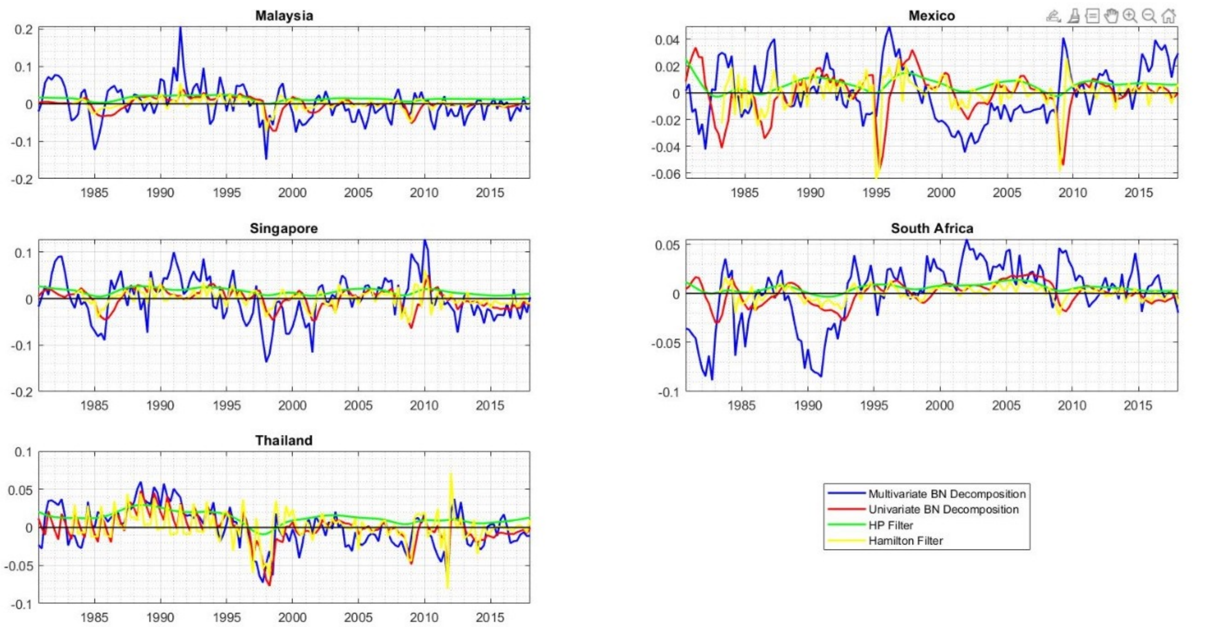
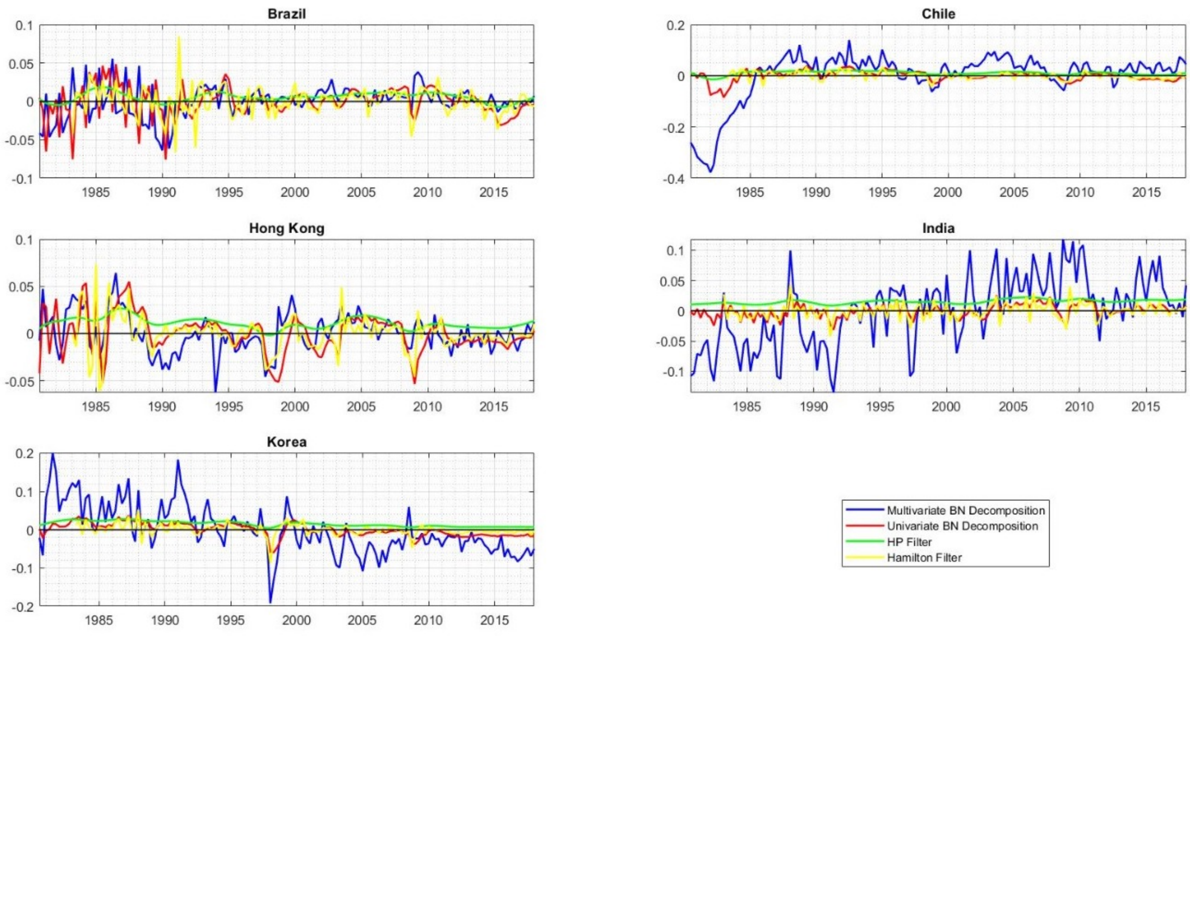


Fig. 12: Estimated output gap compared with alternative methods for emerging market economies (2)



3.6 Robustness checks

In this subsection, I check the robustness of the baseline results to relaxing the small open economy identification restrictions that impose the exogeneity of the foreign block on the domestic block. One way to do this is to allow the lags of the domestic variables to enter the foreign block, which means relaxing $\alpha_{12(L)} = \beta_{12} = 0$ in equation 2.8. In this exercise, world shocks are identified through a standard recursive identification that only imposes that foreign variables do not respond contemporaneously to domestic shocks.

Figures 13 to 15 show that the share of world shocks without imposing the exogeneity of the foreign block for both advanced and emerging market economies is analogous to that in the analysis for the baseline result. Figures 19 to 24 also indicate that the output gap and the output trend for all of the small open economies in the sample are consistent with my baseline analysis. There is a marginal effect on the results and this means that these variance decompositions are robust to relaxing the assumption of the exogeneity of the foreign block to the domestic block for the small open economy identification assumption.

Fig. 13: Share of world shocks where the exogeneity assumption is relaxed for advanced economies

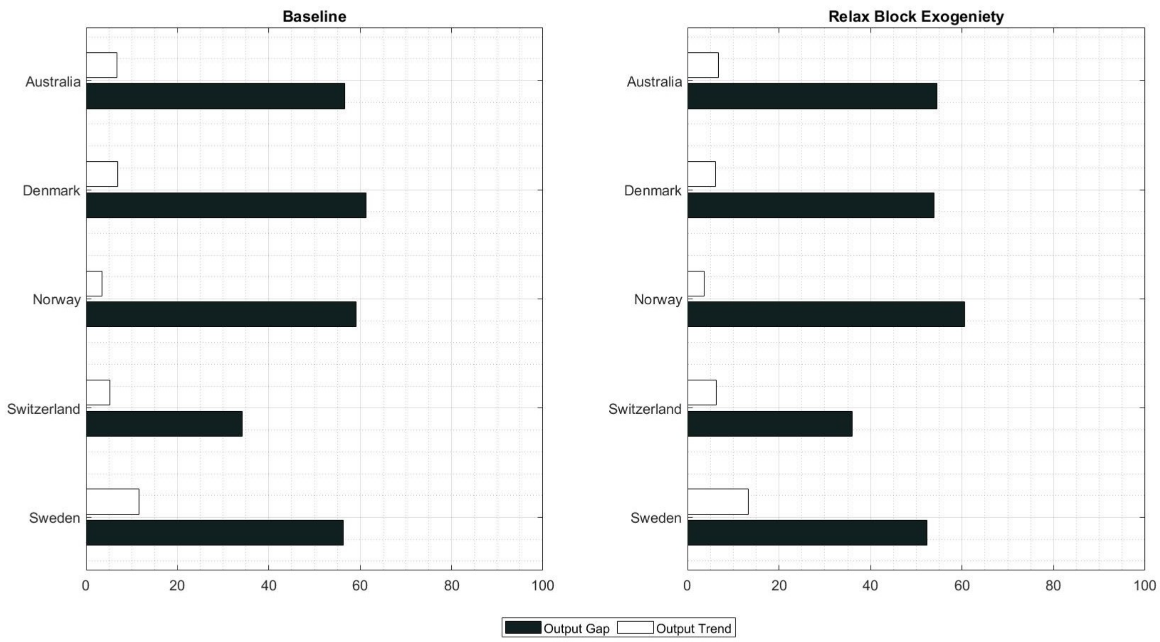


Fig. 14: Share of world shocks where the exogeneity assumption is relaxed for emerging market economies (1)

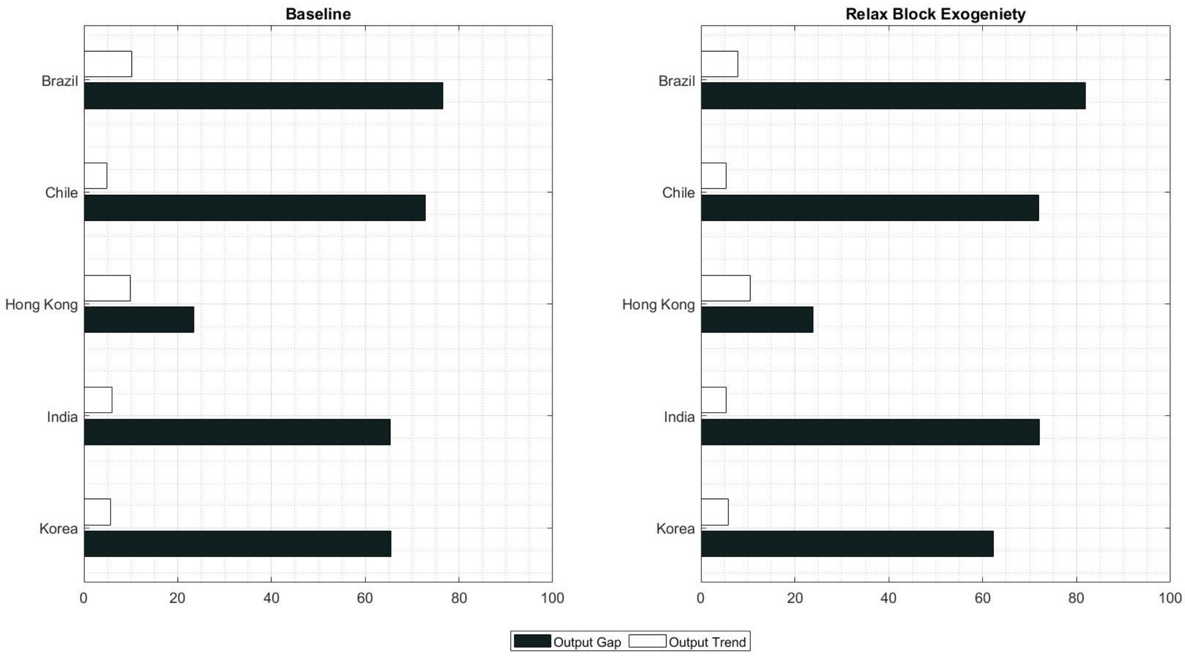
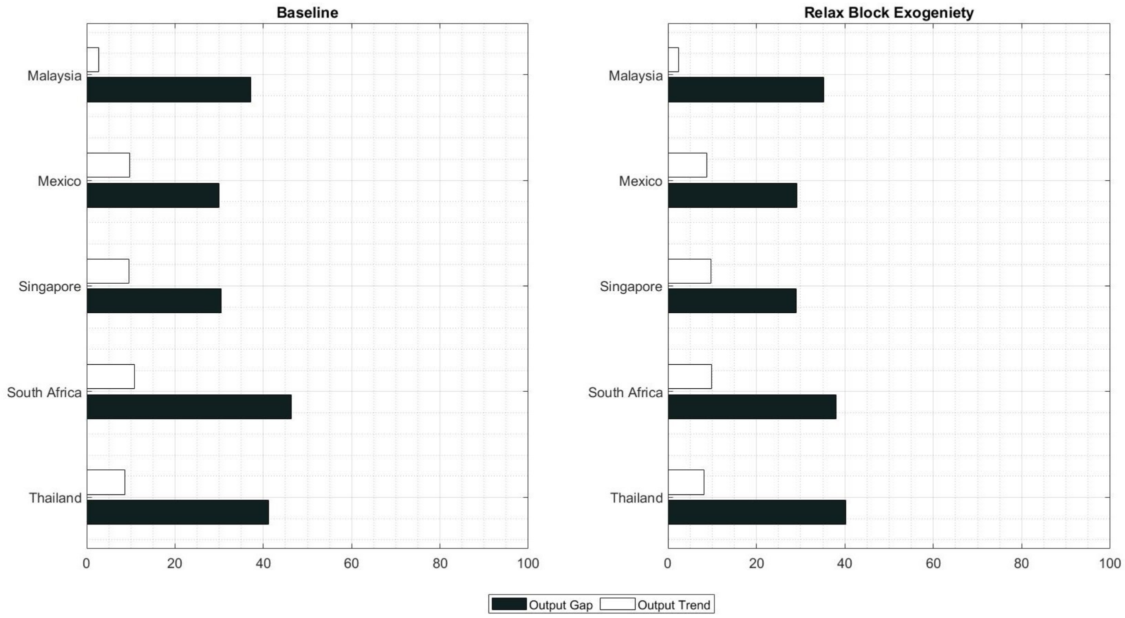


Fig. 15: Share of world shocks where the exogeneity assumption is relaxed for emerging market economies (2)



In the next section, I use commodity price indices from section 3.3 to evaluate the usefulness of the estimated output gap using commodity prices in predicting inflation, and then I compare these to the estimates obtained from the global indicators alone in section 3.4.

Structural breaks Previous studies discuss that estimates of the output gap from different methods can be susceptible to accounting for structural breaks (Kamber et al., 2018; Perron & Wada, 2016). Kamber et al. (2018) mention that the traditional BN decomposition assumes that the trend component of y_t follows a random walk with constant drift. They suggest that one potential concern then is that if there has been a sufficiently significant change in the long-run growth rate, the assumption of constant drift will lead to biased estimates of the output gap. They find a structural break, e.g., 2006Q1, adjust the data for the break in the long-run growth rate in 2006Q1, and apply the BN filter to the adjusted data. They find no evidence for a break in persistence and assume a constant δ for the whole sample. However, in my paper, equation 2.1 shows the time series for the output trend excludes any future deterministic drift as suggested by Morley and Wong (2020). Thus, considering these structural breaks to estimate the output gap is a complicated procedure that is not this paper's primary purpose.

4 Model assessment

4.1 Measures of forecasting performance

Previous studies suggest inflation forecasting models can be used to measure the extent to which output gap estimates are a practical means of improving inflation forecasts (Álvarez & Correa-López, 2020; Camba-Mendez & Rodriguez-Palenzuela, 2003). This depends on a lot of factors, such as the time period of interest, the way in which forecasts are constructed, the benchmark against which such forecasts are compared, and the loss function used to evaluate the quality of different forecasts. In this paper, I try to forecast inflation by using the estimated output gap and past inflation to compare the results with other output measures in different specifications. To do so, I use the mean-squared forecast error (MSFE) to compare the forecast quality in a test known as the DM, as suggested by Diebold and Mariano (2002).[10]

Forecasting inflation. A stable predictive relationship between inflation and the output gap, often referred to as the Phillips curve, provides the basis for counter-cyclical monetary policy in many models. Orphanides and van Norden (2005) evaluate the usefulness of output gap estimates in predicting inflation. In this paper, I follow their model to do the same. Let $\pi_t^m = log(P_t) - log(P_{t-m})$ denote inflation over m quarters, ending in quarter t. Here, I examine forecasts of inflation at various horizons. Note that because of reporting lags, data for quarter t first becomes available in quarter $t+1$. Thus, a forty-eight-quarter-ahead forecast is a forecast that is forty-nine quarters ahead of the last quarter for which the actual data are available. The objective, therefore, is to forecast π_{t+m}^m with data for both quarter $t-1$ and earlier periods.

I examine simple linear inflation forecasting models in the form

$$\pi_{t+m}^m = \alpha + \sum_{i=1}^{n} \beta_i \pi_{t-i}^1 + \sum_{j=1}^{h} \gamma_j y_{t-j} + e_{t+m}, \tag{4.1}$$

where y_{t-i} represents the estimated output gap, and n and h denote the number of lags for inflation and the output gap, respectively. To select the number of lags in the estimation, I apply the Bayes Information Criterion (BIC). The coefficients α, β_i and γ_i are estimated

[10]The paired comparison of specifications at this stage does not consider estimation uncertainty. Furthermore, computing the confidence intervals involves complicated methods such as Monte Carlo simulations that is time-consuming to implement.

by using ordinary least squares (OLS).

The estimation of equation 4.1 and the inflation forecasting process are explained below. To forecast inflation (out-of-sample data) for each quarter, I use the estimates obtained from equation 4.1 (in-sample data). To estimate equation 4.1, I apply forty eight rolling window periods with a fixed initial point; e.g., for Sweden the fixed starting point is 1980Q1 for all estimations. The first estimation window ends at 2005Q4, the second ends at 2006Q1, the third ends at 2006Q2, the fourth ends at 2006Q3, and the last ends at 2017Q4. To avoid any future information being included in the estimation of the output gap, I re-estimate the output gap for each country for the same window period as in the estimation in equation 4.1. Then, I use these estimates for the forty-eight-quarter-ahead forecast of inflation at 2006Q1, 2006Q2, 2006Q3, 2006Q4 to 2018Q1.

I consider equation 4.1 using the estimated output gap from the baseline model (model 1). Then I use the estimated output gap obtained from a model that includes only global economic factors without commodity prices, (results from section 3.4) and the past inflation rate (model 2). To compare the quality of the inflation forecasts that are obtained by using different measures of output, Orphanides and van Norden (2005) suggest using the following equation to find the measurement errors:

$$MSFE = \frac{(\hat{inf} - inf)_t^2 + ... + (\hat{inf} - inf)_{t-48}^2}{49}. \tag{4.2}$$

After using these specifications to forecast inflation, I use equation 4.2 to save the MSFEs from each regression. Table 3 lists the advanced and emerging countries included in the sample for this test.[11] It reports the results of the above-described forecasting models by comparing the MSFEs between the two models. The lower MSFE means that the given output measure does better in predicting inflation in comparison with other measure. My findings show that the estimated output gaps using commodity prices (model 1) have more precise forecasts than model 2.

4.2 The DM test

In this section, I use a test of predictive performance proposed by Diebold and Mariano (2002), which is designed to test the null hypothesis of equal predictive ability between the two models by considering the mean of the differences of the squared prediction errors

[11] Only nine countries are included in this test due to data availability for quarterly inflation.

Table 3: Mean squared forecasting error in equation 4.1

	Estimates using commodities	Estimates without commodities
Australia	8.35	11.13
Norway	7.21	11.52
Sweden	6.27	6.32
Brazil	30.31	35.43
Chile	18.14	17.15
India	4.87	22.34
Korea, Rep	13.36	17.29
Mexico	27.61	20.16
South Africa	8.09	14.14

Note: These results are being reported for the forty-eight-quarter-ahead inflation forecasting model. The lower mean squared forecasting error in the model means the output gap measure does better in forecasting inflation.

of these models. Under the null hypothesis, the test statistics (DM) is asymptotically (standard) normally distributed. The null hypothesis of no difference will be rejected if the computed DM statistic falls outside the range of $-z_{\alpha/2}$ to $+z_{\alpha/2}$ (at the 95% level); that is, if

$$|DM| > z_{\alpha/2}, \tag{4.3}$$

where $z_{\alpha/2}$ is the upper (or positive) z-value from the standard normal table that corresponds to half of the desired α level of the test. In Appendix B, I explain the basic concept of how to compute the Diebold-Mariano Test in detail.

Table 4 shows the results related to this test. Based on the above-proposed method, I compare the usefulness of the output gap estimates in the baseline estimation with the estimates obtained in section 3.4. The check mark means that the first model (model 1) is better than the other model, at the 95% level, in forecasting inflation. If there is a circle sign in the table, this means there is no statistically significant difference between the two models in forecasting inflation. In general, the relative usefulness of output gap estimates is approved, compared to other output measures for forecasting inflation.

Data. This section applies quarterly data on the headline inflation rate and the first difference of the log of real output as a proxy for output growth. It also includes the cyclical component of the natural logarithm of real GDP as captured by the HP-filter (with a smoothing parameter of 1600) and the BP-filter as other alternatives in this exercise. Due to the data availability, the sample includes three advanced and six

Table 4: DM test results for forecasting inflation – at the 95% level

	DM Statistics	Estimates using commodities (1)	Estimates no commodities (2)
Australia	-2.43	✓	×
Norway	0.71	✓	×
Sweden	-1.78	○	○
Brazil	-2.83	✓	×
Chile	2.71	✓	×
India	-2.90	✓	×
Korea, Rep	-2.68	✓	×
Mexico	-1.56	○	○
South Africa	-2.84	✓	×

Note: These results are being reported for the four-quarter-ahead inflation forecasting model. Model 1 includes estimated output gaps by using commodities and past inflation to forecast inflation. Model 2 includes the estimated output gaps obtained from a model that includes only global economic factors without commodity prices and past inflation. Circle symbol means there is no difference between the two forecasting models at the 95% level. The check-marks mean the baseline model does better than the other one, at the 95% level, in forecasting inflation.

emerging market economies.

My results relate to several strands of literature that discuss the reliability of estimated output gaps using various measures. For instance, Camba-Mendez and Rodriguez-Palenzuela (2003) find that under multivariate specifications, unobservable-components type models of the output gap have limited forecasting power for inflation because they under-perform in arbitrary autoregressive models. Moreover, Quast and Wolters (2020) propose a simple modification of Hamilton's time series filter that yields reliable and economically meaningful real-time output gap estimates, compared to other measures such as HP-filter or BP-filter. To provide a wider comparison, I consider various measures of output to include in a model used to forecast inflation. First, I replace the estimated output gap in equation 4.1 with the first difference of the log of real output (output growth), as suggested by Orphanides and van Norden (2005) (model 3). Then I use HP-filtered output and past inflation in equation 4.1 (model 4), and BP-filtered output with past inflation (model 5). Lastly, I assume equation 4.1 without the output gap to forecast inflation; this is referred to as an autoregressive model (AR) (model 6). Table A2 in Appendix A reports the extent to which the output gap estimates in the baseline estimation provide an improved means of improving forecasts of inflation compared to other measures. My results show that based on the DM test, output gap estimates obtained by using BN decomposition and considering the commodity price shocks improve the reliability of forecasting inflation compared to other output measures.

5 Conclusion

Central banks may not always be successful in estimating potential output and, in turn, the output gap, even though this measure is one of the key determinants of their optimal monetary policy of keeping inflation under control (Orphanides, Porter, Reifschneider, Tetlow, & Finan, 2000; Smets, 2002; Svensson, 2003; Walsh, 2003). Due to the difficulties inherent in estimating potential output and the output gap, policymakers need to use several economic indicators to obtain reliable estimates. This study's premise is based on the importance of global shocks to commodity prices for measuring the output gap.

To my knowledge, this is the first paper to use multiple commodity price indices as world shocks to estimate the output gap for advanced and emerging market economies. The findings show that much of the influence of global factors on the output gap are reflected by a set of commodity price shocks (fuel, agricultural, and metals prices). One of the main explanations for this is that changes in commodity prices reflect changes in the production of goods (output) in world markets (Kilian, 2008). This paper offers several findings. First, world shocks appear to be more important for the output gap, relative to the output trend. Second, the output gaps in advanced economies appear to be more affected by world shocks, relative to emerging market economies. Third, commodity price shocks account for much of the reported shares of world shocks in the output trend. This paper also evaluates the proposed method for estimating the output gap by using a model that forecasts inflation. Relatively speaking, the output gap estimates obtained in the baseline specification perform better in forecasting inflation compared to other output measures.

Appendices

Appendix A

Table A1: Imports of good and services (% of GDP)

Country	Imports of good and services
Australia	18.23
Brazil	10.33
Chile	26.66
Denmark	36.80
Hong Kong SAR, China	128.23
India	13.88
Korea, Rep.	31.96
Malaysia	67.62
Mexico	21.11
Norway	32.89
Singapore	164.67
South Africa	25.35
Sweden	32.44
Switzerland	45.80
Thailand	42.88

Imports of goods and services represent the value of all goods and other market services received from the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communications, construction, financial information, and business, personal, and government services. They exclude compensation to employees, investment income (formerly called factor services) and transfer payments.

Table A2: The DM test results for other inflation forecasting models – at the 95% level

	Australia	Norway	Sweden	Brazil	Chile	India	Korea, Rep	Mexico	South Africa
Output growth (3)	1.36	1.69	-1.89	1.86	0.62	-0.33	1.23	-0.29	0.91
	○	○	✓	○	○	○	○	○	○
HP-filtered output (4)	-21.34	-6.54	-0.81	-13.18	-14.45	5.45	-3.13	-1.13	-2.32
	✓	✓	○	✓	✓	×	✓	○	✓
BP-filtered output (5)	-0.44	-0.43	1.54	-7.28	0.45	-2.34	-2.38	-1.52	-2.42
	○	○	○	✓	○	✓	✓	○	✓
Past inflation (6)	0.83	0.74	-3.84	5.31	-0.55	1.04	1.29	-1.19	1.89
	○	○	✓	×	○	○	○	○	○

Note: Baseline model (model 1) model includes estimated output gaps and past inflation to forecast inflation. Each model is compared with the baseline model. Model 3 includes the growth rate of GDP and past inflation. Model 4 uses HP-filtered output and past inflation, model 5 includes BP-filtered output and past inflation to forecast inflation. Model 6 includes only past inflation. Circle symbol means there is no difference between two forecasting models at the 95% level. The check-marks mean the first model (model 1) is better than the other model, at the 95% level, in forecasting inflation. The cross sign means the other model is better than the baseline model in forecasting inflation.

Fig. 16: Output trend and output for advanced economies

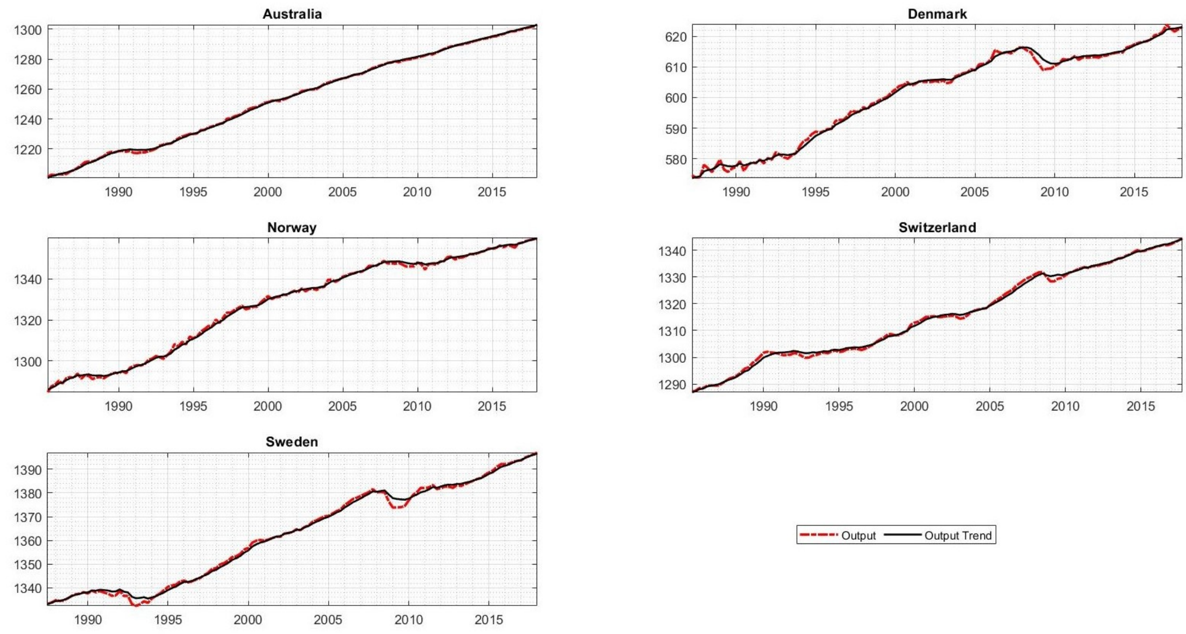


Fig. 17: Output trends and output for emerging economies (1)

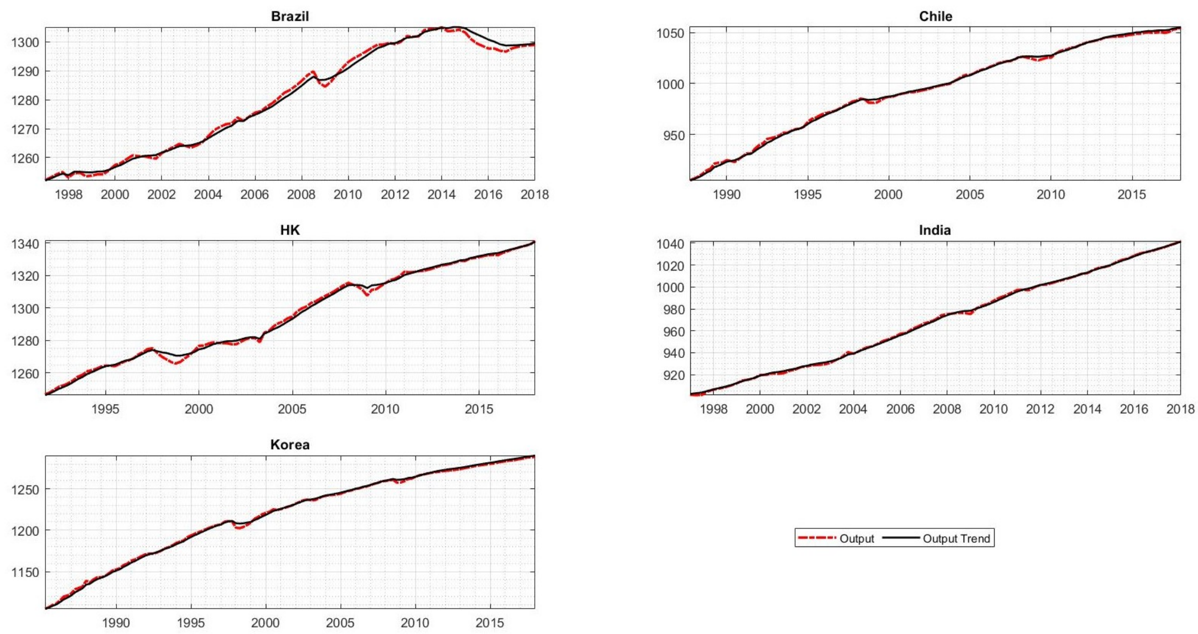


Fig. 18: Output trends and output for emerging economies (2)

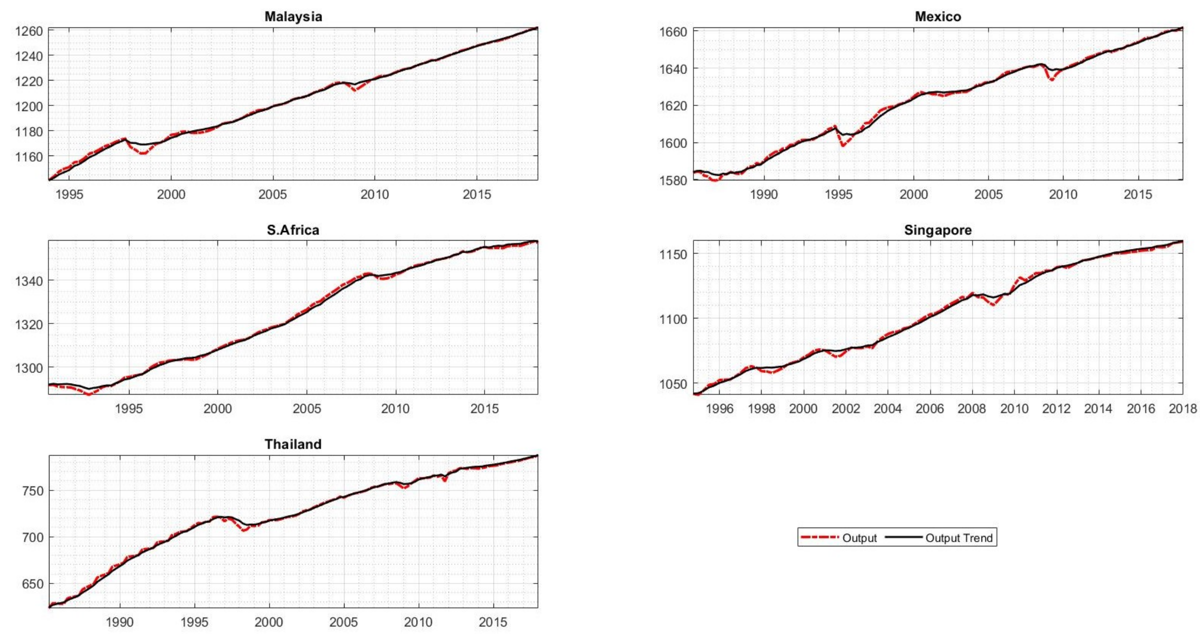


Fig. 19: Robustness checks on the output gap for advanced economies

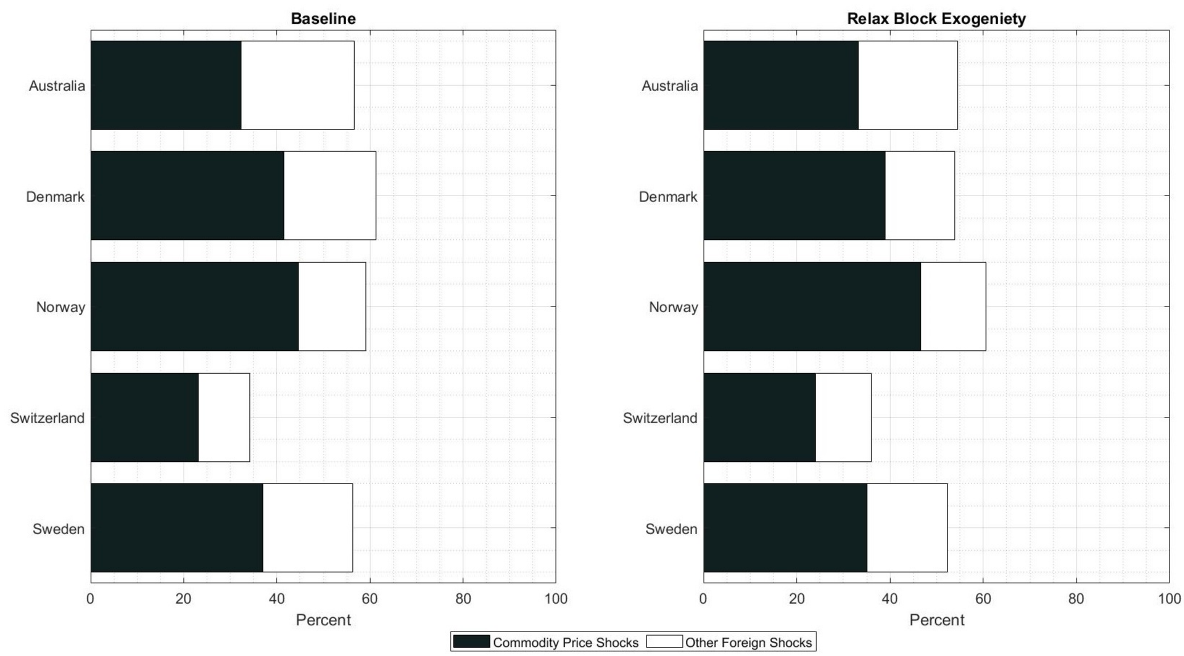


Fig. 20: Robustness checks on the output gap for emerging economies (1)

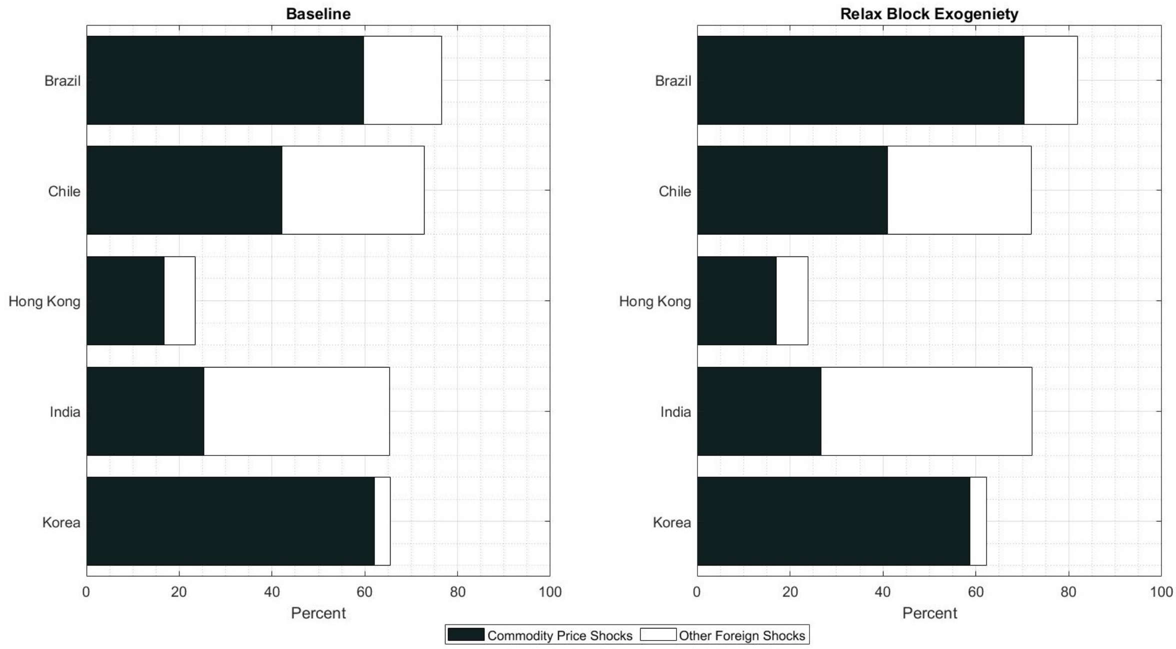


Fig. 21: Robustness checks on the output gap for emerging economies (2)

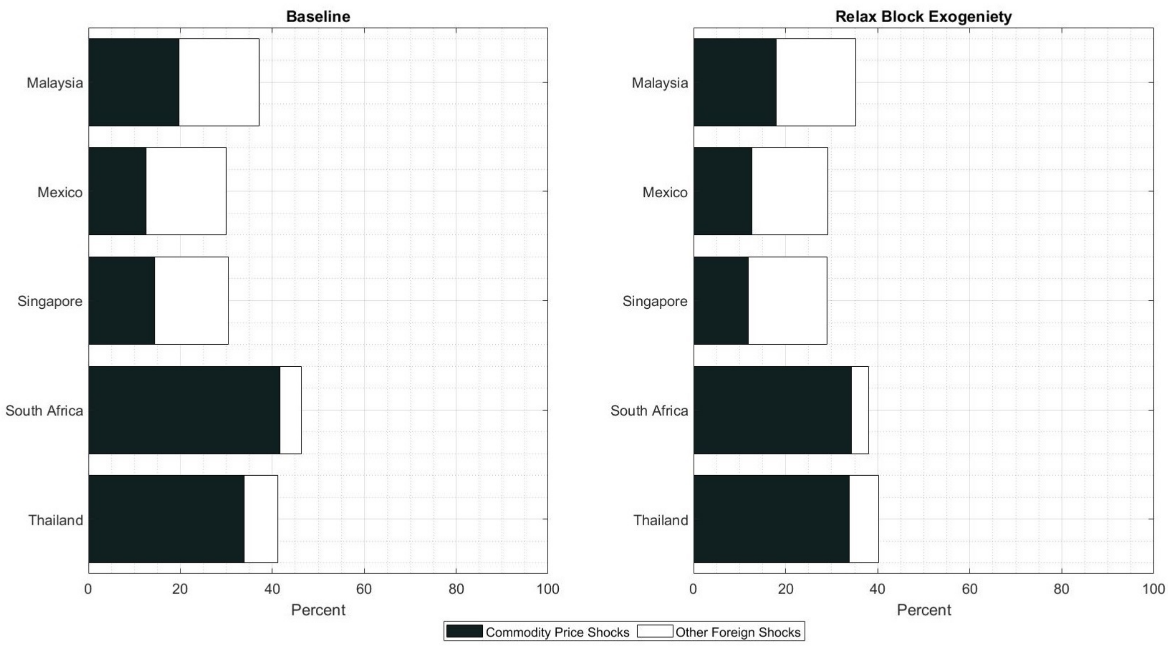


Fig. 22: Robustness checks on the output trend for advanced economies

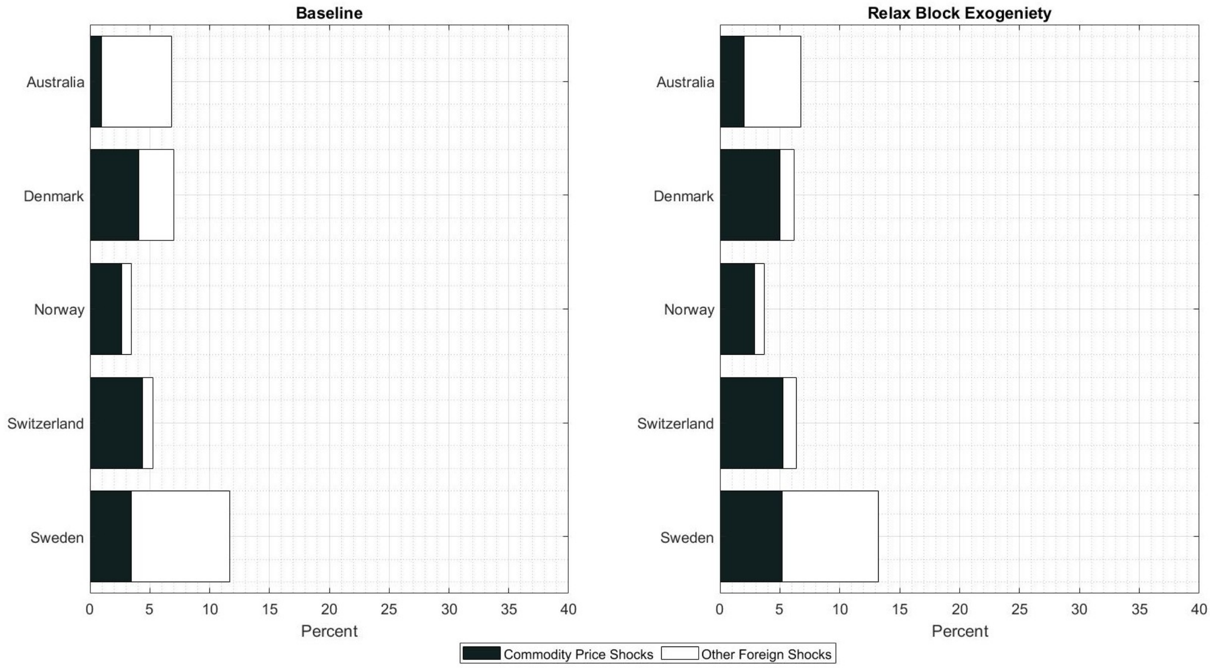


Fig. 23: Robustness checks on the output trend for emerging economies (1)

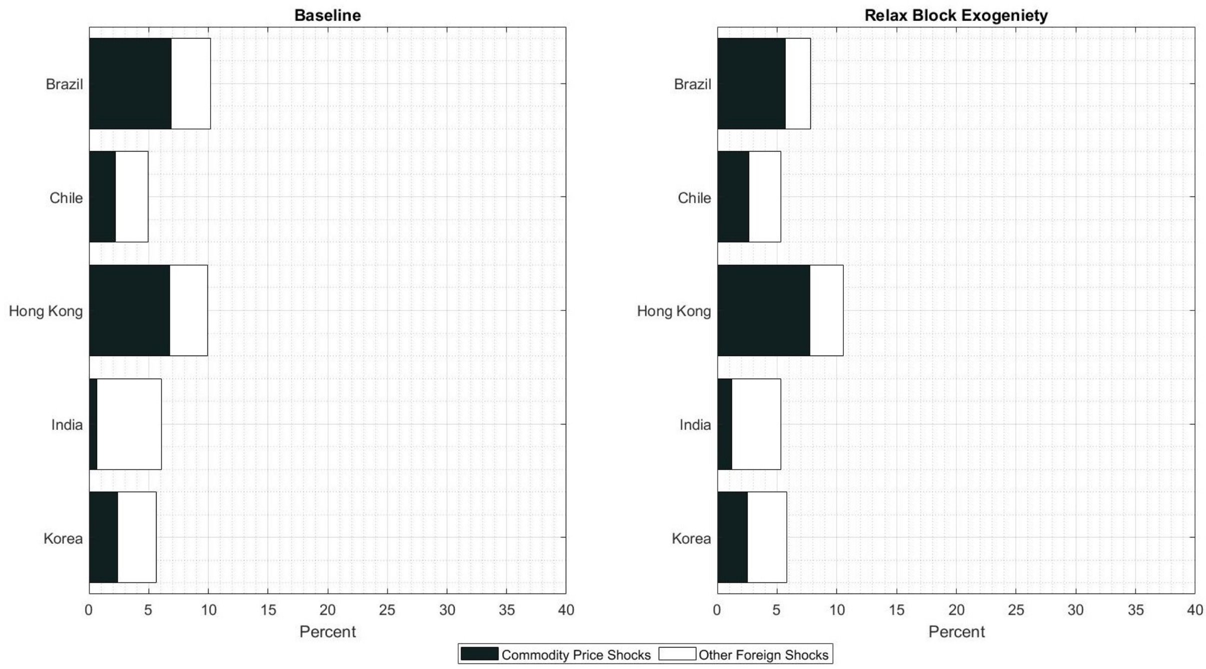
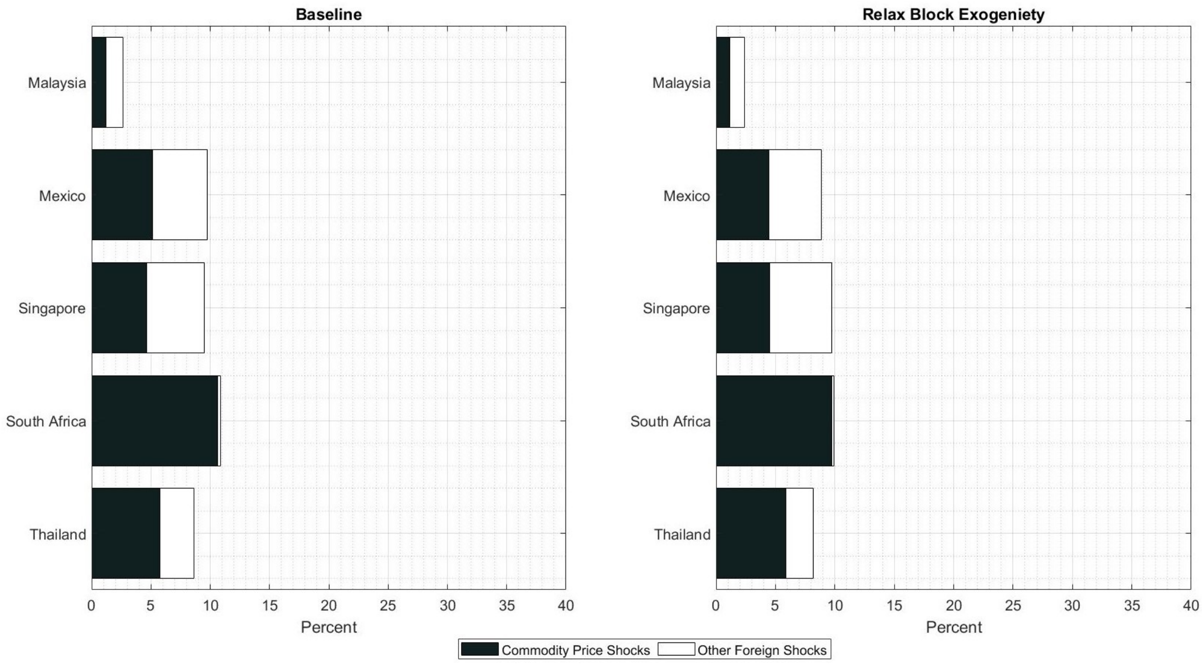


Fig. 24: Robustness checks on the output trend for emerging economies (2)



Appendix B

Output gap computation In this section, I briefly explain how the output gap is computed in equation 2.5.

$$\tilde{y}_t = -e_i B(I - B)^{-1} X_t.$$

For simplicity of calculation, let consider $\phi = -e_i B(I - B)^{-1}$ which means $\tilde{y}_t = \phi X_t$. To compute the output gap in this paper, I include the following data in the matrix X_t,

- commodity price indices
- factors obtained from foreign economic indicators
- factors obtained from domestic economic indicators
- first difference of natural logarithm of GDP.

I put all these variables in columns beside each other in matrix X_t. Then recursively, I substitute equation 2.3 into equations 2.4 and 2.5 which each time I add zeros to the first row and exclude the last row of the matrix X_t to obtain the lower triangle matrix. Then, using the updated equation 2.7, I find the share of foreign and domestic shocks on the output gap.

DM test I use Diebold and Mariano (2002)' test to determine whether forecasts are significantly different. Let e_i and r_i be the residuals for the two forecasts, i.e.

$$e_i = y_i - f_i \qquad \textit{and} \qquad r_i = y_i - g_i.$$

Let d_i be defined as one of the following measurements,

$$d_i = e_i^2 - r_i^2 \qquad \textit{or} \qquad d_i = |e_i| - |r_i|.$$

The time series d_i is called the loss-differential. Obviously, the first of these formulas is related to the MSE error statistic and the second is related to the MAE error statistic. The following formulas are defined,

$$\overline{d} = \frac{1}{n}\sum_{n}^{i=1} d_i \qquad \mu = E[d_i]$$

For $n > k \geq 1$, define

$$\gamma_k = \frac{1}{n} \sum_{i=k+1}^{n} (d_i - \overline{d})(d_{i-k} - \overline{d})$$

As described in Autocorrelation Function γ_k is the autocovariance at lag k. For $h \geq 1$, define the Diebold-Mariano statistic as follows:

$$DM = \frac{\overline{d}}{\sqrt{[\gamma_0 + 2\sum_{h-1}^{k=1} \gamma_k]/n}}$$

It is generally sufficient to use the value $h = n^{1/3} + 1$. Under the assumption that $\mu = 0$ (the null hypothesis), DM follows a standard normal distribution: $DM \sim N(0, 1)$. So, there is a significant difference between the forecasts if

$$|DM| > z_{\alpha/2},$$

where $z_{\alpha/2}$ is the two-tailed critical value for the standard normal distribution.

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