Empirical Essays in Natural Resources, Commodity Prices, and Applied Macroeconomics

by

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A thesis submitted in partial fulfillment of the requirements for the Doctorate in Philosophy Degree in Economics

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Abstract

This thesis presents three distinct chapters that look at different challenges faced by advanced and emerging market economies. Given the issues explored in these chapters, I contribute to several strands of economic literature. Yet, each chapter is motivated by its policy relevance and is embedded in the issues advanced and emerging market countries face.

Chapter 1 explores the impact of income inequality on domestic investment in resource-rich countries. Income inequality may affect investment through different mechanisms. For instance, it could distort incentives for domestic investment; high-income inequality may discourage investment in public goods since low-income non-investors may benefit more from the returns on investment. As a result, countries with higher income inequality are expected to contribute less to their domestic investment. To investigate the relationship between income inequality and domestic investment, I use the data for 57 resource-rich countries from 1982-2015. Due to endogenous relationships among variables, I use generalized method-of moments estimators that employ lagged regressors as instruments in the estimation. Using a variety of income inequality measures, I find a negative and significant relationship between these two economic indicators: income inequality and domestic investment. This result could help resource-rich countries achieve higher growth from their resource endowments.

The second chapter studies the extent to which worldwide shocks can explain country-specific inflation fluctuations. My benchmark model proxy world shocks with shocks to commodity prices. First, using a factor model of commodity prices, I extract three leading factors characterizing their co-movement. Then, I use the commodity price factors in a structural vector autoregressive model to investigate the fraction of inflation fluctuations that commodity price shocks can explain. My estimation is based on the data for 67 advanced and emerging market economies from 1970-2014. Furthermore, I examine the impact of world shocks on inflation through additional mechanisms, such as changes in the world interest rate and the global economic activity index. Compared to the previous literature, I find the increased importance of world shocks in explaining country-specific inflation fluctuations. This result can guide policymakers in setting the relevant monetary policy to control or prevent inflationary pressures in an economy.

Finally, the third chapter studies whether commodity price shocks matter for estimating the output gap. First, I apply the Beveridge and Nelson decomposition method and calculate the share explained by world shocks in the variance decomposition of the output gap. In my analysis, world shocks affect the output gap through commodity price indices and global economic factors. My study includes five advanced and ten emerging market economies from 1980-2018. Then, I investigate whether commodity price shocks can improve the accuracy of this estimation. To do this, I exclude commodity price indices from my model to estimate the output gap. Finally, I use output gaps estimated with and without commodity price indices in an inflation forecasting model to compare the forecast errors of predicted inflation. Using a forecast error test, I find that the estimated output gap using commodity price indices would provide better results in forecasting inflation than other output measures.

Declaration of Authorship

I, Farzaneh Davarzani, declare that this thesis titled, "Empirical Essays in Natural Resources, Commodity Prices, and Applied Macroeconomics" and the work presented in it are my own.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ______________________

Date: 2022 March 31

General Introduction

This dissertation includes three chapters that look at different challenges faced by advanced and emerging market countries.

The first chapter examines the impact of income inequality on domestic investment in resource-rich countries. The second chapter investigates the extent to which commodity price changes can affect domestic inflation fluctuations in advanced and emerging market countries. Finally, the third chapter studies whether commodity price shocks matter for estimating output gaps in advanced and emerging market countries.

Chapter 1 examines the relationship between income inequality, natural-resource rents, and domestic investment in resource-rich countries. The motivation behind this paper is to investigate whether higher income inequality adversely affects domestic investment in resource-rich countries. Income inequality is a crucial impediment to economic growth in resource-rich countries, and, in many countries, domestic investment comprises a non-negligible share of gross domestic product. So, it is possible that income inequality also adversely affects domestic investment. However, no literature has examined the link between income inequality, natural-resource-rent usage, and domestic investment.

To accomplish this, I apply difference and system generalized method-of-moments estimators to a dynamic panel of 57 resource-rich countries from 1982-2015. This methodology allows me to overcome challenges such as reverse causality between dependent and independent variables by instrumenting for potentially endogenous variables. My results indicate a negative and significant relationship between income inequality and domestic investment in resource-rich countries. I also check the consistency of the baseline results using various measures and specifications.

In my second chapter, I study the extent to which commodity price shocks can explain domestic inflation fluctuations. Previous studies underestimate how much these shocks can affect domestic inflation (less than 10%) compared to my findings. This result could be due to the measures they use to proxy for world shocks. Recent papers suggest using a factor model with a large panel of commodity series as a useful method to extract factors characterizing the co-movement of commodity prices and their central characteristics. Thus, I extract the co-movements of 43 commodity prices by using a factor model to capture the impact of commodity price shocks. I use a structural vector autoregression approach to build a model that includes a foreign block and a domestic block. Then, I incorporate the co-movement of the commodity price series obtained from the factor model into the foreign block to investigate the impact of commodity price shocks on domestic inflation fluctuations.

My results suggest that commodity price shocks explain 26% of domestic inflation fluctuations. This statistic implies a larger contribution of world shocks to changes in domestic inflation rates, compared to previous studies. I also highlight the importance of other mechanisms contributing to domestic inflation fluctuations, such as the world interest rate or a global economic indicator. I add these measures as another channel through which these world shocks are transmitted to domestic inflation. With those additional measures, world shocks explain 34% and 38% of inflation fluctuations, respectively.

My third chapter also relates to the use of commodity price indices as a proxy for world shocks. This chapter examines whether commodity price shocks matter for estimating the output gap. This paper estimates the output gap for 15 countries over the period 1980Q1-2018Q4. I construct the potential output, which is referred to as the *"output trend"*, and the output gap that is consistent with Beveridge and Nelson (1981)'s method (BN decomposition). I apply the BN decomposition method to investigate the role of world shocks in driving the output trend and the output gap, respectively. To do so, I use the vector autoregressive specification that includes a foreign block and a domestic block. The foreign block includes commodity price indices in addition to global economic factors. To obtain the global economic factors, I apply the factor model to extract the common factors of economic activity for six major economies: the U.S., the U.K., Japan, France, Canada, and Germany.

My results suggest that world shocks have a larger impact on the output gap relative to the output trend for almost all the countries in the sample. Moreover, most of the influence of world shocks on the output gap results from commodity price shocks for both advanced and emerging market economies. I also use a Phillips curve to evaluate the usefulness of the estimated output gap in forecasting inflation. First, I estimate the output gap without commodity price indices in the foreign block. Then, I use both estimated output gaps separately in forecasting inflation to compare the forecast errors. The result suggests that the estimated output gap using commodity price indices improves the accuracy of the forecasts compared to the other.

Acknowledgments

This Ph.D. dissertation would not have been possible without the support of many individuals. Foremost, I would like to express my sincere gratitude to my supervisor at the University of Ottawa, Dr. Lilia Karnizova, for her dedication to supporting me through my thesis and research. Her patient motivation, immense knowledge, and continuous guidance helped me throughout my research and writing.

I cannot express enough thanks to my other supervisors at Carleton University Drs. Raúl Razo-Garcia and Minjoon Lee for their insight and encouragement. I learned a lot from these two scholars, and I appreciate the support they gave me throughout completing my Ph.D. thesis. I would also like to acknowledge my thesis committee members, Drs. Francesca Rondina and Maral Kichian, for their helpful comments and suggestions. Their skillful guidance made my thesis much better than it could otherwise have been.

A special thanks go to the director of the University of Ottawa's Ph.D. program, Dr. Louis-Philippe Morin, and the head of the Department of Economics, Dr. Catherine Deri-Armstrong, for their continuous support. I would also like to thank the University of Ottawa's Economics Department and its professors and staff for their many kindnesses.

I am grateful to the Mitacs Globalink Research Award and the Faculty of Social Sciences for their generous financial support during my Ph.D. thesis research and writing.

I am grateful to all of those with whom I have had the pleasure to study. This experience would not have been possible without the friendships I made with my fellow graduate students. To Fabien Forge, Joanne Haddad, Lamis Kattan, and Philippe Kabore, it was an absolute pleasure studying and doing research together. I look forward to seeing you all again as we embark on new careers and undertake research that will hopefully make this world a better place. To Azadeh Farahnakian, Mansoureh Abbasi, and Modjgan Alishahi, experiencing a new life together away from our home was challenging. It would not have been possible for me to have completed this chapter of my life without your presence in it.

Lastly, my sincere gratitude goes to my parents, who always give me the courage to follow my dreams. You are my inspiration; you are the reason I have become the strong woman I am today. A lot of what I have achieved up to this moment is due to your support. Thank you so much for your many sacrifices, your love, and your everlasting support.

To the passengers of Ukraine Flight PS752

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Chapter 1

The Impact of Income Inequality on Domestic Investment in Resource-Rich Countries

Abstract

This paper examines a relation between income inequality, natural-resource rents and domestic investment in resource-rich countries. While previous studies have found that the unequal distribution of natural-resource rents has a negative impact on general economic performance, little is known about its direct implications for domestic investment. In this paper, I apply difference and system generalized method-of-moments estimators to a dynamic panel of 57 resource-rich countries, over the period 1982-2015. My findings show that, on average, countries with higher income inequality contribute relatively lower proportions of their natural-resource rents to domestic investment than do countries with lower income inequality. This result is robust to a variety of income-inequality measures, estimation approaches, and alternative specifications. The results could help resource-rich countries in their efforts to achieve higher growth using their resource endowments.

1.1 Introduction

The paradox of plenty has been a long-standing issue in economics. It states that many countries with large natural-resource endowments experience worse economic outcomes relative to countries with fewer natural resources (Corden and Neary, 1982). This phenomenon is commonly referred to as the natural-resource curse (NRC) (Sachs and Warner, 2001). Many factors can explain this paradox: low levels of domestic investment and high levels of income inequality. As suggested by Solow (1974), since the stock of natural resources is finite, if resource-rich countries wish to maintain their present consumption levels, then they should increase their rates of investment to offset the eventual absence of this income source. This is commonly referred to as *Hartwick's rule*, (Hartwick, 1978). However, at first glance, investment-to-GDP ratios show the opposite pattern. For example, over the period 1982-2015, the median investment-to-GDP ratio of non-resource-rich countries was roughly 28% compared to 16% for resource-rich countries.[1] It is important to understand the lower levels of investment that take place in these resource-rich countries compared to investment levels in non-resource rich ones because it has been shown that investment is a key driver of economic growth in developing countries (e.g., Collier et al. (2010)).

In this paper, I investigate the impact of resource-rent inequality on the contribution of natural-resource rents to domestic investment. I address this question by using longitudinal data on 57 resource-rich countries from 1982-2015. Since there exists no publicly available measure of resource-rent distribution, I use income inequality, specifically the Gini coefficient of income, as a proxy. In estimating this relationship, I control for country-specific heterogeneity and attempt to address the fact that many variables are jointly determined (endogenous relationships). To do so, I estimate two different generalized method-of-moments (GMM) models. First, I use a difference GMM estimator that employs lagged levels of the regressors as instruments (Arellano and Bond, 1991). Second, given that these lagged levels may be weak instruments to use in difference equations as in Blundell and Bond (1998), I also employ a system GMM estimator that uses past changes in the regressors as instruments for the current-level regressors.

Resource-rent inequality may affect investment through different mechanisms. For instance, it may potentially distort incentives for domestic investment in many ways. If resource-rent inequality is high, this may deter investors from investing in public goods

[1] Resource-rich countries constitute countries with a positive share of natural-resource rents to GDP. Non-resource-rich countries are those with limited endowments of natural resources.

since the payoffs may disproportionately accrue to those who do not invest in public goods (non-investors). Behzadan et al. (2017) note that income inequality is a key impediment to economic growth in resource-rich countries. Since, in many countries, domestic investment comprises a non-negligible share of gross domestic product, roughly one-fifth of GDP, as is emphasized above, it is plausible that income inequality also adversely affects domestic investment. Moreover, resource-rent inequality discourages investors since the investment returns are distributed among all populations. This would contribute to a lower level of investment in the economy. However, no existing literature has examined the link between income inequality, natural-resource-rent usage, and domestic investment.

The literature on domestic investment provides two insights. First, the explanations for domestic investment have emphasized that domestic savings, GDP, and foreign aid play positive roles in contributing to domestic investment (Bernanke, 1983; Ndikumana, 2000; Strum, 2001). Factors that have negative impacts on domestic investment are a higher cost of debt servicing, terms of trade, general government final consumption expenditures, and the poor quality of institutions (Ndikumana, 2000; Ahmed and Miller, 2000; Bleaney and Greenaway, 2001; Nguyen et al., 2003; Lim, 2013). The second insight from this literature is about why domestic investment is low. One explanation points to overconsumption (Weinstein and Zeckhauser, 1975; Neumayer, 2004). If the economy exhibits overconsumption, then by definition, the level of domestic investment will be lower (abstracting from any international flows of capital). Lower levels of domestic investment translate into lower levels of capital stock and output (Bernanke, 1983; Gylfason and Zoega, 2006). Another explanation is that domestic rents have been invested in foreign countries where they can potentially earn higher rates of return (Collier et al., 2010) or face lower levels of taxation or regulation (Darby et al., 2014; Azémar and Dharmapala, 2019). In this regard, Hartwick (1978) emphasizes that a significant fraction of resource rents should be invested domestically in economic, reproductive assets to generate an additional source of income. I control for these key variables to study the relation between income inequality, natural resource rents, and domestic investment.

My paper relates to studies which emphasize the *Dutch Disease* as one explanation for the NRC (Corden and Neary, 1982; Corden, 1984; Sachs and Warner, 2001; Davis and Tilton, 2005; Frankel, 2010). This phenomenon describes how countries' trade sectors may be adversely affected by an exported natural resource(s). Higher demand for domestic currency drives up the real exchange rate, decreases the competitiveness of exported goods and services, and increases the attractiveness of imports. This event depresses trade sectors, making the economy less diverse and more resource-dependent. If a country's stock of natural resources is depleted or an important natural resource becomes subject to a negative price shock, then its economy can experience a sharp contraction (Van Wijnbergen, 1984; Sachs and Warner, 1995; Papyrakis and Gerlagh, 2004). One strategy to limit the consequences of Dutch Disease is to impose capital controls that limit the impact of a natural resource on this exchange-rate channel (García-Cicco and Kawamura, 2015). For example, countries like Norway have placed their excess foreign exchange in sovereign wealth funds (SWF).[2] This limits the appreciation of their domestic currency and lays money aside for domestic investment (Collier et al., 2010).

This paper also relates to the literature that emphasizes the role of income inequality in resource-rich countries. In particular, I discuss two of the most closely related studies. Goderis and Malone (2011) focus on how natural-resource booms (price or quantity) affect income inequality. These authors find that a natural-resource boom leads to a decrease in income inequality in the short run but a persistent rise in income inequality in the long run. A second closely related work is Behzadan et al. (2017), who find that income inequality has a negative effect on the economic performance of resource-rich countries: resource-rich countries with higher income inequality experience lower economic growth. The authors propose a model that includes a two-country economy—one with a high level of income inequality and one with low inequality—with three sectors that each producing one good: a manufactured good, a natural-resource good, and a non-tradeable luxury good. An increase in natural-resource rents in the high-inequality country leads to a larger share of the non-tradeable luxury good consumption. This phenomenon leads to a contraction in the labor supply in the sector whose labor force benefits from learning-by-doing. This contraction in the labor force in the tradable sector has two effects. First, a reduction in labor leads to lower productivity growth through the learning-by-doing mechanism. Second, it leads to a higher likelihood of importing manufactured goods. Once the natural resource is depleted, the country will experience subpar economic performance. These authors empirically show that income inequality plays an important role in economic growth.

The results in my paper suggest that, on average, countries with higher income inequality assign lower proportions of their natural-resource rents to domestic investment. According to the estimates, countries with Gini coefficients above 0.43, on average, make less domestic investment when the natural resource rents increase. While this investigation into domestic investment is new, the results are broadly consistent with the existing literature that examines the role of income inequality, resource-rent usage, and economic outcomes. For example, Behzadan et al. (2017) find that countries with higher income inequality experience lower economic growth. I build on their empirical model to reinforce this point and emphasize the

[2] A sovereign wealth fund (SWF) is a state-owned investment fund or entity that comprises pools of money that are derived from a country's reserves. These reserves are funds that have been set aside for investment to benefit the country's economy and its citizens.

role of income inequality in the NRC.

This paper, to my knowledge, is the first to link income inequality, natural-resource-rent usage, and domestic investment. I include not only natural resource rents and income Gini coefficient but also other key determinants of domestic investment from the literature as regressors. The proposed channel herein suggests that countries with higher income inequality contribute less of their natural-resource rents to domestic investment, leading to lower capital stock and output levels in these countries. This result is in line with what Behzadan et al. (2017) found that income inequality affects economic growth negatively. They use output determinants as independent variables to investigate whether income inequality affects natural resource rents' contribution to economic growth. In this paper, I use their findings as a point of departure for my investigation by using the same methodology as in their paper.

The rest of the paper is organized as follows. In Section 2, I discuss the data and empirical methodology. Section 3 presents a discussion of the results and some robustness checks. Section 4 concludes.

1.2 Empirical Strategy and Data

1.2.1 Empirical Strategy

Some countries experienced a noticeable decrease in domestic investment after a significant increase in natural-resource rents. Table 1-A.5 list those countries such as Peru, Venezuela, Botswana, and South Africa. They experienced significant growth in natural-resource rents, followed by a decrease in growth in domestic investment that ranged from 1.03% to 15.19% over the period 1982-2015.[3] To answer the question as to whether countries with higher income inequality invest less of their natural-resource rents domestically, several determinants of domestic investment are considered in the estimation. Specifically, some of the empirical literature discuss the determinants that positively affect domestic investment, such as domestic savings, GDP, and foreign aid (Ndikumana, 2000; Strum, 2001). Output is the primary determinant of domestic investment (Bernanke, 1983). The domestic interest rate, or the cost of capital, is a major determinate of the savings level. Thus, the lower the interest rate, the higher the demand for new capital (and investment) (Feldstein and Horioka, 1979; Dooley et al., 1987; Bayoumi, 1990). Most foreign aids assist in creating conditions that promote sustainable growth, for instance, in improving infrastructure (Strum, 2001).

Some empirical papers discuss other determinants that negatively affect domestic invest-

[3]Both natural-resource rents and domestic investment are expressed as a percentage of GDP.

ment, such as higher debt servicing, general government final consumption expenditures, and lower institutional quality (Ndikumana, 2000; Ahmed and Miller, 2000; Bleaney and Greenaway, 2001; Nguyen et al., 2003; Lim, 2013). To be more specific, higher debt servicing crowds out investment, and this effect becomes stronger as debt servicing absorbs a growing share of GDP (Nguyen et al., 2003). The overall structure of governmental institutions also plays a role in encouraging or discouraging investment. Institutional quality can influence aggregate investment through measures such as contract enforcement and protecting property rights (Lim, 2013). The terms of trade can also work as a proxy for external shocks that can negatively or positively impact private domestic investment. On the one hand, A decline in the terms of trade, which means the price of exports falls relative to imports, might worsen the current account deficit and, in turn, negatively affect domestic investment. On the other hand, an increase in the terms of trade can have a positive impact on private domestic investment (Ajide and Lawanson, 2012). To assess the importance of income inequality to the contribution of resource rents to domestic investment, my baseline specification takes the following form:

$$Invs_{it} = \beta_0 + \beta_1 Invs_{it-1} + \beta_2 Nr_{it} + \beta_3 (Gini_i \cdot Nr_{it}) + \beta_4 X_{it} + \delta_i + \delta_t + \varepsilon_{it}, \tag{1.1}$$

where $Invs_{it}$ is the domestic investment as a share of GDP in country i at time t. I include a lagged investment as an explanatory variable in the estimation since, for many countries, domestic investment is a highly persistent process (Bernanke, 1983; Ndikumana, 2000; Lim, 2013). Nr_{it} is the sum of the natural-resource rents (profits from oil, natural gas, coal, minerals, and forestry), and $Gini_i$ is the income Gini coefficient. In this paper, ideally, I should use the Gini coefficient on the distribution of natural-resource rents. Since this measure is not available, I use the income Gini coefficient by country to proxy each country's natural-resource-rent distribution. Due to data-availability issues, I treat the Gini coefficient as fixed and take the average coefficient value over the sample period for each country. The rationales for treating the Gini coefficient as fixed are (i) missing random observations for many countries and (ii) the fact I am interested in the evolution of natural-resource rents and their relationship with an overall measure of income inequality not year-to-year changes in income inequality.

To answer the question posed in this paper—whether countries with higher income inequality display lower levels of domestic investment in the presence of larger natural-resource rents—I include an interaction term between the Gini coefficient and the natural-resource rents. Finally, X_{it} contains a vector of the control variables the existing literature emphasizes as being important determinants of domestic investment. Specifically, this vector includes institutional quality and the interaction between the quality of governmental institutions and natural-resource rents, as in Mehlum et al. (2006), and also inflation, growth in the terms of trade, government final consumption expenditures, the log of real GDP per capita, foreign aid, total debt servicing and gross domestic savings. Finally, I include country-specific intercepts and time-fixed effects to capture unobserved heterogeneity.

In estimating equation 1.1, several econometric issues need to be addressed. First, including a lagged dependent explanatory variable and country-specific intercepts is problematic. This issue is the well-known Nickell bias, which arises because there exists a correlation between the dependent variable, domestic investment, from the previous period and the current error term (see Nickell (1981)). Second, many of the explanatory variables are jointly determined. Thus, it is unclear whether the causality is unidirectional (e.g., the causality may run from GDP to domestic investment or from domestic investment to GDP). To overcome these issues, I use two different approaches. First, I estimate equation 1.1 using a first-difference Arellano-Bond GMM estimator (AB-GMM) (Arellano and Bond, 1991). The AB-GMM is a dynamic panel estimator in first differences. The AB-GMM estimator circumvents the issues described above since (i) taking the first-difference of the equation removes the country-specific intercepts, and (ii) the AB-GMM estimator uses lagged levels of the independent variables as instruments for potentially endogenous variables.

To estimate equation 1.1, I consider the possibility that all of the independent variables are endogenous; the exception is for any term that interacts with the Gini coefficient (the term of interest), for which I do not use an instrument since it is averaged over the period 1982-2015. Any interaction term with an averaged Gini coefficient (a lagged one) is not a valid instrument. In a first-difference equation, I do not use the first lag as an instrument because $Invs_{it-1} - Invs_{it-2}$ is correlated with $\varepsilon_{it} - \varepsilon_{it-1}$. At the same time, since there is no serial correlation of the error terms (see Table 1-A.9), $\Delta\varepsilon_{it}$ is uncorrelated with $\Delta Invs_{it-\tau}$ for $\tau \geq 2$ so that the additional lags are valid when used as instruments in an instrumental variable estimation. I also consider the growth rate of the terms of trade as being exogenous, and I do not use an instrument for that variable as in Bleaney and Greenaway (2001) and Behzadan et al. (2017). Instrumenting for potentially endogenous variables removes concerns about endogeneity and reverse causality since the correlation between the instrumented variables and the error term should be zero. If there is not enough variation in Nr_{it} within countries, then the interaction term is strongly correlated with the fixed effects. Table 1-A.6 provides some evidence that there is enough time variation in Nr_{it} within and across countries. The first-difference equation is depicted below:

$$\Delta Invs_{it} = \beta_1 \Delta Invs_{it-1} + \beta_2 \Delta Nr_{it} + \beta_3 (Gini_i \cdot \Delta Nr_{it}) + \beta_4 \Delta X_{it} + \Delta\delta_t + \Delta\varepsilon_{it}. \tag{1.2}$$

One well-known issue with the AB-GMM framework is that it may have a weak-instruments problem. For example, Bond et al. (2001) argue that the lagged levels of the regressors in the AB-GMM estimation are poor instruments to use in the first-difference equation. For instance, if there is a unit root problem in the panel, then the lagged levels of the series might be weakly correlated with the subsequent first differences. To address this issue, Im et al. (2003) propose unit-root tests for dynamic heterogeneous panels that are based on the mean of the individual unit-root statistics. In particular, it offers a standardized t-bar test statistic based on the (augmented) Dickey-Fuller statistics averaged across the groups in the study. However, it is not certain whether lagged values are uniformly valid instruments. I use Im et al. (2003)'s unit-root test as in Behzadan et al. (2017) to investigate whether the panel has a unit-root problem. As shown in the unit-root test in Table 1-A.7 in appendix A, there is no non-stationary problem in the panel.

To address the weak-instruments problem, I implement a second GMM approach based on Blundell and Bond (1998) (system GMM), which I refer to as a BB-GMM estimator. This estimator is based on a system of two equations, where the first equation is the regression equation in the levels and the second equation is the regression equation in the first-difference. The first equation (which is in levels) uses lagged differences as instruments, whereas the second equation (in differences) uses lagged levels as instruments, and this approach is more likely to make the instruments valid (Bond et al., 2001; Roodman, 2009). However, since the estimation is a system that contains levels, this potentially introduces Nickell-bias issues. However, Blundell and Bond (1998) argue that this approach is valid as long as changes in any instrumenting variables are uncorrelated with the fixed effects.

Finally, both GMM approaches rely on assumptions about the instruments' exogeneity and no autocorrelation between the error terms, which would make some lags invalid as instruments. In the AB-GMM setup, one instrument per variable would lead to exact identification. However, this would not allow me to test the validity of the instruments. Thus, I use two lags as instruments in the AB-GMM estimation, which allows me to test the validity of the instruments. I report the Hansen test statistics using two lags for the AB-GMM and one lag for the BB-GMM in Table 1-A.8 in appendix A. This result validates the assumptions that the instruments are exogenous. I also report the Arellano-Bond test statistics in Table 1-A.9 in appendix A. These results verify that there is no error autocorrelation in the chosen lagged instruments.

1.2.2 Data

The data used in this paper were obtained from the World Bank World Development Indicators (WDI);[4] the exception is for one variable: the quality of institutions. The data for institutional quality were obtained from the International Country Risk Guide (ICRG) database. In this study, I use an unbalanced panel that consists of 57 countries for the period 1982-2015 (annual frequency). The choice of countries was based on having a positive share of natural-resource rents to GDP and the availability of data on the explanatory variables. Unfortunately, this dataset does not have complete information for all countries. For example, data on the independent variables in this study are missing for resource-rich Canada and Norway.

In this paper, I use the data from WDI for natural resource rents. This is the only source of data that includes the information for the most extended period across many countries. Regarding the natural resource rents data, one concern is the reliability of the data for some countries and whether the same variable has been measured consistently over time and across countries for natural resource rents. To consider this concern, I exclude Gulf countries where the credibility of the data is questioned. Furthermore, natural resource rents are considered depleted, such as fuels or metals (non-renewable resources) to investigate the question posed in this paper. Renewable resources can be used repeatedly since renewable resources can be exploited sustainably. Thus the flow of income from the resource is steady. In contrast, non-renewable resources are used only for a limited time, resulting in Dutch disease.

The data on gross domestic investment consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements, plants, machinery, equipment purchases, roads, railways, schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. One of the concerns here is that the data on investment includes information on productive investment and unsustainable investment, such as residential structures or buildings. Thus, it is not possible to distinguish between these two types of investment due to data availability which might affect the credibility of the results.

Table 1-1 reports the summary statistics for the variables. In appendix A, Table 1-A.4 includes a list of countries in the data. I dropped any countries that were classified as communist since the literature is in doubt over the accuracy of the reported statistics on inequality (e.g., Behzadan et al. (2017)). Four countries were classified as communist, leading to $N = 57$ after dropping them. All variables as a percentage of GDP were retrieved from

[4] There are other databases but none of them were superior to this one.

the WDI, except for the data on foreign aid. To obtain this variable, I divided the net official development assistance received (current USD) by the total GDP (current USD) (both from the WDI) to find the percent GDP share of foreign aid. This paper will use both public and private components of gross capital formation.

Table 1-1: Summary statistics for the period 1982-2015

Variables	Number of observations	Mean	Std. Dev.	Min	Max
Domestic investment (% of GDP - Annual change)	1864	-0.011	3.563	-25.351	18.478
Domestic investment (% of GDP - Level)	1869	21.453	7.31	1.763	50.688
Natural resource rents (% of GDP)	1926	7.246	8.036	0.011	63.52
Gini coefficient (Constant)	1938	0.452	0.074	0.301	0.621
Institutional quality (Average of 4 indices)	1910	0.495	0.146	0.045	0.954
Inflation, GDP deflator (Annual %)	1924	0.705	0.799	-0.276	267.62
Growth rate of terms of trade (2000 = 100)	1913	0.006	0.152	-0.622	3.494
Government expenditures on consumption (% of GDP)	1863	13.421	4.921	2.057	54.515
Log of real GDP per capita (Constant 2010 USD)	1927	7.663	1.138	5.572	10.856
Total debt service (% of GNI)	1725	5.212	4.068	0.101	73.282
Gross domestic saving (% of GDP)	1869	17.429	11.572	-15.545	60.49
Foreign aid (% of GDP - Current USD)	1875	0.0516	0.0787	-0.0062	0.740

Sources: World Development Indicators and International Country Risk Guide. More information about the sources, definition and construction of these variables is included in Tables 1-A.1-1-A.3. Some outliers for some variables have not been eliminated, such as total debt servicing and inflation; however, these outliers might affect the results.

1.3 Results

1.3.1 Results using the Arellano-Bond method

Table 1-2 shows the estimates that were obtained using the AB-GMM approach. The term of interest is the natural resource rents that interacts with the Gini coefficient. I use different combinations of explanatory variables to indicate that the coefficient sign on the term of interest is stable. First, one might assume that countries that earn natural-resource rents contribute more to domestic investment. In column (1), I estimate the impact of natural-resource rents on domestic investment while only controlling for the lagged investment and the squared lagged investment. While the coefficient for the natural-resource rents is positive, it is not statistically significant at conventional levels. In column (2), I try to check if income inequality might distort incentives for domestic investment in resource-rich countries. Thus, I add the interaction term between the natural-resource rents and the Gini index. In this estimation, the coefficient for natural-resource rents is positive. However, the coefficient for the interaction term is negative but not significant. This result could suggest that countries with higher income inequality (all else being equal) contribute less of their natural-resource rents to domestic investment. In particular, income inequality could have an important role in contributing natural resource rents to domestic investment in resource-rich countries.

Columns (3), (4), and (5) show that the choice of determinants does not affect the sign of the coefficient of the interaction term. My main focus in both approaches (AB-GMM and BB-GMM) is on a specification that includes all explanatory variables (see column (5)). While the coefficient for the interaction term remains negative, it does not exhibit statistical significance. However, it is important to highlight that the independent variables are instrumented due to the endogenous relationships among the jointly determined variables, such as domestic investment and GDP. Additionally, Bond et al. (2001) argue that the lagged levels of the regressors in the AB-GMM estimation are poor instruments to correlate with the first-difference regressors. To address the well-known potential issue that the AB-GMM might include weak instruments, I also use the BB-GMM approach. Column (6) includes the estimation results for the period 1982-1997, which is the shorter period as in Behzadan et al. (2017). Table 1-A.10 reports the summary statistics for this analysis. The purpose of this estimation is that it provides a similar benchmark to compare the results from Behzadan et al. (2017). Their analysis finds that the interaction term on the resource rents and the Gini index is negative (-4.358) and significant (at the 1% level) for economic growth.

1.3.2 Results using the Blundell-Bond method

Table 1-3 shows the estimates obtained when using the BB-GMM approach. I estimate the same six equations to compare the results obtained from different specifications. Column (1) again estimates the impact of natural-resource rents on domestic investment, only controlling for the lagged investment and the lagged investment squared. The coefficient on the natural-resource rents is positive and significant at the 1% level. In addition, the coefficient is nearly twice as large as the coefficient in column (1) in Table 1-2. In column (2), I add the interaction term between the resource rents and the Gini index. Again, the interaction coefficient is negative and significant at the 10% level, with a nearly identical magnitude to the one estimated when using the AB-GMM approach.

Columns (3), (4), and (5) show estimates of this relationship when additional control variables are included. In contrast to the results obtained when using the AB-GMM, the coefficient on the interaction term between the natural-resource rents and the Gini index is significant at the 5% level and negative across all specifications. This result suggests that the contribution of natural-resource rents to domestic investment is lower for countries with higher income inequality. The last column includes the estimation results for the period

Table 1-2: Arellano-Bond estimation results

D.Invs	AB-GMM (1)	AB-GMM (2)	AB-GMM (3)	AB-GMM (4)	AB-GMM (5)	AB-GMM (6)
Natural resource rents	0.162	6.056	10.207	6.769*	5.385*	9.313
	(0.104)	(7.599)	(13.329)	(4.122)	(3.145)	(6.639)
Natural resource rents×Gini index		-12.458	-18.859	-15.249	-11.678	-19.792
		(15.922)	(28.331)	(9.405)	(7.385)	(16.159)
Investment (lagged one period)	-1.83***	-1.745**	-0.484	-0.510*	-0.765***	-0.86
	(0.506)	(0.795)	(0.463)	(0.269)	(0.265)	(1.157)
Investment (lagged one period) squared	0.028***	0.026*	0.004	0.006	0.008	0.001
	(0.009)	(0.015)	(0.007)	(0.005)	(0.005)	(0.019)
Lag Log of GDP			13.027	12.975**	5.707	-36.219
			(18.073)	(5.625)	(5.768)	(21.962)
Government expenditures on consumption			-0.0007	-0.243	0.249	1.056
			(0.002)	(0.198)	(0.225)	(1.006)
Inflation			0.0932		-0.002***	0.001
			(0.588)		(0.0007)	(0.002)
Natural resource rents×Institutional quality			-3.383		.009	-0.974
			(5.438)		(0.61)	(3.025)
Institutional quality			14.574		0.794	15.204
			(37.918)		(7.118)	(20.013)
Growth rate of terms of trade				-2.308	-4.191**	-2.711
				(1.519)	(1.715)	(2.405)
Total debt service				0.1	-0.477**	0.058
				(0.196)	(0.192)	(0.333)
Gross domestic savings				0.077	0.252	0.106
				(0.209)	(0.188)	(0.724)
Foreign aid				0.209	0.373	0.104
				(0.329)	(0.714)	(0.124)
Time span	1982-2015	1982-2015	1982-2015	1982-2015	1982-2015	1982-1997
Number of observations	1811	1754	1727	1558	1550	652
Number of countries	57	57	57	57	57	57

Note: Values in parentheses are standard error. Dependent variable is domestic investment (Gross Capital Formation-% of GDP) measured by $(Invs_t - Invs_{t-1})$. Year Fixed effects are included in all of the estimations. Arellano-Bond estimation follows a two-step GMM procedure. All variables, except the interaction term with Gini index, the growth rate of terms of trade, and the year fixed effects, are instrumented with a maximum of 1 further lag for the lagged investment and two further lags for the rest of the variables. The last column includes the estimation result for a shorter period as in Behzadan et al. (2017). ***P<%1, **P<%5, *P<%10

1982-1997, which is the shorter period as in Behzadan et al. (2017). Table 1-A.10 reports the summary statistics for this analysis. For the remaining discussion, I treat the results obtained in column (5) in Table 1-3 as the baseline results in the paper.

The additional control variables in the regressions exhibit the expected signs. The total amount of the debt servicing has a negative and significant effect, which is consistent with previous empirical findings (Greene and Villanueva, 1991; Leung, 2003). The rationale for this finding can be derived from three related theories: (1) a higher debt implies a larger portion of output committed to debt servicing, and this reduces consumption and investment (Krugman, 1988), (2) higher debt obligations can reduce the supply of loan funds available to a country (i.e., credit rationing), and (3) higher levels of debt increase macroeconomic

Table 1-3: Blundell-Bond estimation results

D.Invs	BB-GMM (1)	BB-GMM (2)	BB-GMM (3)	BB-GMM (4)	BB-GMM (5)	BB-GMM (6)
Natural resource rents	0.291***	5.596*	4.262*	2.924**	3.855*	1.565*
	(0.097)	(2.964)	(2.197)	(1.38)	(1.94)	(0.873)
Natural resource rents×Gini index		-11.531*	-12.327**	-6.642**	-8.914**	-3.514*
		(6.583)	(5.84)	(3.127)	(4.327)	(2.129)
Investment (lagged one period)	-0.679***	-0.499**	0.058	-0.519***	-0.127	-0.52***
	(0.17)	(0.219)	(0.141)	(0.178)	(0.143)	(0.189)
Investment (lagged one period) squared	0.008**	0.004	-0.005*	0.007**	-0.002	0.004
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Lag log of GDP			-0.167	3.087*	0.820	-0.553
			(1.416)	(1.574)	(3.007)	(1.178)
Government's consumption expenditures			-0.0005	-0.186	-0.178*	0.329***
			(0.0004)	(0.207)	(0.092)	(0.12)
Inflation			-0.118		-0.0005	-0.00008
			(0.096)		(0.0007)	(0.0005)
Natural resource rents×Institutional quality			2.779*		0.0878	-0.169
			(1.541)		(0.33)	(0.364)
Institutional quality			3.516		1.679	10.88**
					(2.819)	(4.189)
Growth rate of terms of trade				-2.329**	-1.920**	-3.104***
				(1.082)	(0.944)	(0.875)
Total debt service				-0.111	0.351**	-0.099
				(0.164)	(0.171)	(0.141)
Gross domestic savings				0.0515	-0.154	0.264***
				(0.091)	(0.072)	(0.067)
Foreign aid				0.437	0.304	0.293
				(0.789)	(0.535)	(0.328)
Time span	1982-2015	1982-2015	1982-2015	1982-2015	1982-2015	1982-1997
Number of observations	1811	1811	1785	1645	1604	703
Number of countries	57	57	57	57	57	57

Note: Values in parentheses are standard error. Dependent variable is domestic investment (Gross Capital Formation-% of GDP) measured by ($Invs_t - Invs_{t-1}$). Year Fixed effects are included in all of the estimations. Blundell-Bond estimation is by a two-step GMM procedure. All variables, except the growth rate of terms of trade, the interaction term with income inequality indices, and the year fixed effects, are instrumented with a maximum of 1 further lag. The last column includes the estimation result for a shorter period consistent with Behzadan et al. (2017). I treat the results obtained in column (5) as the baseline results in the paper. ***P<%1, **P<%5, *P<%10

uncertainty (e.g., the chance of default), which reduces the incentive to invest. The coefficient for gross domestic savings is positive and significant, which is consistent with the previous findings (Feldstein and Horioka, 1979; Dooley et al., 1987; Bayoumi, 1990). This finding can be justified from a long-standing view that the savings level is a major determinate of the domestic interest rate and, thus, the cost of capital (abstracting from an international perspective). A lower interest rate leads to a higher demand for new capital and investment.

To emphasize the importance of controlling for income inequality, consider the impact of a marginal change in natural-resource rents on domestic investment. This marginal effect can be captured by the following equation,

$$\frac{\partial \Delta In\hat{v}s_{it}}{\partial N\hat{r}_{it}} = \hat{\beta}_2 + \hat{\beta}_3(Gini_i) + \hat{\beta}_4(Institutional\ quality_i). \tag{1.3}$$

Using equation (1.3) I can solve for what Behzadan et al. (2017) refers to as the *critical level of income inequality*. This critical level implies that for any income inequality beyond a certain level, a marginal increase in natural-resource rents will lead to a fall in domestic investment (in their case, growth). Conversely, income inequality below a critical level suggests that a marginal change in natural-resource rents will increase domestic investment. I set the results of equation (3) to zero to obtain this critical value,

$$Gini^* = \frac{-(\hat{\beta}_2 + \hat{\beta}_4(Institutional\ quality_i))}{\hat{\beta}_3} = \frac{-3.898}{-8.914} \approx 0.43. \tag{1.4}$$

In this calculation, institutional quality is set to be the average of institutional quality for all 57 countries in Table 1-1. Thus, for any country with a Gini index level above (below) 0.43, an increase in natural-resource rents as a share of GDP will lead to a negative (positive) change in domestic investment. In Table 1-A.11, I list the countries above and below this critical level of income inequality, such as Botswana and Chile for the former and Algeria and Niger for the latter. Since the cutoff point is a function of the parameters, its measurement includes some uncertainties that resulted from the estimated parameters. To compute the variance of the cutoff point ($Gini^*$), I use the multivariate Delta method. Using this method, the standard error of the cutoff point is 0.145.[5] The t-statistics, for the tests that the cutoff point is significantly different from zero and one, are respectively 2.812 and -4.060. Therefore, the null hypothesis is rejected at the 5% level in both cases.

These results suggest that if income inequality is a good proxy of rents inequality when rents are concentrated within a small number of (potential) investors, this is detrimental to domestic investment. This result is in line with a model in which unequal rent distributions disincentivize investors since the payoffs are shared across the population and thereby disproportionately accrue to non-investors over investors. This phenomenon would lead to lower investment, capital, and output levels. On the contrary, when resource rents are equally distributed (a country with low income inequality), this would lead investors to invest in more capital. Gaitan and Roe (2012) also develop an infinite-horizon, two-country model of trade in which countries are identical, except that one country is endowed with natural

[5] See the calculations of the variance and formulas In appendix B.

resources and the other is not. They show that this phenomenon can be explained in part by an inelastic demand for the natural resource that increases growth in trade revenues and induces the resource-abundant country to invest relatively less than the country lacking in natural resources. My result has important implications since there exists a close connection between the level of investment and the rate of economic growth, as documented by previous studies (Kormendi and Meguire, 1985; Khan and Reinhart, 1990; Ben-David, 1997). Thus, understanding the drivers of income inequality may also have implications for economic growth.

1.3.3 Robustness Checks

Next, I test the robustness of my baseline results by using different measures of income inequality, subsets of the sample, addressing the potential collinearity between income inequality and institutional quality, using the principal component analysis method as an alternative measure of institutional quality, by changing the controlling variables and performing a subsample analyses. The result of these specifications is reported in Table 1-4. The main results from this robustness analysis are as follows:

Income held by the top 10%. In the baseline results in the paper, the Gini index is used as the measure of income inequality. As an alternative, I consider the income held by the top 10% of a population as the measure of a country's income inequality. I find that the Gini income coefficient and the income share of the top 10% are highly correlated, with a correlation coefficient of 0.75. To remain consistent with the baseline specification, I take the average of the top 10% share of income from 1982-2015. Table 1-4 column (1) reports these estimates. Qualitatively, I find similar signs to those in the main results. The coefficient on the natural-resource rents is positive and significant, and the coefficient on the interaction term between income inequality and natural-resource rents is negative and significant at the 10% level. One rationale for this outcome is that natural-resource rents may disproportionately accrue to those in the top 10% of the income distribution. In Table 1-A.12, I list countries that are above and below the critical level of income inequality. The critical level of income inequality using equation (1.3) in this specification is as follows,

$$\textit{The top 10\% share of income}^{*} = \frac{-(6.436 + (0.541 \times 0.494))}{-16.933} = \frac{-6.703}{-16.933} \approx 0.40. \qquad (1.5)$$

Standard World Income Inequality Database (SWIID). The SWIID provides measures of income equality that were computed using a Bayesian estimation approach. This measure standardizes observations that have been collected from a variety of different

Table 1-4: Blundell-Bond estimation results—Robustness checks

D.Invs	BB-GMM (1) Top 10%	BB-GMM (2) SWIID	BB-GMM (3) Residuals	BB-GMM (4) Excluded countries	BB-GMM (5) PCA	BB-GMM (6) Excluding financial crisis	BB-GMM (7) Exchange rate
Natural resource rents	5.986*	2.606*	0.171	14.824*	4.346*	2.835	-0.453
	(3.098)	(1.019)	(0.502)	(8.752)	(2.365)	(1.835)	(1.143)
Natural resource rents×Gini index				-31.51*	-9.817*	-7.158*	-1.706
				(19.485)	(5.326)	(4.235)	(1.492)
Natural resource rents×Top 10%	-16.205*						
	(8.488)						
Natural resource rents×SWIID		-5.558*					
		(2.279)					
Natural resource rents×Residuals			-1.373**				
			(0.517)				
Investment (lagged one period)	-0.625***	0.061	-0.436	0.6004	-0.129	-0.302**	-0.394
	(0.163)	(0.125)	(0.384)	(0.489)	(0.131)	(0.131)	(0.363)
Investment (lagged one period) squared	0.006*	-0.002	0.003	-0.018	-0.002	0.001	-0.0004
	(0.004)	(0.002)	(0.005)	(0.011)	(0.002)	(0.002)	(0.006)
Lag log of GDP	0.608	4.576***	-1.133	10.395	1.64	2.116*	-0.766
	(1.957)	(1.6)	(1.64)	(7.254)	(2.773)	(1.158)	(0.905)
Government's consumption expenditures	0.106	-0.138*	-0.18	-1.150*	-0.177**	-0.090	0.222
	(0.165)	(0.074)	(0.242)	(0.625)	(0.083)	(0.102)	(0.177)
Inflation	-0.003*	-0.001	0.002	0.007*	-0.0005	-0.0006	-0.027
	(0.001)	(0.0004)	(0.002)	(0.003)	(0.0005)	(0.0005)	(0.027)
Natural resource rents×Institutional quality	-0.977	0.035	-0.8	-2.737		0.712**	2.135
	(0.689)	(0.214)	(1.301)	(1.925)		(0.307)	(2.352)
Institutional quality	35.71*	1.729	-4.165	24.557	-0.076	1.427	-4.504
	(20.79)	(2.151)	(33.277)	(17.637)	(0.351)	(2.468)	(10.495)
Natural resource rents×PCA					0.058		
					(0.044)		
Growth rate of terms of trade	-2.809**	-1.569**	-1.383	10.755	-2.203*	-2.312***	1.424
	(1.144)	(0.588)	(2.771)	(7.96)	(1.12)	(0.683)	(3.183)
Total debt service	-0.199	.0700	0.124	1.782*	0.339*	0.095	0.019
	(0.228)	(0.0943)	(0.082)	(1.06)	(0.197)	(0.113)	(0.125)
Gross domestic savings	0.024	0.077	0.182	-0.559*	0.008	0.122	0.329*
	(0.124)	(0.061)	(0.142)	(0.324)	(0.07)	(0.0614)	(0.182)
Foreign aid	0.005	-1.370	0.145	0.404*	0.141	-0.026	-3.548
	(0.056)	(4.274)	(0.733)	(0.182)	(0.571)	(0.373)	(210.71)
Volatility of exchange rate							0.0004
							(0.0006)
Time span	1982-2015	1982-2015	1982-2015	1982-2015	1982-2015	1982-2008	1994-2015
Number of observations	1571	1444	1604	1448	1604	1205	118
Number of countries	57	57	57	51	57	57	7

Note: Values in parentheses are standard error. Dependent variable is domestic investment (Gross Capital Formation-% of GDP) measured by $(Invs_t - Invs_{t-1})$. Year Fixed effects are included in all of the estimations. Blundell-Bond estimation follows two-step GMM procedure. All variables, except the growth rate of terms of trade, the interaction term with income inequality indices, and the year fixed effects are instrumented with a maximum of 1 further lag. ***P<%1, **P<%5, *P<%10

databases.[6] By using multiple data sources, the SWIID potentially provides a more accurate description of income inequality. The Bayesian measure is also highly correlated with the Gini index (0.82), Table 1-A.14. Consistent with the variable construction in the baseline specification, I average the measure of inequality for each country over the period 1982-2015. Table 1-4 column (2) shows the results obtained when using this measure. Similar to the baseline specification results, the interaction term between natural-resource rents and income inequality is negative and significant at the 10% level. However, the coefficient on natural-resource rents alone is no longer significant. Table 1-A.13 lists the countries that are above and below the critical level of income inequality. The critical level of income inequality using

[6] Solt (2016) provides a thorough discussion of this methodology.

equation (1.3) in this specification is as follows:

$$SWIID^* = \frac{-(2.606 + (0.035 \times 0.494))}{-5.558} = \frac{-2.623}{-5.558} \approx 0.47. \tag{1.6}$$

Relationship between the Gini index and institutional quality. One potential issue in the baseline specification is that the income inequality in many countries is strongly correlated with these countries' institutional quality. Behzadan et al. (2017) emphasizes that this correlation might be either linear or non-linear. To investigate this correlation, I regress the Gini index on institutional quality and a quadratic term of this variable and obtain the residuals. I replace the Gini index values with the residuals, which should be linearly and quadratically independent from institutional quality. I re-run the estimation using this measure of income inequality. The results are reported in Table 1-4 column (3). I again find that the coefficient of interest (the interaction term) is both negative and significant at the 5% level.

Countries with non-negligible shares of natural-resource rents. The choice of resource-rich countries in the baseline specification coincides with those chosen in Behzadan et al. (2017). However, there are some countries where the contribution of natural resource rents to GDP is relatively low. Since there is not much variation in natural-resource rents among these countries, I exclude those where natural-resource rents are negligible (countries that receive less than 0.75% of their GDP from natural-resource rents). This cutoff point is chosen based on the first decile in the sample. The contribution of natural resource rents to GDP for some countries known to be resource-rich is low. For instance, this ratio for Austria is 0.21%; for the United States, it is 1.22%; and for Brazil, it is 2.91%. So, the cutoff point (the first decile in the sample) is not too low to drop countries with negligible shares of natural-resource rents. Table 1-4 column (4) shows the estimated coefficients. I find that the point estimate is larger (-31.51 instead of -2.418) compared to the baseline results and is statistically significant at the 10% level.

PCA. In the baseline specification, the variable "institutional quality" is constructed using an average of four measures from the ICRG, which covers the rule of law, government corruption, bureaucratic quality, and ethnic tensions. Table 1-A.15 reports the summary statistics for these measures. These four categories capture what is most often referred to as institutional quality. However, a simple arithmetic average may potentially decrease the variation between countries. To address this concern, I use principal component analysis (PCA) on the measures reported from the ICRG. PCA uses an orthogonal linear transformation to convert a set of observations of possibly correlated variables into a set of linearly uncorrelated variables (referred to as *principal components*). I use the first principal component, which captures the largest variability in the data (Jolliffe, 1986). I re-estimate the baseline equation using this measure of institutional quality. These results are reported in Table 1-4 column (5). The coefficient on the interaction term between income inequality and natural-resource rents is negative and significant at the 10% level, nearly identical to the baseline results.

Excluding the Global Financial Crisis. The Global Financial Crisis of 2008 was one of most serious financial crises to have taken place since the Great Depression of the 1930s. To eliminate the impact of this phenomenon, I create a subsample that excludes the years after 2008. Thus, I average the measure of income inequality over 1982-2008 for each country to obtain an averaged Gini index. I re-estimate the baseline equation for 1982-2008 to investigate whether the result is robust to this change. These results are reported in Table 1-4 column (6). The coefficient on the interaction term between income inequality and natural-resource rents is negative and significant at the 10% level, nearly identical to the baseline results.

Exchange rate volatility. Some resource-rich countries might invest their natural-resource rents in foreign countries, where these investments can potentially provide higher rates of return. This means Foreign Direct Investment (FDI) is one of the factors that might crowd out domestic investment. To capture the differential in this investment opportunity, I include the exchange-rate volatility as another explanatory variable in the estimation not only because the exchange rate volatility deters FDI but also the exchange-rate uncertainty can have a positive or negative impact on the investment (Bahmani-Oskooee and Hajilee, 2013). Most studies argue that exchange-rate volatility results in price volatility. Price volatility, in turn, could have positive or negative effects on domestic investment (Hartman, 1972). I use exchange-rate data from the IMF's dataset to construct this variable. This data is normally quoted in U.S. dollars and is reported daily to the IMF by the issuing central bank. This data is available for a limited set of countries, so the number of observations is small in this specification. To obtain the real exchange rate, I take the last observation of each month, multiply it by the monthly U.S. CPI and then divide it by the monthly domestic CPI. Based on the monthly data, I compute the standard deviation for each year to obtain the exchange-rate volatility. I re-run the estimation while including the exchange-rate volatility to capture this effect. The results are shown in Table 1-4 column (7). The coefficient on the interaction term is also negative but not significant since the number of observations smaller.

More domestic-investment lags as explanatory variables. In the baseline specification, I include one lag in domestic investment as an explanatory variable in the estimation. Arezki et al. (2015) discuss the impact of a large oil discovery on economic indicators. They indicate that after this oil discovery, investment experiences a boom that lasts for about five years. Other macroeconomic variables are likely to be affected by this discovery during these five years. Further, since domestic investment is a highly persistent process for many countries (Bernanke, 1983; Ndikumana, 2000; Lim, 2013), using multiple lags in domestic investment as explanatory variables could be relevant to determining whether the results are robust. To do so, I include two to five lags of this variable in the estimation. These results are reported in Table 1-A.16 in appendix A. Column (1) reports the results of the baseline specification in the estimation. The coefficient on the interaction term between income inequality and natural-resource rents is negative and significant at the 10% level in all specifications except when using five lags on investment as explanatory variable.

1.4 Conclusion

Economic theory suggests that endowments of natural resources should benefit countries since they can act as a windfall of wealth. However, in reality, these countries often struggle to develop and achieve rates of growth that are comparable to those of countries with few natural resource endowments. As highlighted by Solow (1974), if resource-endowed countries wish to maintain their present consumption paths, then their investment rates should be higher than those of non-resource-rich countries so as to offset the decline in their stock of natural resources. Empirically, however, resource-rich countries exhibit lower relative investment rates than non-resource-endowed countries do. In this paper, I set out to investigate one contributor to this empirical fact: income inequality.

The findings show that, on average, countries with higher income inequality contribute less of their natural-resource rents to domestic investment. The magnitude of this effect is economically large and robust. A variety of studies in the social sciences emphasize what is known as the *alarming Gini coefficient level* in income (above 0.40), which coincides with increased political instability and social tensions (see, e.g., Tao et al. (2014)). The results of this paper are in line with the alarming level of income inequality among countries that invest lower proportions of their resource rents domestically. I find that countries with Gini coefficients above 0.43, on average, reduce domestic investment when there is an increase in the natural resource rents. This result is robust to various sensitivity checks, including alternative measures of income inequality and institutional quality, changes to the econometric framework and the controlling variables, and sub-sample analyses.

Income inequality has become a predominant issue in many countries around the world. The emphasis on inequality has generally focused on social and political instability, crime, health outcomes, education, and economic growth. However, this paper shows that lower levels of domestic investment should also be added to the list of the negative consequences of income inequality pointing to the increasing need to address one of the most important issues of the 21st century.

1-A Appendix

Table 1-A.1: Sources of the variables

Source of Data	Variables Name
World Bank World Development Indicators (2018)	Domestic investment, Natural resource rents, Gini coefficient, Inflation, Growth rate of terms of trade, Government's consumption expenditures, Log of real GDP per capita, Total amount of debt servicing, Gross domestic savings, Foreign aid.
International Country Risk Guide (ICRG) Database	Institutional quality

Table 1-A.2: Main variables' definition

Variables	Definition and Comments
Domestic investment (% of GDP)	Gross capital formation (land improvements; plant, machinery, and equipment purchases; and construction of roads, railways, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings).
Natural resource rents (% of GDP)	Total natural resource rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. The estimates of natural resources rents are calculated as the difference between the price of a commodity and the average cost of producing it. This is done by estimating the price of units of specific commodities and subtracting estimates of average unit costs of extraction or harvesting costs. These unit rents are then multiplied by the physical quantities countries extract or harvest to determine the rents for each commodity as a share of gross domestic product.
Gini coefficient (Constant)	Average of Gini index between the years 1982-2015. A Gini index of 0 represents perfect equality, while an index of 1 implies perfect inequality.

Note: Dependent variable is domestic investment in differences. Natural resource rents is included in the estimation separately and jointly with Gini index.

Table 1-A.3: Other explanatory variables' definition

Variables	Definition and Comments
Institutional quality	Average of 4 variables, Corruption in government, Rule of law, Bureaucratic quality, Ethnic tensions indexed between 0 and 1 (1 represents highest quality).
Inflation, GDP deflator	Inflation is measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency.
Growth rate of terms of trade	The percentage ratio of the export unit value indexes to the import unit value indexes, measured relative to the base year 2000.
Government's consumption expenditures	General government final consumption expenditure (% of GDP) - all government current expenditures for purchases of goods and services. It also includes most expenditures on national defense and security but excludes government military expenditures that are part of government capital formation.
Log of real GDP per capita	GDP per capita (constant 2010 USD and divided by midyear population). GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2010 U.S. dollars.
Total debt services	Sum of principal repayments and interest (% of GNI) actually paid in currency, goods, or services on long-term debt, interest paid on short-term debt, and repayments (repurchases and charges) to the IMF.
Gross domestic savings	Gross domestic savings (% of GDP) are calculated as GDP less final consumption expenditure (total consumption).
Foreign aid	Net official development assistance received (% of GDP) which consists of disbursements of loans made on concessional terms (net of repayments of principal) and grants by official agencies of the members of Development Assistance Committee (DAC), by multilateral institutions, and by non-DAC countries to promote economic development and welfare in countries and territories in the DAC list of ODA recipients. Data are in current U.S. dollars.

Sources: World Bank - World Development Indicators (WDI), Institutional Quality: ICRG Data Set.

Table 1-A.4: List of countries

Algeria	Egypt, Arab Rep.	Mali	Thailand
Angola*	El Salvador	Mexico	Togo
Argentina	Ethiopia*	Morocco	Trinidad and Tobago
Bangladesh	Gabon	Mozambique*	Tunisia
Bolivia	Gambia, The	Namibia	Turkey
Botswana	Ghana	Nicaragua	Uganda
Brazil	Guatemala	Niger	United States
Burkina Faso	Guinea	Nigeria	Uruguay
Cameroon	Guinea-Bissau	Pakistan	Venezuela, RB
Chile	Honduras	Panama	Zambia
China*	India	Paraguay	
Colombia	Indonesia	Peru	
Congo, Dem. Rep.	Jordan	Philippines	
Costa Rica	Kenya	Senegal	
Cote d'Ivoire	Madagascar	South Africa	
Dominican Republic	Malawi	Sri Lanka	
Ecuador	Malaysia	Tanzania	

Note: There are four communist countries in the data set. Although low income inequality is a matter of ideology in communist countries, the same cannot be said for accurate reporting of economic statistics. Therefore, a restricted sample is created, and the communist countries are excluded from the analysis. After excluding those communist countries, there are 57 countries included for the estimation.

Table 1-A.5: Countries with noticeable decrease in domestic investment accompanied by an increase in natural resource rents

Country	Year	Natural resource rents	Growth rate of Nr	Growth rate of Invs	Gini index
Venezuela, RB	1989	18.13	1.34	-15.19	0.49
Honduras	1982	8.27	0.93	-6.96	0.55
Nicaragua	1990	6.72	1.41	-8.19	0.51
Colombia	1999	3.40	1.41	-6.85	0.55
Dominican Republic	1985	1.45	0.83	-3.73	0.49
South Africa	1985	10.07	0.96	-3.49	0.62
Ecuador	1999	6.58	1.27	-4.37	0.51
Dominican Republic	2003	1.15	1.85	-6.19	0.49
Venezuela, RB	2000	18.37	0.83	-2.35	0.49
Argentina	1999	1.13	0.79	-1.92	0.47
Argentina	2000	2.10	0.87	-1.82	0.47
Argentina	1989	3.07	1.57	-3.13	0.47
Peru	2000	1.90	0.75	-1.03	0.50
Uruguay	1982	0.75	1.22	-1.59	0.44
Argentina	2002	4.83	1.84	-2.22	0.47
Botswana	2006	7.99	1.09	-1.25	0.60

Note: This table indicates some countries which experience noticeable decrease in domestic investment after a significant increase in natural-resource rents.

Table 1-A.6: Standard deviation of annual natural resource rents

	Std. Dev.		Std. Dev.		Std. Dev.		Std. Dev.
Algeria	6.432	Egypt, Arab Rep.	4.505	Malaysia	7.292	Sri Lanka	0.186
Argentina	1.531	El Salvador	0.382	Mali	3.747	Tanzania	2.376
Bangladesh	0.419	Gabon	8.171	Mexico	2.455	Thailand	0.794
Bolivia	4.703	Gambia, The	1.576	Morocco	1.651	Togo	6.852
Botswana	2.703	Ghana	4.407	Namibia	8.303	Trinidad and Tobago	4.426
Brazil	1.404	Guatemala	0.654	Nicaragua	1.641	Tunisia	2.720
Burkina Faso	4.404	Guinea	5.686	Niger	3.282	Turkey	0.286
Cameroon	2.389	Guinea-Bissau	4.523	Nigeria	12.283	Uganda	4.969
Chile	4.839	Honduras	1.419	Pakistan	0.722	United States	0.604
Colombia	2.024	India	1.206	Panama	0.105	Uruguay	0.500
Congo, Dem. Rep.	9.830	Indonesia	2.478	Paraguay	0.510	Venezuela, RB	5.257
Costa Rica	1.897	Jordan	1.550	Peru	4.601	Zambia	5.913
Cote d'Ivoire	1.687	Kenya	1.136	Philippines	0.993		
Dominican Republic	1.229	Madagascar	2.281	Senegal	1.115		
Ecuador	4.156	Malawi	2.677	South Africa	2.532		

Weighted average of within-country variations	5.320
Total variation in the dataset	8.036
Ratio of within-country variation to total variation	0.662

Note: This table displays the within-country-variation of Nr_{it}. To have the interaction term not correlated with the fixed effects, the variation-within-countries of Nr_{it} should be large enough. First, I summarize the standard deviation of Nr_{it} by country for the 1982-2015 period. To differentiate among countries, the results are weighted by the relative natural resource shares. Second, I calculate the total variance in natural resources (this includes variations within and across countries). Third, I take the within-country variation to the total variation. This calculation implies that 66% of the variations in Nr_{it} come from within-countries.

Table 1-A.7: Im-Pesaran-Shin unit-root test of the panel

H_0: All panels contain unit roots	Number of panels = 57
H_1: Some panels are stationary avg.	Number of periods = 32.79

	Statistic	p-value
W-t-bar	-6.5558	0

Note: The null hypothesis in IPS unit root test stated that all the series included have unit root or in a simpler way are non-stationary. While, on the other hand, alternative hypothesis stated that some of the series included in the panel are stationary. In this test, the dependent variable is included in the null hypothesis. Thus, rejection of the null means that there is no integration of order one in the panel and the domestic variable is stationary. IPS is the average of augmented Dicky fuller test statistics and follows a normal distribution.

Table 1-A.8: Hansen over-identification test of validity of instruments

Table 1-2	AB-GMM (1)	AB-GMM (2)	AB-GMM (3)	AB-GMM (4)	AB-GMM (5)	AB-GMM (6)
Hansen Test	0.52	0.17	0.10	0.17	0.21	0.75
Table 1-3	BB-GMM (1)	BB-GMM (2)	BB-GMM (3)	BB-GMM (4)	BB-GMM (5)	BB-GMM (6)
Hansen Test	0.04	0.47	0.22	0.20	0.99	0.31

Note: The values for the Hansen test are P-values. The Hansen test for validity of instruments has a null hypothesis that the instruments are exogenous, and the alternative as not exogenous. If P-value is higher than 10%, the null hypothesis cannot be rejected. H_0: Instruments are exogenous. H_A : Instruments are not exogenous.

Table 1-A.9: Test of Arellano-Bond for autocorrelation of error terms

Table (1)	BB-GMM (1)		BB-GMM (2)		BB-GMM (3)	
Orders	z	P-value	z	P-value	z	P-value
1	-5.45	0.00	-4.56	0.00	45.85	0.00
2	-1.34	0.18	-1.52	0.13	-0.82	0.41
3	0.98	0.32	-0.37	0.71	-0.19	0.84
	BB-GMM (4)		BB-GMM (5)		BB-GMM (6)	
Orders	z	P-value	z	P-value	z	P-value
1	-4.68	0.00	-3.72	0.00	-4.12	0.00
2	-1.96	0.14	-0.98	0.32	-0.98	0.33
3	1.51	0.13	0.04	0.26	-0.55	0.58

Note: The test for AR (1) in first differences is not informative. Since $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$ is mathematically correlated to $\Delta\varepsilon_{it-1} = \varepsilon_{it-1} - \varepsilon_{it-2}$, because of the term ε_{it-1} negative first-order serial correlation is expected in differences. The test for AR (2) and above in first differences is more important, because it detects autocorrelation in levels. Thus to check the first-order serial correlation in levels, the second-order correlation in differences should be considered, because this will show the correlation between the ε_{it-1} in $\Delta\varepsilon_{it}$ and the ε_{it-2} in $\Delta\varepsilon_{it-2}$. In baseline result, there is no statistically significant autocorrelation in the error terms at order 2 and above in all regressions. Thus, using two further lags as instruments is appropriate.

Table 1-A.10: Summary statistics for the period 1982-1997

Variables	Number of Observations	Mean	Std. Dev.	Min	Max
Domestic investment (% of GDP - Annual change)	868	-0.177	3.899	-25.351	18.478
Domestic investment (% of GDP - Level)	872	20.742	7.365	1.763	48.396
Natural resource rents(% of GDP)	902	6.897	8.008	0.011	63.52
Gini coefficient (Constant)	912	0.45	0.074	0.301	0.621
Institutional quality (Average of 4 indices)	884	0.494	0.165	0.045	0.954
Inflation, GDP deflator (Annual %)	899	1.383	11.625	-0.208	267.62
Growth rate of terms of trade (2000 = 100)	893	-0.0009	0.137	-0.523	0.976
Government's consumption expenditures (% of GDP)	867	13.63	5.704	2.975	54.515
Log of real GDP per capita (Constant 2010 USD)	902	7.534	1.089	5.608	10.62
Total debt service (% of GNI)	790	6.642	4.641	0.22	73.282
Gross domestic saving (% of GDP)	872	16.575	10.759	-15.545	56.943
Foreign aid (% of GDP - Constant USD)	873	0.0664	0.0968	-0.004	0.740

Note: Summary statistics for column (6) of Table 1-2 and 1-3 which display the estimation results for shorter period (1982-1997) consistent with Behzadan et al. (2017). Some outliers for some variables have not been eliminated, such as total debt servicing and inflation; however, these outliers might affect the results.

Table 1-A.11: Gini index—Baseline result

Countries with Gini index below the critical level of income inequality							
Algeria	0.34	Guinea	0.41	Niger	0.37	Tunisia	0.39
Bangladesh	0.30	India	0.35	Pakistan	0.31	Turkey	0.40
Congo, Dem. Rep.	0.42	Indonesia	0.39	Philippines	0.42	Uganda	0.42
Cote d'Ivoire	0.40	Jordan	0.36	Sri Lanka	0.36	United States	0.40
Egypt, Arab Rep.	0.31	Madagascar	0.42	Tanzania	0.37		
Gabon	0.42	Mali	0.40	Thailand	0.41		
Ghana	0.39	Morocco	0.39	Trinidad and Tobago	0.41		
Argentina	0.47	Costa Rica	0.47	Kenya	0.49	Paraguay	0.51
Bolivia	0.53	Dominican Republic	0.48	Malawi	0.5	Peru	0.49
Botswana	0.6	Ecuador	0.51	Malaysia	0.47	Senegal	0.43
Brazil	0.57	El Salvador	0.47	Mexico	0.49	South Africa	0.61
Burkina Faso	0.43	Gambia, The	0.47	Namibia	0.62	Togo	0.43
Cameroon	0.43	Guatemala	0.54	Nicaragua	0.5	Uruguay	0.44
Chile	0.52	Guinea-Bissau	0.43	Nigeria	0.43	Venezuela, RB	0.48
Colombia	0.55	Honduras	0.55	Panama	0.54	Zambia	0.52

Note: There are 25 countries in this estimation which an increase in natural resource rents leads to an estimated higher domestic investment.

Table 1-A.12: Income held by top 10%—Robustness check

Countries with Gini index below the critical level of income inequality							
Algeria	0.34	Ghana	0.39	Jordan	0.36	Tanzania	0.37
Bangladesh	0.30	India	0.35	Morocco	0.39	Tunisia	0.39
Egypt, Arab Rep.	0.31	Indonesia	0.39	Niger	0.37	Pakistan	0.31
						Sri Lanka	0.36
Argentina	0.47	Dominican Republic	0.48	Malawi	0.50	Senegal	0.43
Bolivia	0.53	Ecuador	0.51	Malaysia	0.47	South Africa	0.61
Botswana	0.60	El Salvador	0.47	Mali	0.40	Thailand	0.41
Brazil	0.57	Gabon	0.42	Mexico	0.49	Togo	0.43
Burkina Faso	0.43	Gambia, The	0.47	Namibia	0.62	Trinidad and Tobago	0.41
Cameroon	0.43	Guatemala	0.54	Nicaragua	0.50	Turkey	0.40
Chile	0.52	Guinea	0.41	Nigeria	0.43	Uganda	0.42
Colombia	0.55	Guinea-Bissau	0.43	Panama	0.54	United States	0.40
Congo, Dem. Rep.	0.42	Honduras	0.55	Paraguay	0.51	Uruguay	0.44
Costa Rica	0.47	Kenya	0.49	Peru	0.49	Venezuela, RB	0.48
Cote d'Ivoire	0.40	Madagascar	0.42	Philippines	0.42	Zambia	0.52

Note: There 13 countries in this specification in which an increase in natural resource rents as a share of GDP leads to an estimated higher domestic investment as a share of GDP. The critical level of income inequality in this exercise is 0.40.

Table 1-A.13: SWIID data—Robustness check

Countries with Gini index below the critical level of income inequality							
Algeria	0.34	Ghana	0.39	Morocco	0.39	Thailand	0.41
Bangladesh	0.30	Guinea	0.41	Niger	0.37	Trinidad and Tobago	0.41
Burkina Faso	0.43	Guinea-Bissau	0.43	Nigeria	0.43	Togo	0.43
Cameroon	0.43	India	0.35	Pakistan	0.31	Tunisia	0.39
Congo, Dem. Rep.	0.42	Indonesia	0.39	Philippines	0.42	Turkey	0.40
Cote d'Ivoire	0.40	Jordan	0.36	Senegal	0.43	Uganda	0.42
Egypt, Arab Rep.	0.31	Madagascar	0.42	Sri Lanka	0.36	United States	0.40
Gabon	0.42	Mali	0.40	Tanzania	0.37	Uruguay	0.44
Argentina	0.47	Dominican Republic	0.48	Kenya	0.49	Panama	0.54
Bolivia	0.53	Ecuador	0.51	Malawi	0.5	Paraguay	0.51
Botswana	0.6	El Salvador	0.47	Malaysia	0.47	Peru	0.49
Brazil	0.57	Gambia, The	0.47	Mexico	0.49	South Africa	0.61
Costa Rica	0.47	Guatemala	0.54	Namibia	0.62	Venezuela, RB	0.48
Chile	0.52	Honduras	0.55	Nicaragua	0.5	Zambia	0.52
Colombia	0.55						

Note: There are more countries in this specification in which an increase in natural resource rents as a share of GDP leads to an estimated higher domestic investment as a share of GDP. The critical level of income inequality in this exercise is 0.47.

Table 1-A.14: Correlation of Gini index with other alternatives

Variables	Gini coefficient	Income held by top 10\%	SWIID
Gini coefficient	1		
Income held by top 10\%	0.75	1	
SWIID	0.82	0.71	1

Note: There is almost high correlation between Gini index and other measures which leads to a similar estimation results.

Table 1-A.15: Summary statistics of institutional quality's measures

Variables	Number of Observations	Mean	Std. Dev.	Min	Max
Corruption of government	1873	2.611	0.936	0.083	6
Rule of law	1906	2.942	1.165	0.416	6
Ethnic tensions	1901	3.671	1.397	0.166	6
Bureaucratic quality	1704	1.96	0.76	0.166	4

Note: The data for these four institutional quality variables is from the International Country Risk Guide (ICRG) database for the period 1982-2015. Average of 4 variables indexed between 0 and 1 (1 represents highest quality) is considered to obtain institutional quality.

Table 1-A.16: Using more lags of investment as explanatory variables —Robustness checks

D.Invs	BB-GMM (1) one lag of Investment	BB-GMM (2) two lags of Investment	BB-GMM (3) three lags of Investment	BB-GMM (4) four lags of Investment	BB-GMM (5) five lags of Investment
Natural resource rents	3.855*	3.47*	4.126*	3.28*	4.511
	(1.94)	(2.024)	(2.26)	(1.992)	(3.012)
Natural resource rents×Gini coefficient	-8.914**	-8.239*	-9.868*	-8.042*	-9.738
	(4.327)	(4.536)	(5.116)	(4.68)	(7.016)
Investment (lagged one period)	-0.127	-0.299*	-0.299*	-0.116	-0.585*
	(0.143)	(0.149)	(0.149)	(0.237)	(0.344)
Investment (lagged two periods)		0.012	-0.014	-0.048	-0.069
		(0.024)	(0.066)	(0.072)	(0.057)
Investment (lagged three periods)			0.083*	0.122	0.122
			(0.036)	(0.104)	(0.087)
Investment (lagged four periods)				-0.034	0.086
				(0.114)	(0.113)
Investment (lagged five periods)					-0.0003
					(0.087)
Investment (lagged one period) squared	-0.002	-0.00006	-0.0007	-0.003	0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
Lag log of GDP	0.820	-0.572	2.08	-0.552	1.498
	(3.007)	(1.16)	(2.384)	(2.81)	(1.741)
Inflation	-0.178*	-0.0008	-0.0003	0.00001	0.0007
	(0.092)	(0.0006)	(0.0007)	(0.0007)	(0.0008)
Government's consumption expenditures	-0.0005	-0.103	-0.201	-0.272*	-0.224
	(0.0007)	(0.073)	(0.164)	(0.13)	(0.136)
Natural resource rents×Institutional quality	0.0878	0.241	0.278	0.366	-0.776
	(0.33)	(0.524)	(0.37)	(0.574)	(0.797)
Institutional quality	1.679	-1.53	-4.489	2.898	-7.124
	(2.819)	(4.033)	(5.227)	(8.412)	(7.287)
Growth rate of terms of trade	-1.920**	-2.115*	-1.58	-0.315	-2.103
	(0.944)	(1.078)	(1.132)	(1.134)	(1.71)
Total debt service	0.351**	0.207	0.32	0.313*	0.525
	(0.171)	(0.153)	(0.238)	(0.184)	(0.211)
Gross domestic savings	-0.154	0.062	0.125*	0.034	0.121
	(0.072)	(0.066)	(0.067)	(0.101)	(0.117)
Foreign aid	0.304	-0.127	0.267	-0.193	0.541
	(0.535)	(0.362)	(0.528)	(0.899)	(0.620)
Time span	1982-2015	1982-2015	1982-2015	1982-2015	1982-2015
Number of observations	1604	1600	1595	1590	1584
Number of countries	57	57	57	57	57

Note: Values in parentheses are standard error. Dependent variable is domestic investment (Gross Capital Formation-% of GDP) measured by ($Invs_t - Invs_{t-1}$). Year Fixed effects are included in all of the estimations. Blundell-Bond estimation is by two-step GMM procedure. All variables, except the growth rate of terms of trade, the interaction term with income inequality indices, and the year fixed effects are instrumented with a maximum of 1 further lag. I treat the results obtained in column (1) as the baseline results in the paper. ***P<%1, **P<%5, *P<%10

Table 1-A.17: Correlation matrix

Variables	Domestic invs	Natural resource rents	Gini coeff	Inst quality	Inflation	Growth terms of trade	Gov's consumption	Log-GDP	Total debt service	Gross domestic savings	Foreign aid	Lagged invs	Lagged invs squared
Domestic investment	1												
Natural resource rents	-0.05	1											
Gini coefficient	-0.056	-0.09	1										
Institutional quality	0.215	-0.29	0.189	1									
Inflation	-0.053	0.03	0.031	-0.073	1								
Growth terms of trade	-0.04	0.07	0.023	-0.014	-0.024	1							
Government's consumption	0.15	-0.08	0.231	0.256	0.018	-0.024	1						
Log-GDP	0.238	-0.13	0.316	0.507	-0.038	0.0005	0.134	1					
Total debt service	0.05	-0.03	0.056	0.148	-0.003	-0.005	0.081	0.225	1				
Gross domestic savings	0.474	0.24	0.056	0.187	-0.058	0.052	-0.02	0.541	0.166	1			
Foreign aid	-0.053	0.18	-0.352	-0.31	-0.018	0.001	-0.145	-0.512	-0.239	-0.186	1		
Lagged of investment	0.879	-0.05	-0.059	0.217	-0.076	-0.016	0.172	0.246	0.074	0.445	-0.072	1	
Lagged of investment squared	0.849	-0.01	-0.074	0.172	-0.051	-0.014	0.153	0.197	0.055	0.428	-0.066	0.97	1

Note: The correlation matrix indicates that there is a negligible correlation between the variables in the estimation.

1-B Appendix

The estimated cutoff point obtained from equation (1.3) in which $\bar{Q}_i$ represents the average of institutional quality for all 57 countries in the sample is as follows:

$$Gini^* = \frac{-(\hat{\beta}_2 + \hat{\beta}_4\bar{Q}_i)}{\hat{\beta}_3} = \frac{-\hat{\beta}_2 - \hat{\beta}_4\bar{Q}_i}{\hat{\beta}_3} = 0.437$$

To calculate the standard error of the cut-off point as a function of standard error of the parameters, I use the multivariate Delta method.

$$V(Gini^*) = (\frac{\partial Gini^*}{\partial\hat{\beta}_2})^2 V(\hat{\beta}_2) + (\frac{\partial Gini^*}{\partial\hat{\beta}_3})^2 V(\hat{\beta}_3) + (\frac{\partial Gini^*}{\partial\hat{\beta}_4})^2 V(\hat{\beta}_4) +$$

$$2(\frac{\partial Gini^*}{\partial\hat{\beta}_2})(\frac{\partial Gini^*}{\partial\beta_3})Cov(\hat{\beta}_2, \hat{\beta}_3) + 2(\frac{\partial Gini^*}{\partial\hat{\beta}_2})(\frac{\partial Gini^*}{\partial\hat{\beta}_4})Cov(\hat{\beta}_2, \hat{\beta}_4) + 2(\frac{\partial Gini^*}{\partial\hat{\beta}_3})(\frac{\partial Gini^*}{\partial\hat{\beta}_4})Cov(\hat{\beta}_3, \hat{\beta}_4)$$

$$V(Gini^*) = (\frac{-1}{\hat{\beta}_3})^2 V(\hat{\beta}_2) + (\frac{\hat{\beta}_2 + \hat{\beta}_4(\bar{Q}_i)}{\hat{\beta}_3{}^2})^2 V(\hat{\beta}_3) + (\frac{-\bar{Q}_i}{\hat{\beta}_3})^2 V(\hat{\beta}_4) +$$

$$2(\frac{-1}{\hat{\beta}_3})(\frac{\hat{\beta}_2 + \hat{\beta}_4\bar{Q}_i}{\hat{\beta}_3{}^2})Cov(\hat{\beta}_2, \hat{\beta}_3) + 2(\frac{-1}{\hat{\beta}_3})(\frac{-\bar{Q}_i}{\hat{\beta}_3})Cov(\hat{\beta}_2, \hat{\beta}_4) + 2(\frac{-\bar{Q}_i}{\hat{\beta}_3})(\frac{\hat{\beta}_2 + \hat{\beta}_4\bar{Q}_i}{\hat{\beta}_3{}^2})Cov(\hat{\beta}_3, \hat{\beta}_4)$$

$$V(Gini^*) = 0.021$$

Using this method, by looking at the variance of $Gini^*$, it is clear that the variance of the cut-off point is equal to 0.021 and the standard error is equal to 0.145.

Chapter 2

World Shocks, Commodity Prices and Domestic Inflation

Abstract

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

2.1 Introduction

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

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

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

My paper builds on several empirical studies that link the co-movements of commodity prices with inflation. Gospodinov and Ng (2013) extract common factors from a panel of 23 commodity convenience yields to forecast inflation. Using a dynamic latent factor model, Neely and Rapach (2011) find that common fluctuations in international inflation rates around their long-run averages, or global inflation, explain 35% of inflation fluctuations. In contrast, my results use commodity prices to explain the cross-sectional variation in domestic inflation. My paper also investigates the impact of commodity price shocks on domestic prices through commodity prices alone. This is known as the first-round effect (Gelos and Ustyugova, 2017; Auer et al., 2017; Neely and Rapach, 2011; Kose, 2002; Kaldor, 1976). To do this, I use the headline inflation data for the inflation rate to study this channel. World shocks could accordingly spill over into the prices of goods and services other than commodities through production costs in other industries. This channel is known as the second-round effect (Sekine and Tsuruga, 2018). To study the second-round effect, I use the data on the core inflation for the inflation rate. Then, I compare the results obtained on both estimations to see if the results are consistent with the theoretical suggestions.

My paper also contributes to the literature on world-price models that are used to capture world shocks. Some studies focus on the role of single-price models, most notably of oil prices and their impact on inflation. Barsky and Kilian (2001) argue that significant oil price increases were not nearly as essential as thought in terms of their role as a causal mechanism of the stagflation of the 1970s. They document that only ten percentage point of inflation fluctuations are explained by economic contraction during 1973-1975. Hooker (2002) identifies a structural break in core U.S. inflation-unemployment Phillips curves that show that oil prices substantially contributed to inflation before 1981 whereas the pass-through has been negligible in 1986, a six percent. Gisser and Goodwin (1986) find no support that oil price shocks Granger-cause inflation post-1973. However, I find that single measures of world prices may not provide sufficient information to explain the channels through which world shocks are transmitted to domestic inflation. Empirically, Gelos and Ustyugova (2017) estimate country-by-country Phillips curves augmented by commodity prices for the period 2001–2010 using food/oil price indices. They find that the median long-term pass-through of a 10 percentage point food price shock to domestic inflation is 0.2 percentage points for advanced economies and almost 0.8 percentage points for emerging economies. I find that commodity price factors explain 26% of inflation fluctuations for the median country after correcting for the small-sample bias.

To my knowledge, my paper is the first to test the importance of world shocks using commodity price factors to explain inflation fluctuations. The analysis in this paper includes 67 advanced and emerging economies over the period 1970-2014.[1] My results suggest that commodity price factors can explain 26% of inflation fluctuations. This statistic implies a larger contribution of world shocks to changes in domestic inflation rates compared to previous studies. My results show that when a single world price is used in the estimation, less than 13% of inflation fluctuations are explained by commodity price shocks. In this respect, my results echo the conclusions of Fernández et al. (2017) and Fernández et al. (2018), who demonstrate the importance of using multiple world prices for output fluctuations. I also investigate the impact of commodity price shocks through the second-round effect, which suggests that headline inflation fluctuations explained by world shocks are almost 10 percentage points higher than core inflation fluctuations. This finding is consistent with the definition of core inflation that does not include price information on the food and energy sector (Sekine and Tsuruga, 2018).

Finally, this paper highlights the importance of other mechanisms contributing to domestic inflation fluctuations. For instance, I confirm the importance of the world interest rate as an additional transmission channel through which world shocks affect domestic inflation (Gruber and Vigfusson, 2018; Kose, 2002). When the world's real interest rate is included in the SVAR model, the fraction of inflation explained by world shocks increases to 34%. Furthermore, Halka and Kotlowski (2017) discuss the impact of the global economic environment on domestic inflation using the SVAR approach to identify the global shocks. These authors document that low inflation in the examined countries results from favorable commodity price shocks and weak domestic and external demand pressures. Thus, I include a global economic index with commodity price factors as the world shocks in an SVAR, and I find that these shocks explain 38% of inflation fluctuations.

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

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

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

2.2 Commodity price factors

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

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

I use the factor model to extract the co-movements of 43 commodity prices to document the impact of world shocks. This allows me to capture the global commodity movements that carry important implications for researchers and policymakers. I use the HP-filter method over the series of commodities to take the cyclical component of real commodity prices and normalize each series by its standard deviation. Then, I extract factors characterizing the co-movement in commodity prices. Table 2-1 lists the factor loadings of the 1^{st}, 2^{nd}, and 3^{rd} components of the commodity price series obtained from the factor model. From the table, it is clear that none of those factors solely explains the variability of fuel, metals, and agricultural prices. In other words, multiple factors are required to capture the co-movement in commodity prices to proxy for world shocks. This finding is consistent with my result in section 2.4.4 that single-world-price models underestimate the importance of world shocks on domestic business cycles. Following the method suggested by Bai and Ng (2002), I find that the first three leading factors optimally explain the variability of commodity prices. This is why I use these three particular factors in my analysis. Table 2-A.1 shows the test results.

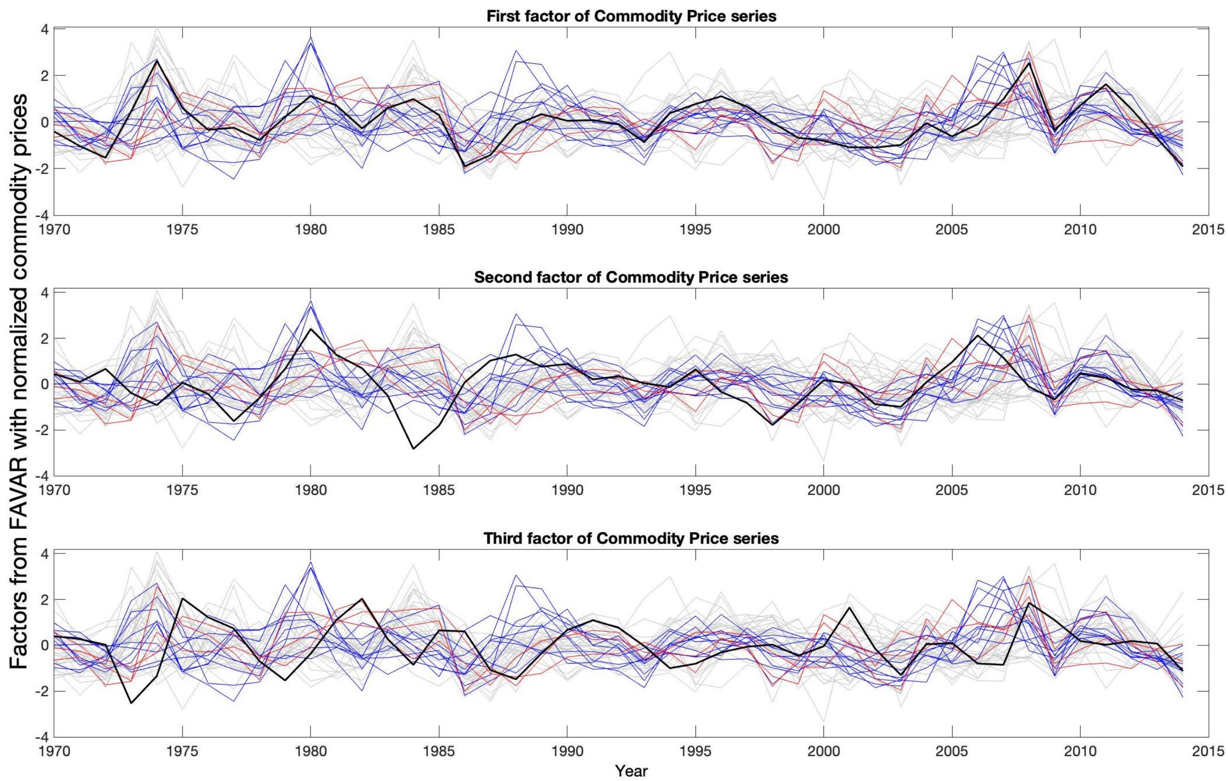
Table 2-1: Factor loadings associated with commodities

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

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

Figure 2-1 shows the 1^{st}, 2^{nd}, and 3^{rd} factors of the commodity series, over the period 1970-2014—the black lines. Two observations are worth pointing out. First, commodity price factors are volatile, and this suggests that commodity price changes could be a potentially important source of inflation fluctuations. Second, there is a relatively strong co-movement among these commodity series. These features are confirmed in Table 2-A.2, which shows the second moments of the commodity price factors. I also use a scree plot to select the number of factors that carry sufficient information on these commodity series. Figure 2-2 displays the scree plot for the common factors (of the commodity series) that confirm that three leading factors explain 54% of the fluctuation in the commodity price

Figure 2-1: Factors characterizing the co-movement in commodity prices over the period 1970-2014

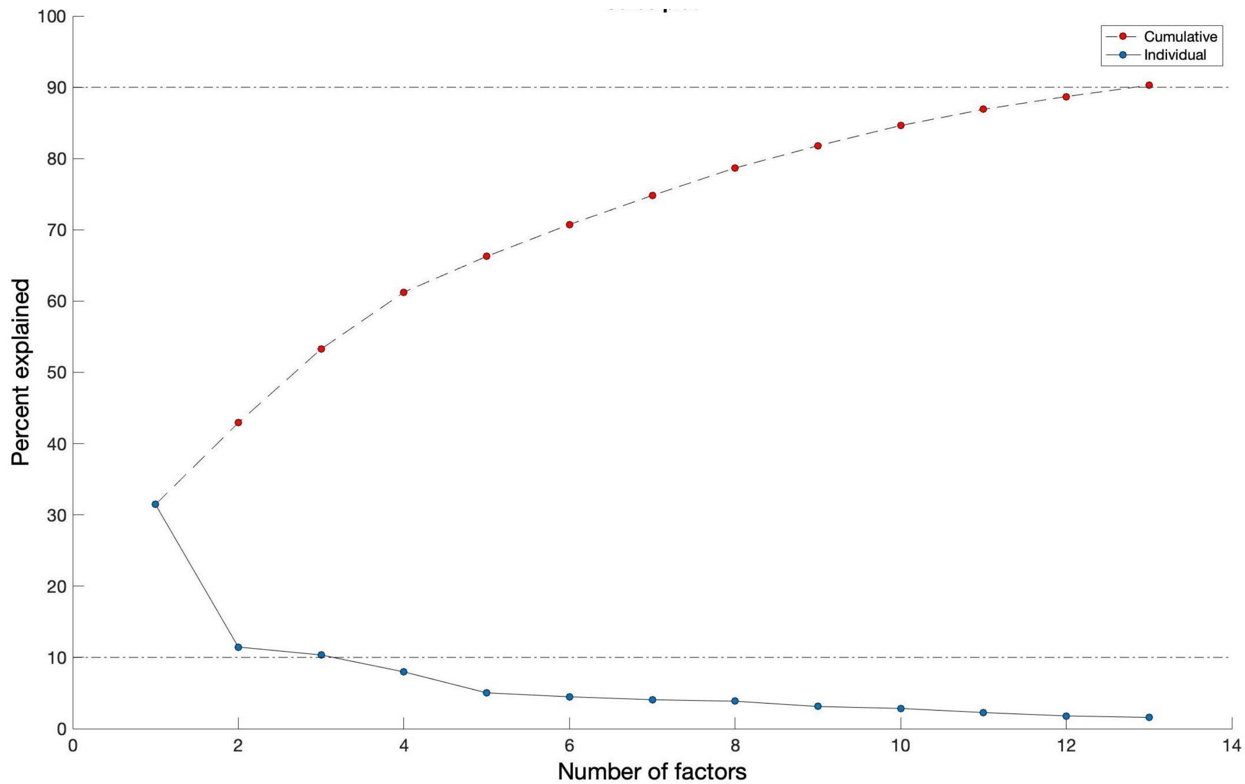


Note: The grey, blue, and red lines are the cyclical components of agricultural, metal, and fuel price series in percent deviations from the trend obtained using HP(100) filtering. The black lines represent the 1^{st}, 2^{nd}, and 3^{rd} factors of the commodity price series over the period 1970-2014.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

series. Thus, in this paper, I apply three commodity price factors to proxy for commodity price shocks. Table 2-A.3 in the appendix lists all of the commodity series used in this sample. I regress the normalized commodity price series on the common factors obtained from the factor model to show how much these factors can explain each commodity (R^2). Table 2-A.4 reports the R^2 of the OLS analysis that includes one, three, six, and ten factors. This table shows that if I use three factors in the SVAR model, they can explain 54% of these commodity series.

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

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



Note: The panel shows that 54% of the fluctuation in the commodity price series can be explained by the first three factors. The red dots show the cumulative percentage that can be explained by these factors and the blue dots show the percentage that can be explained by the i^{th} factor.

of real commodity prices via a static factor model for 23 commodity convenience yields. They find that the two leading factors of convenience yields incorporate useful information for predicting inflation and commodity prices.

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

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

[3]Table 2-A.3 in the appendix lists all of the commodity series used in the sample.

indices from the World Bank Pink Sheet to proxy for world prices, in section 2.4.3, as an alternative measure for world shocks.

2.3 Empirical strategy

2.3.1 SVAR model

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

The foreign block In my baseline specification, the world price vector consists of the real prices of three factors: pc_t^1, pc_t^2, and pc_t^3, which I obtained from the factor augmented autoregressive model applied in section 2.2. The world price vector is as follows,

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

I later augment this price vector to include other world prices, such as the world interest rate, r_t. I assume that world prices are independent of each country's domestic macroeconomic variables. The results obtained in this paper are under the exogeneity assumption of the foreign block to the domestic block. In a multi-country model, foreign variables are usually endogenous. Thus, shutting off the channels of interdependence will affect the estimates, which is one of this paper's limitations. Further, I assume that these prices follow a first-order vector autoregressive system, as follows:

$$p_t = Ap_{t-1} + \mu_t, \tag{2-C.1}$$

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

The domestic block The vector of domestic macroeconomic indicators ${Y_t}^i$ includes annual changes in the inflation rate. I later augment this vector to include other country-specific macroeconomic indicators. These domestic variables are influenced by country-specific shocks ε_t^i and world shocks μ_t. I assume that ε_t^i and μ_t are uncorrelated. There are no restrictions on the domestic block in terms of the Cholesky decomposition in my model since I am not identifying structural shocks in the domestic block. Further, I assume that the world shocks in my model affect the small open economies only through changes in the contemporaneous or past world prices, p_t. These assumptions give rise to the following model,

$$Y_t^i = B^i p_t + C^i\, Y_{t-1}^i + D^i\, p_{t-1} + \varepsilon_t^i. \tag{2-C.2}$$

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

The SVAR model Combining 2-C.1 into equation 2-C.2, I obtain a first-order block-recursive structural vector autoregressive model in the form

$$\begin{bmatrix} p_t \\ Y_t^i \end{bmatrix} = \begin{bmatrix} A & 0 \\ B^i A + D^i & C \end{bmatrix} \begin{bmatrix} p_{t-1} \\ Y_{t-1}^i \end{bmatrix} + \begin{bmatrix} I & 0 \\ D^i & I \end{bmatrix} \begin{bmatrix} \mu_t \\ \varepsilon_t^i \end{bmatrix}, \tag{2-C.3}$$
$$E \begin{bmatrix} \mu_t \mu_t^{\prime} & \mu_t \varepsilon_t^{i\prime} \\ \varepsilon_t^i \mu_t^{\prime} & \varepsilon_t^i \varepsilon_t^{i\prime} \end{bmatrix} = \begin{bmatrix} \Sigma_\mu & 0 \\ 0 & \Sigma_\varepsilon^i \end{bmatrix}.$$

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

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

Another issue is the possibility of small-sample upward bias in the estimation of the model. This bias might occur for two reasons: First, any negative or positive correlation between the foreign and domestic innovations may result in a positive share of commodity price shocks in the variance matrix Σ_ε^i. Second, when a sample is small, the estimates obtained from OLS regressions in auto-regressive models are known to be biased. To overcome these issues, I follow the Monte Carlo procedure to create artificial data. To estimate the model, I use actual data to obtain the non-corrected estimates and subtract the small-sample bias calculated from the Monte Carlo procedure to obtain the corrected estimates. I explain this procedure step by step in section 2-A.1 in the appendix. In discussing the results, I will focus on the corrected estimates for the small-sample bias.

2.3.2 Data

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

The macroeconomic variables are obtained from the World Development Indicators (WDI).[4] The inflation rate is the key variable of interest and is measured by annual changes in the CPI. This variable, headline inflation, reflects the cost to the average consumer of acquiring a basket of goods and services. The conventional Augmented Dickey-Fuller test suggests using annual changes in inflation due to the non-stationarity of the data. Section 2.4.2 investigates the impact of core inflation, instead of headline inflation, in the SVAR model. I obtain annual changes in core inflation by taking the averages of the quarterly samples, by country, over the period 1980-2014. All items are in indices of U.S. city averages, seasonally adjusted (1982-1984=100).

In my estimation, I include countries where the number of observations for the domestic block is at least twenty. This results in 94 countries remaining in the sample. I notice that there are countries with data that are highly volatile or where there are high standard deviations for their CPIs in different years. I exclude these countries from my sample and those that have experienced hyperinflation for multiple years as they result in highly volatile data for the estimation. Table 2-A.5 in the appendix lists excluded countries from my sample and provides information on each country's CPI over the period 1970-2014. Thus, the baseline sample contains 67 countries for the period 1970-2014. The data set for the annual samples is unbalanced. The longest sample consists of data covering 45 years (1970-2014), and the shortest sample covers 20 years (1994-2014).

Quarterly data In the robustness section, using data from the OECD, I also work with quarterly samples of headline inflation rates for 29 of the countries. A country must have at least 100 consecutive quarterly observations to be included in the quarterly sample. Table 2-A.6 in the appendix provides country-by-country information on this sample period and the data source.

2.4 Results

In this section, I start with a baseline model with three factors extracted from 43 commodity prices in real terms to explain the contribution of world shocks to inflation fluctuations (Section 2.4.1). I then consider several variations of the model. In section 2.4.2, I compare the results using core

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

inflation versus headline inflation. In section 2.4.3, I report how world shocks contribute to domestic inflation while controlling for different macroeconomic indicators in the domestic block. In section 2.4.4, I examine the role of including other specifications for commodity prices with inflation in an SVAR. I also analyze the impact of using a single proxy for world prices. Finally, in section 2.4.5, I investigate the role of including other world prices in the foreign block in the SVAR.[5]

2.4.1 Commodity price shocks and inflation fluctuations

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

Table 2-2: The median shares of inflation fluctuations among the sample countries explained by world shocks—baseline result

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

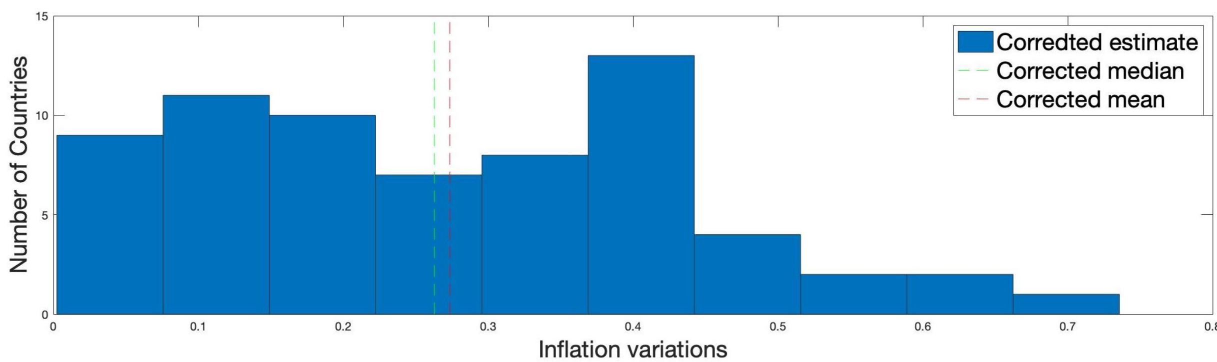
Note: Variance decompositions are based on country-by-country estimates of the SVAR system over the period 1970-2014. In columns 1 and 2, vector Y_t of the domestic variables contains only one domestic indicator, the inflation rate. The small-sample bias in the variance decomposition of inflation is,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

The non-corrected estimates show that commodity price shocks explain, on average, 37% of

[5] This paper does not control the exchange rate regime due to data availability. However, the International Monetary Fund (IMF) dataset includes the information for 11 countries of the sample in this paper. The issue is that the start year for following a specific exchange rate regime is after 2000, which leaves a low number of observations for the analysis. Therefore, it is not possible to re-estimate the model controlling for the exchange rate regime.

the variation in the inflation rate for the median country and 38% of inflation fluctuations for the average share of variances over 67 counties. After correcting for the small-sample bias, between 26% and 27% of the variation in inflation can be explained by world shocks for the median country and the average share of the variances in the inflation rate. I treat the results obtained in the corrected estimates for inflation fluctuations (26%) as the baseline result in my paper. Figure 2-3 displays the fraction of variance explained by the commodity price factors, in terms of the frequency distribution for all countries. Table 2-A.7, in the appendix, reports the results for each country (σ^{π}), separately. Note that the sample is unbalanced because the number of observations for the domestic block is different across countries (from 20 to 45 across 67 countries). This table also reports the confidence intervals for the estimates for each country to show the uncertainty of the baseline results at the 5% level. Figure 2-A.1, in the appendix, presents each country's inflation fluctuations to commodity price shocks over the period 1970-2014.

Figure 2-3: The frequency distribution of the fraction of variance explained by the commodity price factors, over the period 1970-2014.



It is useful to put my estimates in the context of the literature. For example, Gelos and Ustyugova (2017) estimate the impact of a change in one world price on fluctuations in domestic inflation. They indicate that the median long-term pass-through of a 10 percentage-point food price shock to domestic inflation is 0.2 percentage points for advanced economies and almost 0.8 percentage points for emerging economies. They suggest that economies with higher food shares in their CPI baskets, higher fuel intensities, and pre-existing inflation are more prone to experiencing sustained inflationary effects from commodity price shocks. Furthermore, Sekine and Tsuruga (2018) find that the effects of commodity price shocks on headline inflation, on average, are an increase by 1.87 percentage points in response to a 10 percentage-point increase in commodity prices. My paper finds that commodity price shocks can explain 26% of the variation in inflation fluctuations. This result indicates an increased contribution of world shocks to changes in domestic inflation rates, compared to previous studies. This can be an interesting result for policymakers because it compels them to consider the importance of commodity prices on inflation when monetary policy aims to maintain low and stable inflation rates.

2.4.2 Headline inflation versus core inflation's results

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

Table 2-3: Shares of variances explained by world shocks—core & headline inflation

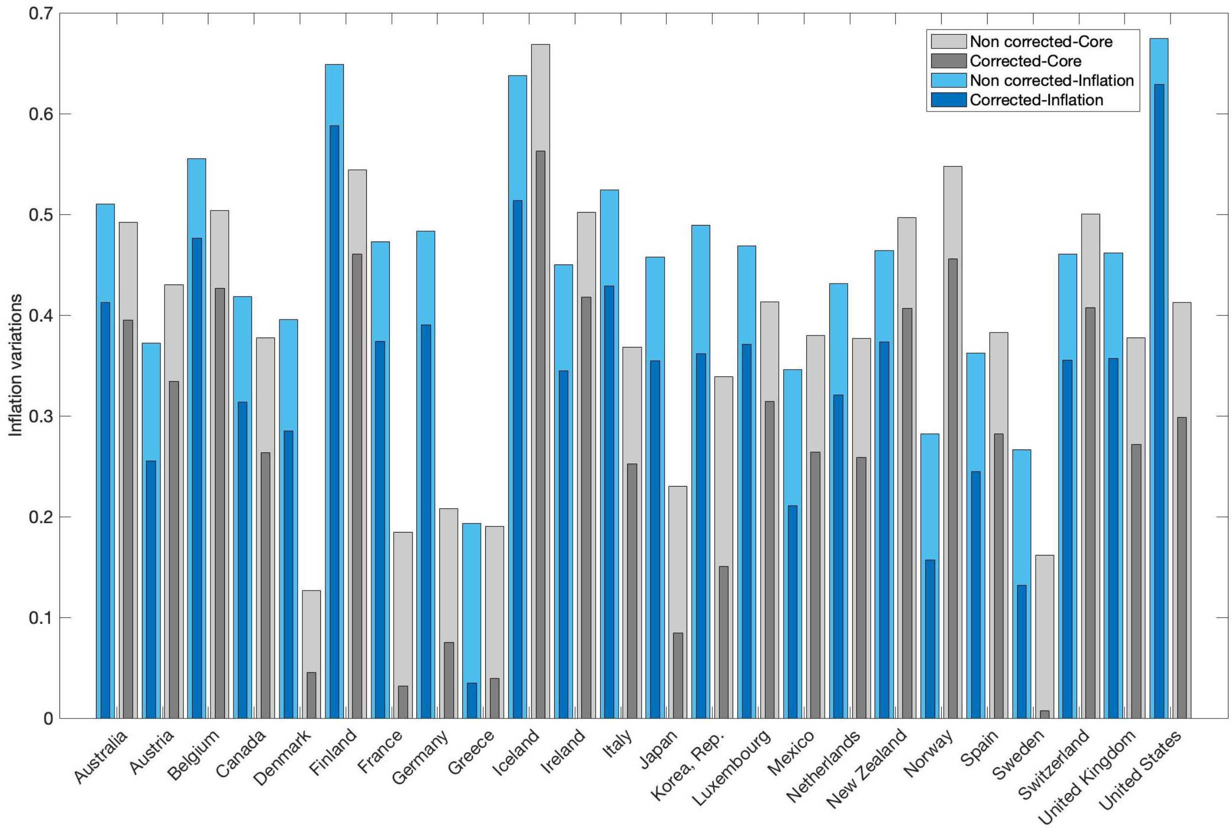
	Median		Mean	
	A. Core inflation	B. Inflation	C. Core inflation	D. Inflation
Non-corrected estimate	0.38	0.45	0.38	0.46
Small-sample bias	0.12	0.11	0.11	0.11
Corrected estimate	0.27	0.35	0.28	0.36
MAD of corrected estimate	0.08	0.07		
Number of countries	24	24	24	24

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

In this section, I perform variance decomposition country by country, using the estimated SVAR system obtained in section 2.3.1. I work with a quarterly sample of commodities that make up the core inflation rate in 24 countries, using the OECD database. Due to limited data availability for core inflation, I include 24 countries for both estimations to have a consistent comparison. In the first column, vector Y_t of the domestic variables contains only core inflation. In the second column, vector Y_t contains only the headline inflation rate. In the third and fourth columns, I show the same estimation results for the average responses of both domestic indicators (core inflation and the inflation rate) to world shocks mediated by commodity price shocks over 24 countries. Table 2-A.8, in the appendix, shows the list of countries included in this section.

The non-corrected estimates in Table 2-3 show that commodity price shocks explain, on average, 38% of the variation in core inflation and 45% of the inflation fluctuations for the median country. They also explain 38% of the variation in core inflation and 46% of the changes in headline inflation, on average, over 24 countries. After correcting for the small-sample bias, world shocks explain 27% of the variation in core inflation and 35% of the fluctuations in headline inflation for the median country, and 26% of the variation in core inflation and 32% of the fluctuations in inflation on

Figure 2-4: Headline inflation and core inflation fluctuations in response to commodity price shocks, over the period 1980-2014.



average. Thus, the estimation results in this section show that headline inflation responds to world shocks by almost ten percentage points more than core inflation. This result is consistent with what Sekine and Tsuruga (2018) suggest theoretically. Since core inflation is the change in the cost of the bundle of goods and services that does not include those from the food and energy sectors, changes in food and energy prices are not included in this measure. Figure 2-4 shows the results for the responses of headline inflation, the indicator I use in the baseline estimation. The figure also shows each country's core inflation fluctuations to commodity price shocks from 1980-2014.

2.4.3 Results with the extended domestic block

In this section, I extend the domestic block to control for country-specific macroeconomic indicators to investigate the impact of commodity price shocks on inflation fluctuations. To answer the question posed in this section, I include three factors characterizing the co-movement in commodity prices in the foreign block (equation 2-C.1) and the inflation rate and the other macroeconomic indicator, both separately and jointly in the domestic block (equation 2-C.2).

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

Data. This section describes the data used for the extended domestic block. In column A in Table 2-4, I use the annual changes in interest rates. I apply the conventional Augmented Dickey-Fuller tests to check the stationarity of the data; I find that the annual changes in interest rates is stationary. Due to data availability, only 38 countries are included in this estimation. These are listed on Table 2-A.9 in the appendix.

In column B in Table 2-4, the exchange rate is the official exchange rate. It is local currency units per USD, in averages for each period. In this estimation, 53 countries are included due to limited data availability for country-specific exchange rates. Table 2-A.10, in the appendix, lists the countries included in this section.

In column C in Table 2-4, for the output, I consider the GDP data in constant local currency units and use the cyclical component of the natural logarithm of real GDP as captured by an HP filter with a smoothing parameter of 100. In this estimation, 38 countries are included, again due to data issues for country-specific real interest rates. Table 2-A.9, in the appendix, lists the countries included in this section.

Table 2-4: The median share of inflation fluctuations explained by world shocks—Extended domestic bloc

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

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

Results. Table 2-4 reports the estimation results for the extended domestic block in section 2.4.3. Column A in Table 2-4 shows the estimation results for inflation fluctuations while I control for real interest rates in the extended domestic block. The non-corrected estimates show that commodity price shocks explain 39% of the variation in inflation fluctuations for both estimations in 38 countries. After correcting for the small-sample bias, 25% and 26% of inflation fluctuations in both estimations can be explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is not affected by the real interest rate when I control for this indicator.

Column B in Table 2-4 shows the estimation results for inflation fluctuations while I control for the exchange rate in the extended domestic block. The non-corrected estimates show that commodity price shocks explain 36% of the variations in inflation in both specifications among the 53 countries for the median country. After correcting for the small-sample bias, 25% of inflation fluctuations for both settings are explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is not affected when I control the exchange rate.

Column C in Table 2-4 shows the estimation results for inflation fluctuations while I control for output and the real interest rate in the extended domestic block. In the first column, vector Y_t for the domestic variables contains only the inflation rate. In the second column, vector Y_t contains three domestic indicators: the inflation rate, output, and the real interest rate. The uncorrected estimates show that commodity price shocks explain 39% and 44% of the variation in inflation fluctuations for the median country in both settings, respectively, in all 38 countries. After correcting for the small-sample bias, 25% of the inflation fluctuations and 32% of the variation in inflation in the extended model are explained by world shocks for the median country. This result indicates that the share of inflation explained by commodity price shocks is almost seven percentage points higher than when I control for both indicators.

2.4.4 Results using various commodity prices

I include different commodity prices in the foreign block (equation 2-C.1). Fernández et al. (2017) suggest going beyond single-world-price model and using three price indices corresponding to major commodity groups. Thus, I try a specification to investigate the impact of single-world-price models. I also use commodity price indices to proxy for world shocks. My results suggest that three factors extracted from all commodity prices have a stronger impact on inflation than the three price indices.

Single-world-price model specification. Many previous studies focused on the impact of a single commodity price, such as the price of oil or food, on domestic inflation. Schmitt-Grohé and Uribe (2016) and Fernández et al. (2017) demonstrate that such an approach underestimates the importance of world shocks in explaining output fluctuations. In this section, I analyze the implications of using a single measure to proxy for the impact of world shocks on fluctuations in inflation. To this end, I include one factor and a single price index at a time in the foreign block (equation 2-C.1). Then, I estimate a number of single-world-price SVAR models to compare the results of these models relative to the SVARs with commodity price factors and the world interest rate. Overall, these results emphasize the need for using multiple price specifications in assessing the effects of world shocks.

The comparative results are reported in Table 2-5. I examine eight alternative single-price models. My focus is on the share of the variances in inflation that are explained by world shocks. I report the estimates that are corrected for the small-sample bias. For ease of comparison, the first row in Table 2-5 reproduces the results from the SVAR model with three factors of commodity price series included in the study and the world interest rate from section 2.4.5 (column 5 in Table 2-6).

Table 2-5: Share of variances using one-price specifications

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

Note: The reported variance shares are group-specific medians, using annual data. The domestic block includes only the inflation rate. Statistics are medians across 67 countries, corrected for the small-sample bias. The first row is reproduced from column 5 in Table 2-6. Here, r_t is measured by the real Treasury bill rate.

I first estimate the SVAR models with one of the three factors of commodity prices, obtained in section 2-1. The results in Table 2-5 show that single-factor models can explain only a small fraction of fluctuations in inflation. I next examine other measures of world prices (the three commodity price indices obtained in section 2.4.3), the world interest rate, and the country-specific terms of trade in the foreign block. The terms-of-trade series is the ratio of trade-weighted exports to imports, measured according to price indices. Schmitt-Grohé and Uribe (2016) indicate that country-specific terms-of-trade shocks represent a significant source of business cycles in emerging economies. The results for specifications 4 to 8, in Table 2-5, also indicate that when only one world price is included in the foreign block, world shocks explain on average less than 6% of the variances in the median country's rate of inflation. Overall, these results emphasize the need for using multiple price specifications in assessing the effects of world shocks on domestic inflation fluctuations.

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

Table 2-A.11, in the appendix, shows the correlations between the three factors obtained from the factor model in section 2.2 and the commodity price indices (agricultural, fuel, and metal prices). It shows that the first factor is highly correlated with these three commodities' indices. In contrast, the second factor is highly correlated with the metals index, and there is some correlation between the third factor and fuel prices.

Results. Column 1 in Table 2-6 reports the results using four factors of commodity prices. The non-corrected estimates show that commodity price shocks explain 52% of the variation in the fluctuations in the inflation rate when I use four factors in a foreign block. After correcting for the small-sample bias, the results for the median country show that 42% of the fluctuations in inflation are explained by the impact of world shocks on domestic inflation. This result indicates that using more factors (more world prices) in the foreign block (equation 2-C.1) has more explanatory power for fluctuations in domestic inflation.

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

2.4.5 Results with the extended foreign block

In this section, I extend the foreign block to include more channels to investigate the extent to which world shocks explain fluctuations in inflation. To answer the question posed in this section, I augment the price vector p_t in the foreign block (equation 2-C.1) to include the other global indicator, g_t, when I re-estimate the SVAR model for each country.

$$p_t = \begin{bmatrix} {p_t}^a \\ {p_t}^f \\ {p_t}^m \\ g_t \end{bmatrix} \tag{2-D.4}$$

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

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

Several papers suggest that U.S. monetary policy generates sizable macroeconomic spillovers to the rest of the world (see e.g., Georgiadis (2016) and Chen et al. (2016)). In addition, it has been argued that each country's economic growth may be driven by a global financial cycle which, in turn, appears to be determined to a large extent by U.S. monetary policy (Habib et al., 2018). To control for the impact of U.S. monetary policy on each country's monetary policy, I extend the domestic block and consider country-specific real interest rates with inflation in the domestic block (see equation 2-C.2). This analysis includes 38 countries due to the data availability.

Data. The data for the global economic index is available quarterly for the period 1973-2015. I compute the annual data by taking the average of the quarterly samples in the index over the period 1973-2014. I take the real three-month U.S. Treasury bill rate to proxy for the world interest rate. I subtract monthly inflation rate from the monthly Treasury bill rate and then average the monthly data into the annual frequencies to obtain this measure. I later use this indicator in the price vector in equation 2-C.1 to include the world interest rate r_t.

Results with the global economic index. Column 3 in Table 2-6 shows the estimation results that are explained by world shocks, mediated by commodity price factors and the global economic index. The statistics point to the increased importance of world shocks in explaining the inflation movements in the model. The non-corrected estimates show that commodity price

Table 2-6: The median share of inflation fluctuations explained by world shocks—extended foreign block

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

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

shocks explain 51% of the variation in the fluctuations in inflation for the median country. Based on the corrected estimates, the shares of the fluctuations in inflation explained by world shocks now account for 38% of the variation in the median country's inflation rate. These shares are about twelve percentage points higher relative to the benchmark SVAR model with the commodity prices (see section 2.4.1). This result is consistent with what Fernández et al. (2017) suggests about other mechanisms used to explain domestic business cycles: Using more price indicators provides more statistical characteristics to capture the impact of the world shocks on inflation fluctuations in advanced and emerging countries. If I consider the same countries included in Kamber and Wong (2020), factors characterizing the co-movement in commodity prices and the global economic index, in my paper, explain 38% of the inflation fluctuations after correcting for the small-sample bias (53% without the correction). However, Kamber and Wong (2020) consider the common factors of the macroeconomic indicators of five advanced economies as proxies for global economic indicators. To this, they add the commodity price indices for agriculture, fuel, and metals in the foreign block to proxy for world shocks that explain 25% of the inflation gap.

Results with annual world interest rate. The resulting shares of the variances that are explained by worlds shocks, mediated by commodity price factors and the world interest rate, are reported in column 4 of Table 2-6 for annual data. The statistics in column 4 in Table 2-6 point to the increased importance of world shocks for explaining the variations of output and inflation in all estimations. Based on the corrected estimates, the shares of inflation fluctuations explained by world shocks now account for 34% of the median country's inflation rate variation. These shares are about ten percentage points higher relative to the benchmark SVAR model with the commodity prices, shown in section 2.4.1.

Results with world and real interest rate. The last column in Table 2-6 shows the estimates for this analysis. The non-corrected estimates in Table 2-6 show that commodity price shocks explain 56% of the fluctuations in inflation for the median country in the extended model estimations across 38 countries. Furthermore, after correcting for the small-sample bias, I find that world shocks explain 43% of the median country's inflation fluctuations.

Results with quarterly world interest rate. I re-estimate the SVAR model with three factors of commodity prices and the world interest rate, using quarterly data. Due to data limitations, the number of countries in the sample decrease to 29. These countries and the available sample periods are listed in the last column of Table 2-A.6, in the appendix. Table 2-7 reports the results for the estimation in which only inflation is included in the domestic block. The findings using quarterly data show that world shocks explain 30% of the variance in inflation, and when using annual data, I find that world shocks explain 35% of the variance in inflation. The estimate using annual data for 67 countries in the sample is 34%. These estimates indicate that the baseline results are robust to using quarterly data.

Table 2-7: World shocks mediated by commodity prices and world interest rate—quarterly data

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

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

2.5 Alternative specifications

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

Excluding large commodity exporters. These countries' market power might violate the identification assumption of the exogeneity of commodity prices to each country. To address this concern, I exclude large commodity exporters from the sample. I identify the top 20% largest exporters for each of the three commodity groups, using annual average exports of the fuel, agricultural, and metals commodities obtained from the WDI database (1970-2014). This exercise excludes 22 countries that are large exporters of commodities. Panel A in Table 2-8 reports the results for the remaining 45 countries. World shocks appear to explain 31% of the variations in inflation in the countries included in this modified sample. These statistics are almost similar to the baseline results. I conclude that market power in commodity production does not affect an economy's susceptibility to world shocks. Table 2-A.12, in the appendix, lists the countries included in this estimation.

Table 2-8: Heterogeneity among countries in response to world shocks

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

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

Oil exporters and oil importers. I compute the country-specific median of net exports of fuel beginning in 1970, using annual data on exports and imports of fuel commodities obtained from the WDI database. A country is defined as an oil exporter (importer) if its median net fuel export share in GDP is positive (negative). Based on this specification, the analysis consists of 14 oil exporters and 53 oil importers (see Panel B of Table 2-8). The effects of commodity price shocks on inflation fluctuations in oil-importing countries (28%) are much stronger than in oil-exporting countries (18%). This result indicates that higher oil prices may increase industry costs and, hence, inflation rates in oil-importing countries. This result is in line with the discussion in Barsky and Kilian (2004), which notes that world shocks appear to be more important in explaining business cycles in oil importers than in oil exporters. Table 2-A.13, in the appendix, lists the countries included in this estimation.

Net commodity traders. World shocks appear to be more important for explaining fluctuations in macroeconomic indicators in countries that are net commodity importers, compared to countries that are net commodity exporters (Barsky and Kilian, 2004). In my analysis, I consider a country is a commodity exporter (importer) if it has had a positive (negative) trade balance, on average, in the three commodities in my study (agricultural products, fuel, and metals) since 1970.[6] I use annual data on agricultural, fuel, and metals commodities to calculate the net trade for each category. This classification yields 23 commodity exporters and 42 commodity importers. Panel C of Table 2-8 indicates that commodity importers experience higher fluctuations in inflation in response to world shocks compared to commodity exporters, which is consistent with the literature. Table 2-A.14, in the appendix, lists the countries included in this estimation.

Level of development. Adler and Mora (2012) discuss how the level of development affects the importance of world shocks as drivers of domestic business cycles. They indicate that advanced countries have more service-oriented economies and, hence, larger shares of non-tradables, which means they are less exposed to world shocks. In contrast, Fernández et al. (2017) argue that advanced countries, especially those with relatively small economies, tend to be more integrated with the rest of the world. These tighter links could imply larger exposures to world shocks. I divide countries into high-income (40 countries) and low-income (26 countries). This categorization is based on per capita gross national incomes, published in WDI 2015.[7] Panel D of Table 2-8 shows the results of this estimation. The share of the inflation variance explained by world shocks in the high-income group is three percentage points higher than the low-income group. These results are fairly robust across income groups. There are no apparent differences in the share of the inflation variance explained by world shocks across income groups. Table 2-A.15, in the appendix, shows the list of countries included in this estimation.

2.6 Conclusion

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

[6] This study does not control for the net trade status of a country in each commodity separately because I use net commodity trader in my model, including all three categories for commodities. So, I do not control for the heterogeneity of net trade status by commodity. Besides, not enough information exists for each category in my sample.

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

in commodity prices after correcting for the small-sample bias. I find an increased contribution of world shocks to changes in domestic inflation rates relative to previous studies.

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

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

2-A Appendix

Table 2-A.1: The Bai & Ng test result for the number of commodity factors

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

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

Table 2-A.2: World prices: second moments of cyclical components

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

Note: Annual data from 1970-2014. The variables pc^1, pc^2, and pc^3 denote co-factors of 43 real commodity prices (agricultural, metal, and fuel), respectively. The variable r denotes the real three-month Treasury bill rate (same specification used in section 2.4.5). The relative standard deviation with respect to GDP is the median over the 67 country-specific relative standard deviations in the sample.

Table 2-A.3: List of commodity price series

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

Note: List of commodities included in equation 2-C.1 to obtain the foreign block. The data is annual prices available in real terms, in 2010 U.S. dollars, for 1970 to 2014. Source: the World Bank Pink Sheet data.

Table 2-A.4: The R^2 of common factors—over the period 1970 to 2014

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

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

Table 2-A.5: List of countries excluded from the estimation

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

Note: List of countries excluded from the sample.

Table 2-A.6: List of countries — baseline results

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

Continue on the next page

Table 2-A.6: List of countries — baseline results (cont.).

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

Table 2-A.7: List of countries—baseline results with confidence intervals at 95% level

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

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

Table 2-A.8: List of countries in the estimation using core inflation

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

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

Table 2-A.9: List of countries in the estimation with real interest rate

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

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

Table 2-A.10: List of countries in the estimation with exchange rates

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

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

Table 2-A.11: Correlation between commodity factors and indices

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

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

Table 2-A.12: List of countries—Excluding large commodity exporters

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

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

Table 2-A.13: List of countries—Oil exporters vs oil importers

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

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

Table 2-A.14: List of countries—Net commodity traders

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

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

Table 2-A.15: List of countries—Income level

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

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

2-A.1 The small-sample bias procedure

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

1. For a given country, let $\hat{F}$, $\hat{G}$, and $\hat{\Sigma}$ denote the estimates of F, G, and Σ obtained using actual data. Let $\hat{\sigma}$ denote the associated estimate of the share of the variance of Y_t explained by μ_t. Use $\hat{F}$, $\hat{G}$, and $\hat{\Sigma}$ to generate artificial time series for Y_t and p_t of the desired length from the SVAR model given in equation 2-C.1. I generate artificial time series for 250 years.

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

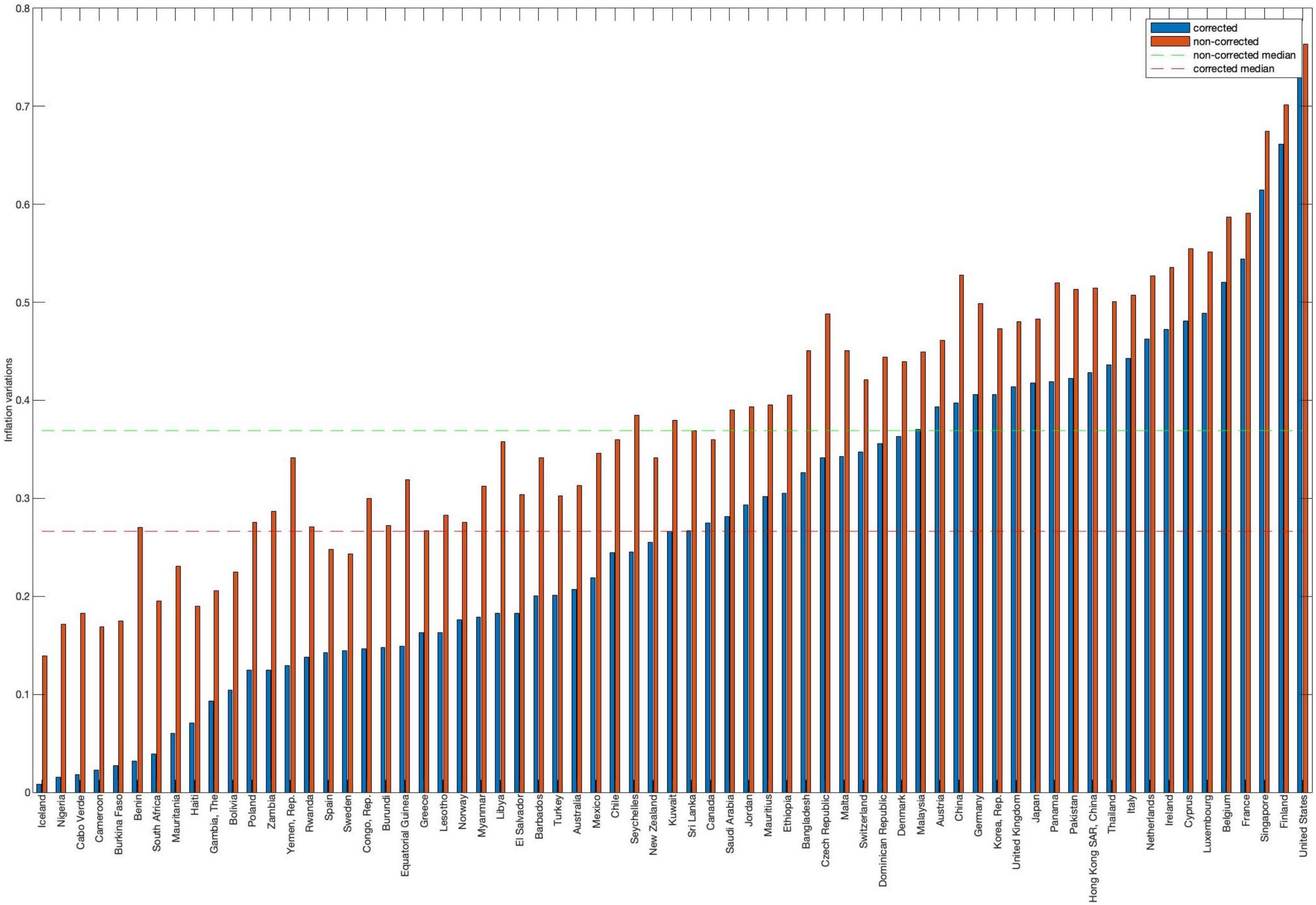
3. Steps 1 and 2 yield an estimate of the matrices F, G, and Σ from the simulated data. I use these estimates to compute the share of the variance of Y_t explained by μ_t shocks, which is denoted by σ.

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

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

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

Figure 2-A.1: Inflation fluctuations to commodity price shocks – Baseline result.



Chapter 3

Do Commodity Prices Matter for Estimating the Output Gap?

Abstract

This paper evaluates the importance of commodity prices in estimating the output gap. I use the Beveridge and Nelson decomposition method and compute the share of domestic and world 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 market economies, over the 1980-2018 period. My results suggest that world shocks appear to be more important for the output gap, relative to the output trend, and emerging market economies' output trends appear to be more affected by world shocks compared to advanced economies. Also, commodity price shocks account for much of the reported shares of world shocks in the output gap for both advanced and emerging market 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.

3.1 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; Walsh, 2003; Svensson, 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 and Wong, 2020). Still, more can be done to improve this estimate by considering other useful indicators. Fernández et al. (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, 2008b). 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 and 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 Kamber and Wong (2020) 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 trend and the output gap. This paper considers global and country-specific indicators

[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.

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 (Kamber and Wong, 2020). 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 (Kilian, 2008b; Jiménez-Rodríguez and Sánchez, 2005), 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 et al. (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 and van Norden, 1997). The HP-filter also suffers from obvious end-of-sample problems.[4] In a multivariate concept, Morley and Wong (2020) apply BN decomposition to estimate the output gap that is based on a VAR model that directly allows

[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 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 and van Norden, 1997).

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 et al., 2002), using such a model to forecast inflation would be a sensible way to account for the reliability of estimated output gaps (Bjornland et al., 2008; Clark and McCracken, 2006; Garratt et al., 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.

3.2 Empirical strategy

3.2.1 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 and 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 3-B.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

$$\tau_t = \lim_{j \to \infty} E_t[y_{t+j} - j.\mu], \tag{3-B.1}$$

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

$$c_t = y_t - \tau_t. \tag{3-B.2}$$

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,

$$X_t = BX_{t-1} + H\nu_t, \tag{3-B.3}$$

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 3-B.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

$$\tau_t = y_t + e_i B(I - B)^{-1} X_t, \tag{3-B.4}$$

Defining e_i as a selector row vector with 1 as its i^{th} element and zero otherwise in equation 3-B.4, and the output gap can be written as

$$\tilde{y}_t = -e_i B(I - B)^{-1} X_t. \tag{3-B.5}$$

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 3-B.3 into equation 3-B.4 and 3-B.5, the change of output trend and the output gap can be written as follows:

$$\Delta\tau_t = e_i(I-B)^{-1}HC\vartheta_t, \tag{3-B.6}$$

$$\tilde{y}_t = -e_i\{\sum_{k=0}^{t-1} B^{k+1}(I-B)^{-1}HC\vartheta_t\} - e_iB^{t+1}(I-B)^{-1}e_i'y_0. \tag{3-B.7}$$

Since the coefficient $B \in (0,1)$, the second part of equation 3-B.7 is expected to disappear. Considering equations 3-B.6 and 3-B.7, both the output gap and output trend are linear functions of both the foreign and domestic shocks. Therefore, equations 3-B.6 and 3-B.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 and Preston, 2010; Zha, 1999). Thus, the VAR specification form is

$$\begin{bmatrix}\Gamma_t^*\\ \Gamma_t\end{bmatrix} = \begin{bmatrix}\alpha_{11(L)} & 0\\ \alpha_{21(L)} & \alpha_{22(L)}\end{bmatrix}\begin{bmatrix}\Gamma_{t-1}^*\\ \Gamma_{t-1}\end{bmatrix} + \begin{bmatrix}\beta_{11} & 0\\ \beta_{21} & \beta_{22}\end{bmatrix}\begin{bmatrix}\epsilon_t^*\\ \epsilon_t\end{bmatrix} \tag{3-B.8}$$

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 3-B.8 into a form implied by equation 3-B.3. Then, equations 3-B.4 and 3-B.5 are applied to the BN decomposition to estimate the output trend and output gap, followed by the use of equations 3-B.6 and 3-B.7 to investigate the role of world shocks here. In section 3.3.6, 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 Kamber and Wong (2020) 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, Kamber and Wong (2020) 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 Kamber and Wong (2020). 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 et al. (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 3-B.9:

$$\Gamma^* = \begin{bmatrix} P_t^* \\ F_t^* \end{bmatrix}, \textit{ where } \quad P_t^* = \begin{bmatrix} p^f \\ p^m \\ p^a \end{bmatrix}, \quad F_t^* = \begin{bmatrix} f_{1,t}^* \\ f_{2,t}^* \\ \vdots \\ f_{n,t}^* \end{bmatrix} \tag{3-B.9}$$

Later, in section 3.3.4, I report the estimated output gap while the commodity price

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

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

$$\Gamma = \begin{bmatrix} F_t \\ y_t \end{bmatrix}, \ where \qquad F_t = \begin{bmatrix} f_{1,t} \\ f_{2,t} \\ \vdots \\ f_{n,t} \end{bmatrix}. \tag{3-B.10}$$

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 reliable 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 3-B.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 Kamber and Wong (2020). 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.

3.2.2 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 3-A.1 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 3-1 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 3-1: 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

[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.

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

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.

3.3 Results

3.3.1 Estimated output gap using BN decomposition

In this section, I use commodity price indices in the foreign block to estimate the output gap. Figures 3-1 to 3-3 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.

Figures 3-5 and 3-6, 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 figures show that the estimates of the output trends lie close to their actual outputs for both advanced and emerging market economies.

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

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

Figure 3-1: Estimated output gap for advanced economies

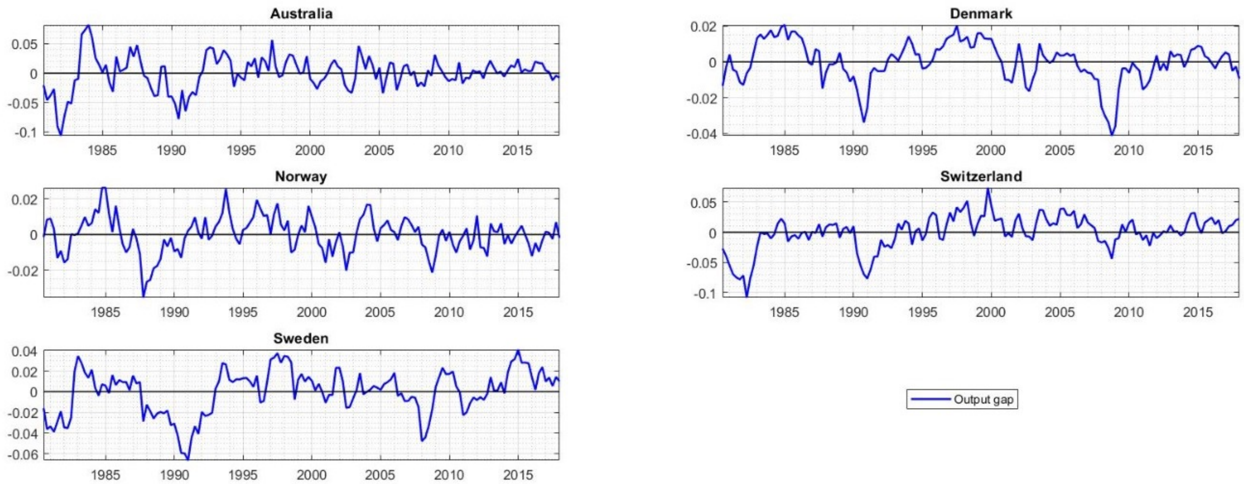


Figure 3-2: Estimated output gap for emerging market economies (1)

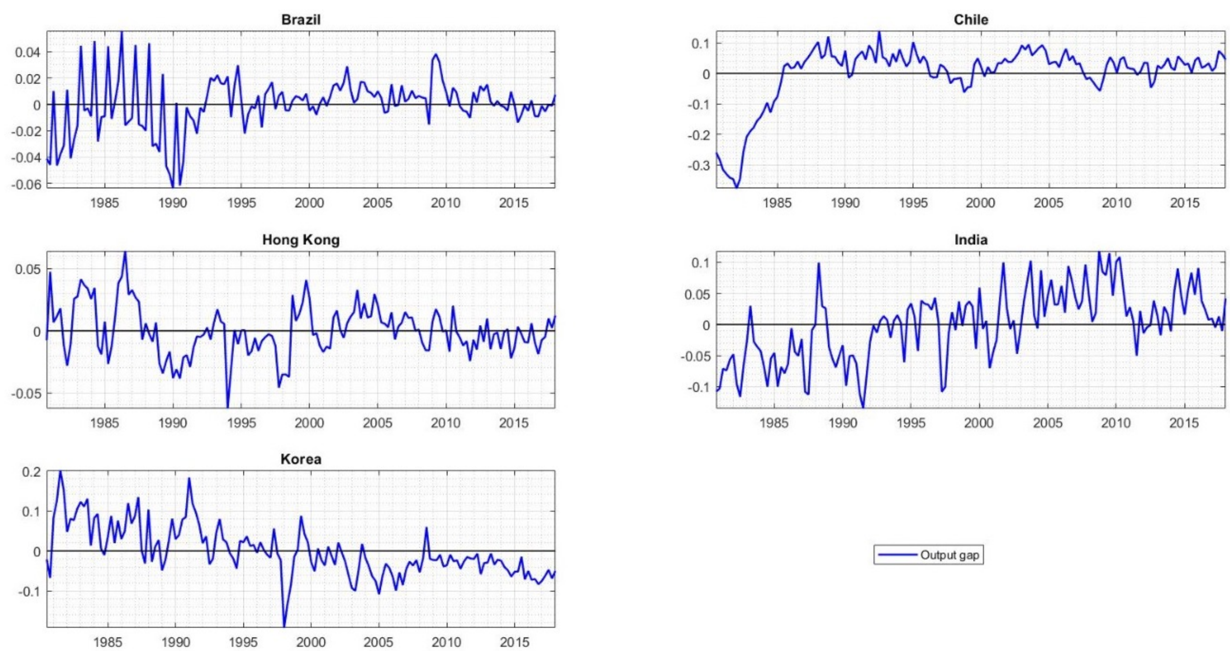
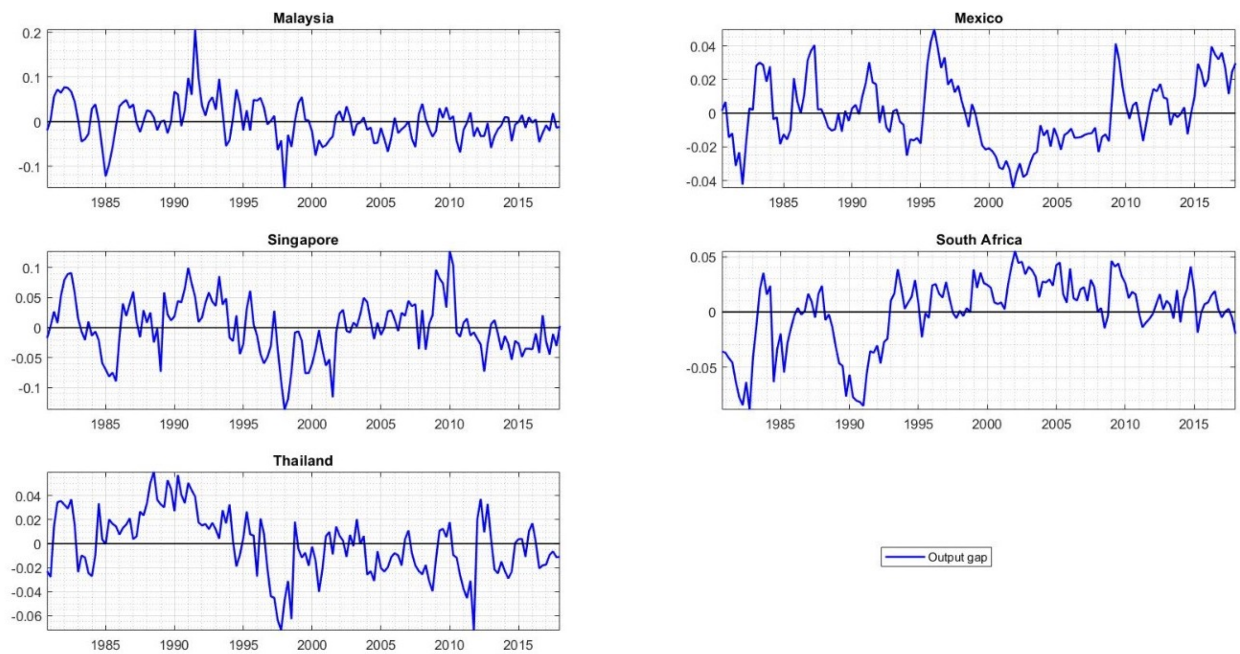


Figure 3-3: Estimated output gap for emerging market economies (2)



3.3.2 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 3-B.6 and 3-B.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):

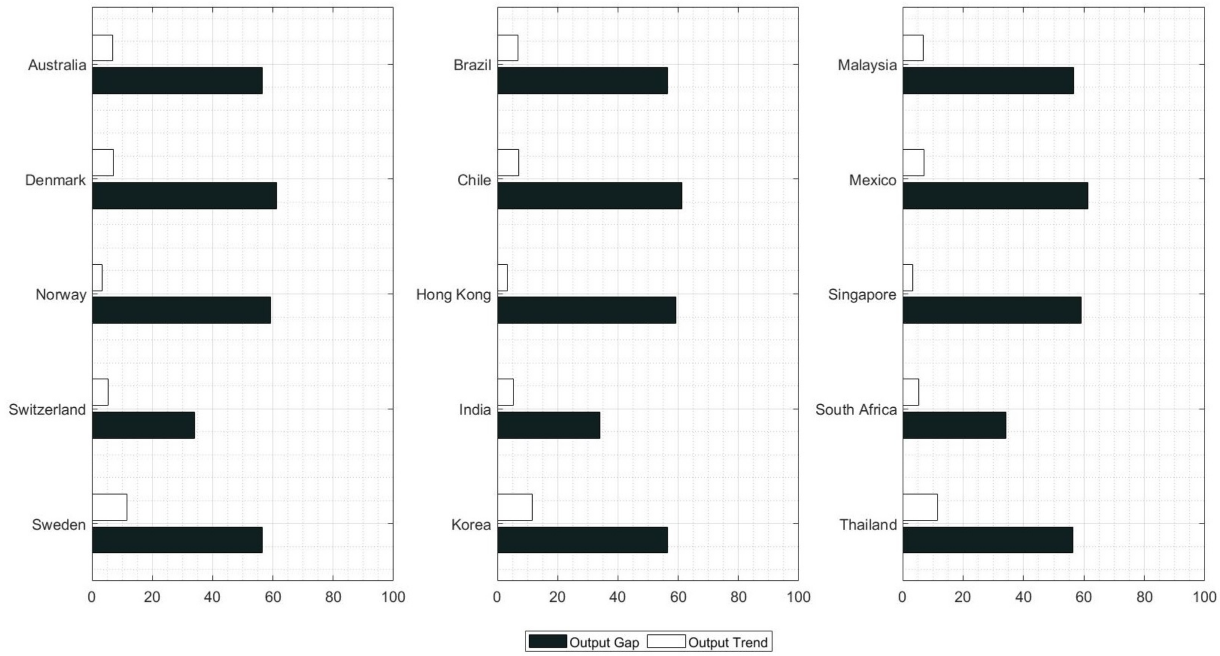
$$\psi_y^\tau = \frac{\sum_{j=1}^{N^*} \left\{e_k(I-B)^{-1}HCe_j'\right\}^2}{e_k(I-B)^{-1}H\Sigma_\nu H' e_k (I-B)^{-1\prime} e_k'} \tag{3-C.11}$$

$$\psi_{\tilde{y}} = \frac{\sum_{j=1}^{N^*}(e_k \sum_{i=0}^{\infty}\left\{B^{i+1}(I-B)^{-1}HCe_j'\right\})^2}{e_k\left\{\sum_{i=0}^{\infty}\left[B^{i+1}(I-B)^{-1}H\Sigma_\nu H'\left\{B^{i+1}(I-B)^{-1}\right\}'\right]\right\}e_k'}, \tag{3-C.12}$$

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 3-4 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 3-4 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 3-4 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.

Figure 3-4: Shares of world shocks for advanced and emerging market economies.



3.3.3 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 3-5 and 3-6 present the variance decomposition of commodity price shocks and the other foreign shocks that drive the output trend and output gap, respectively. Figure 3-5 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 3-6 shows that, for

Figure 3-5: Share of commodity price shocks in the output gap.

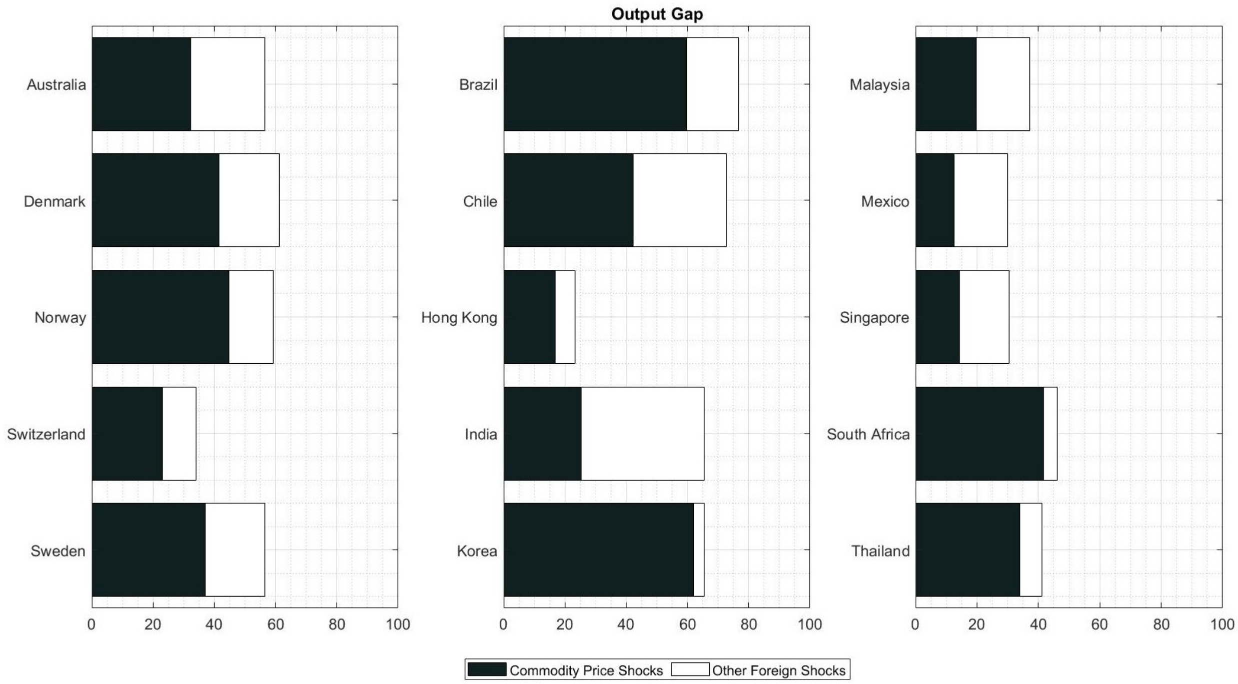
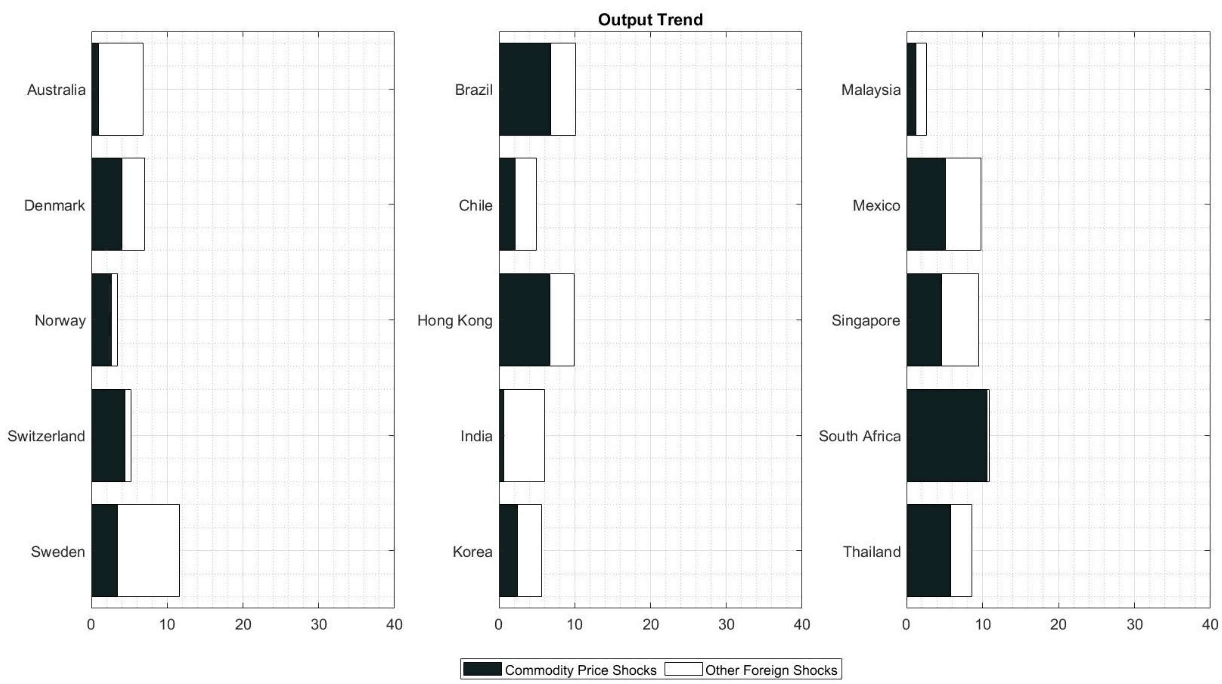


Figure 3-6: Share of commodity price shocks in the output trend.



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.

3.3.4 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 3.2.1 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 3-7 to 3-9 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 3.4, I evaluate whether alternative estimates of the output gap improve predictions for inflation, compared to other measures.

Figure 3-7: Estimated output gap both with and without commodities for advanced economies

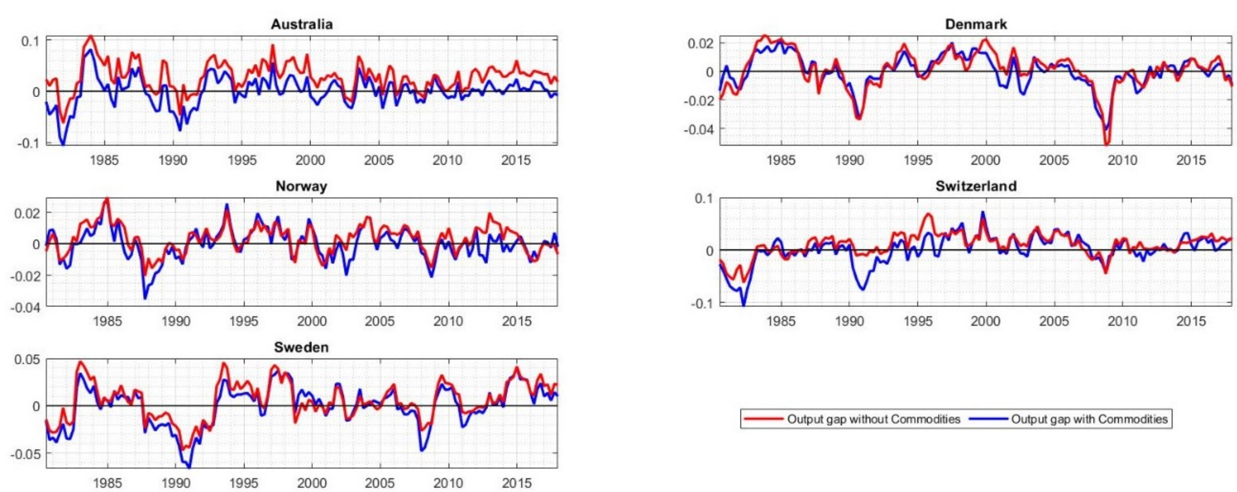


Figure 3-8: Estimated output gap both with and without for emerging market economies (1)

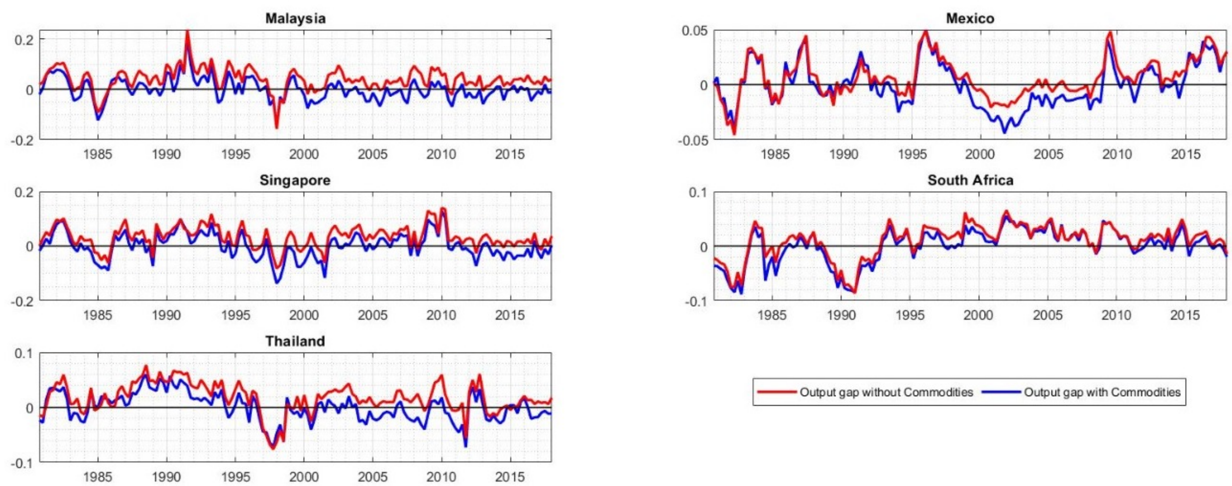
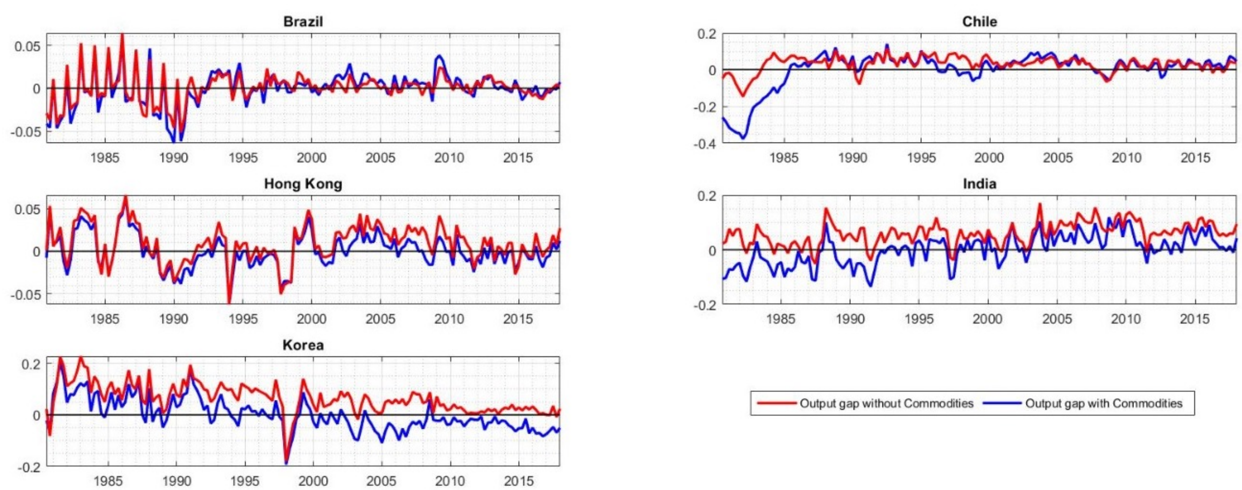


Figure 3-9: Estimated output gap both with and without commodities for emerging market economies (2)



3.3.5 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 3-10 to 3-12 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 3-2 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).

Figure 3-10: Estimated output gap compared with alternative methods for advanced economies

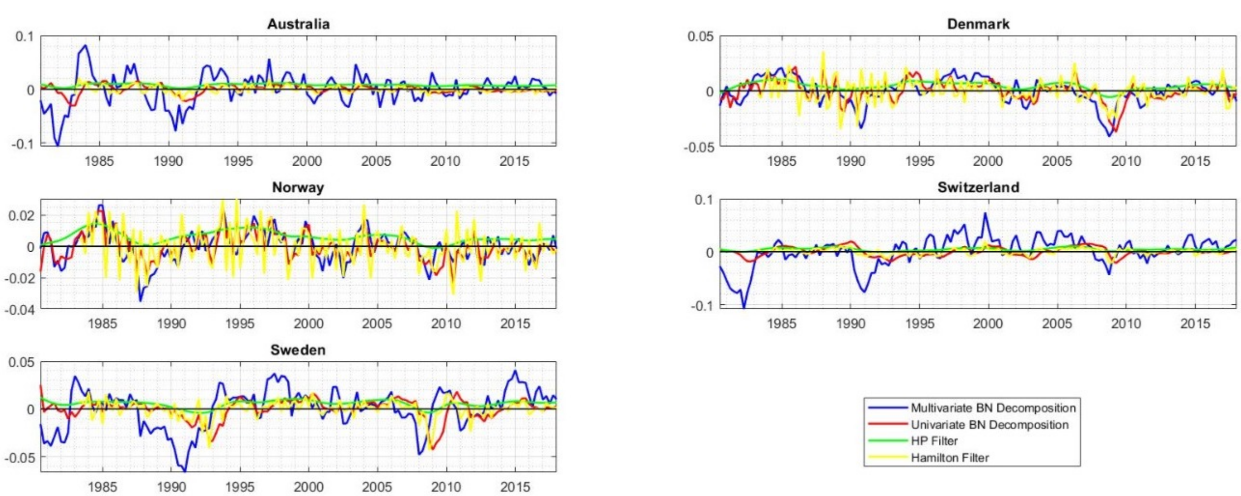


Table 3-2: Correlation coefficient between the baseline estimates and alternative methods

	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.

Figure 3-11: Estimated output gap compared with alternative methods for emerging market economies (1)

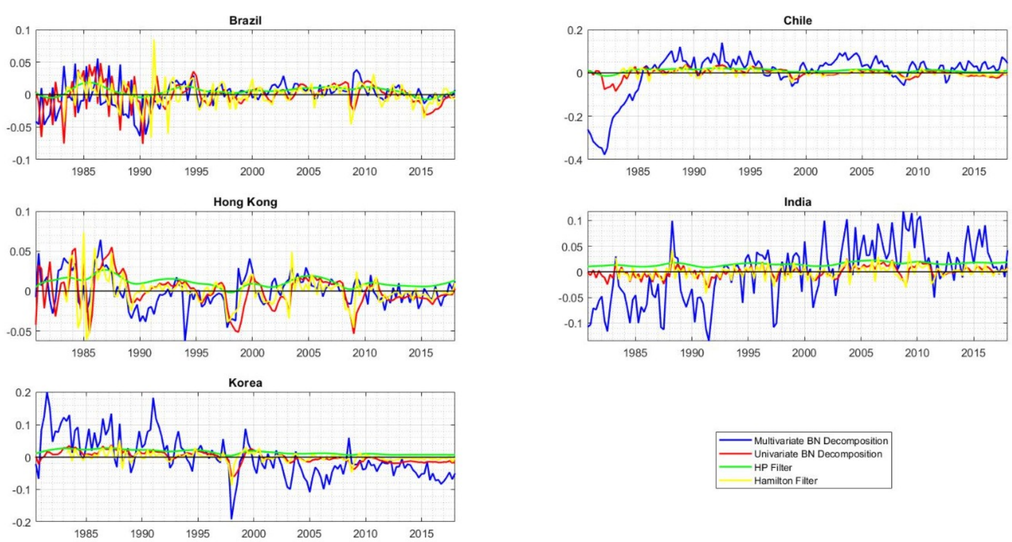
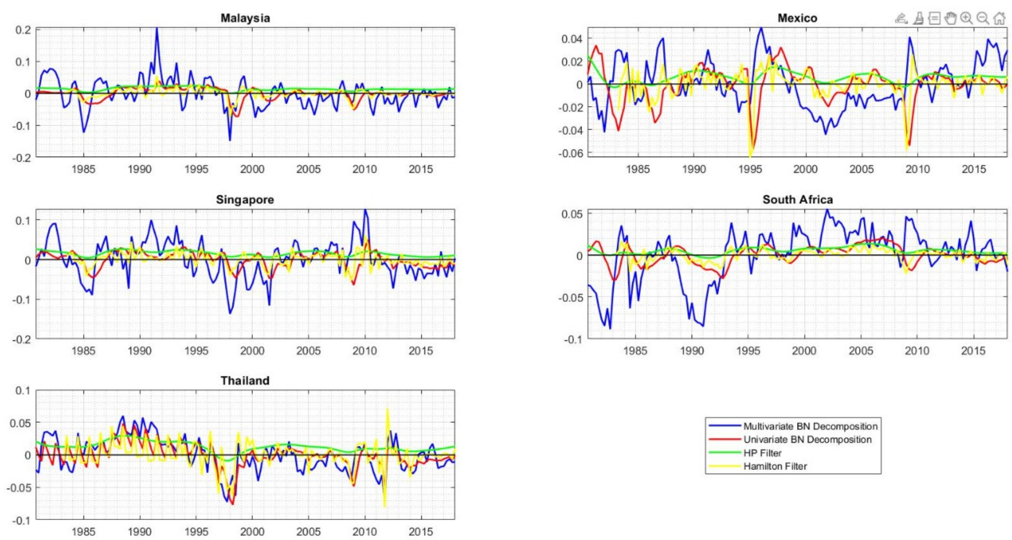


Figure 3-12: Estimated output gap compared with alternative methods for emerging market economies (2)



3.3.6 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 3-B.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 3-13 to 3-15 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 3-A.4 to 3-A.9 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.

Figure 3-13: Share of world shocks where the exogeneity assumption is relaxed for advanced economies

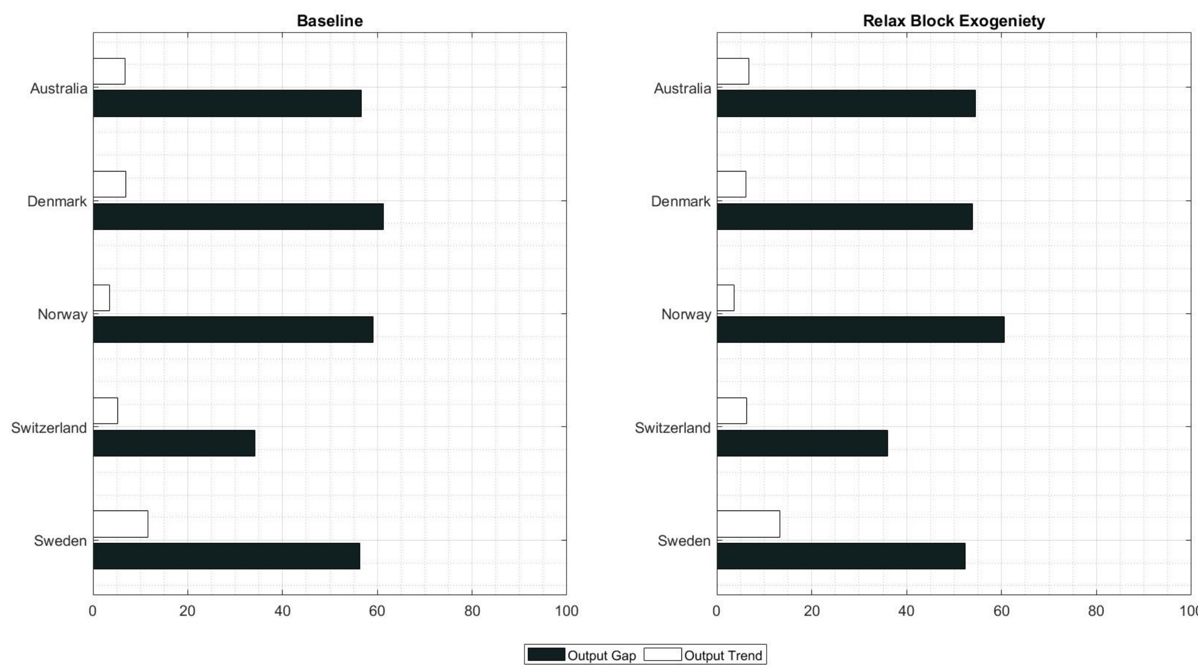


Figure 3-14: Share of world shocks where the exogeneity assumption is relaxed for emerging market economies (1)

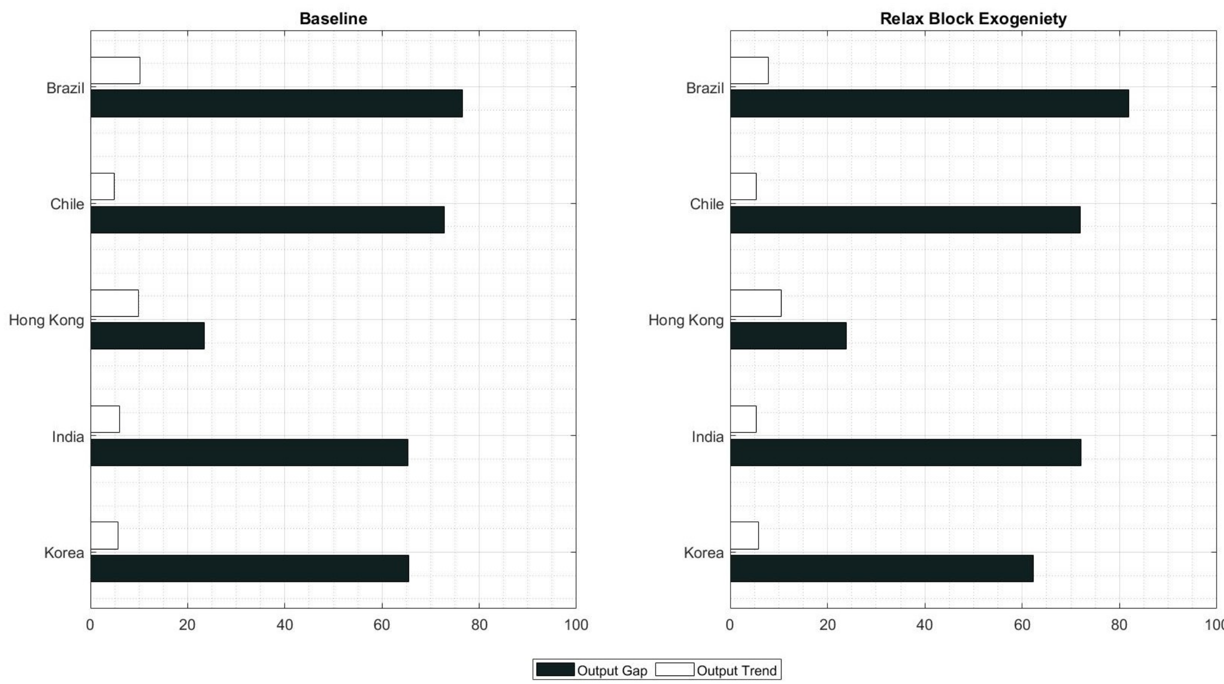
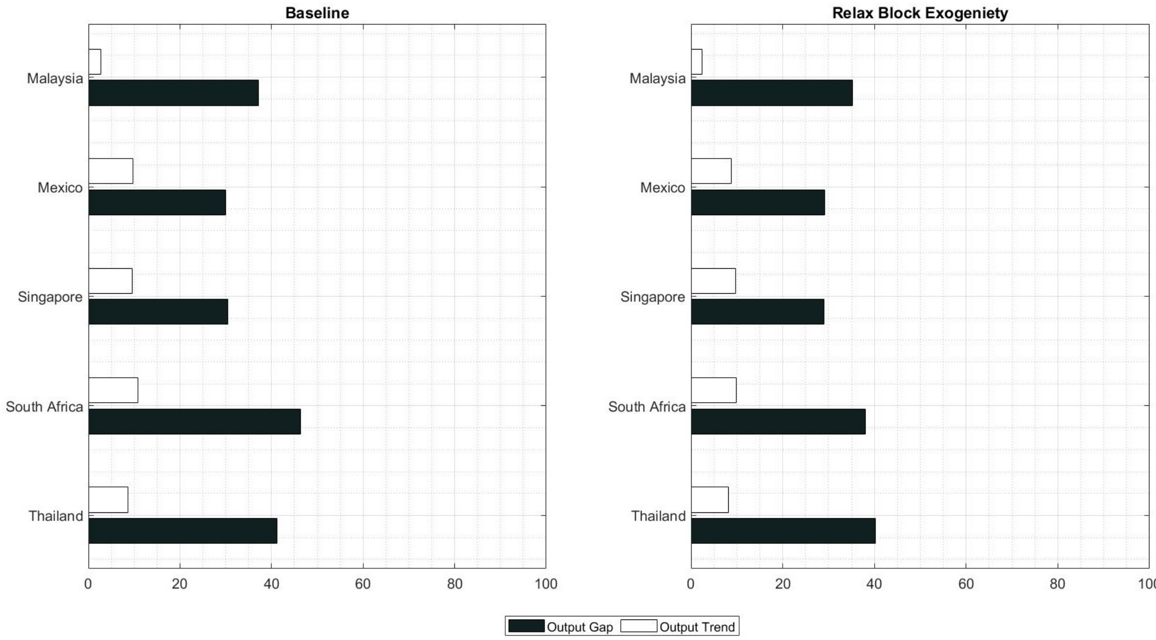


Figure 3-15: Share of world shocks where the exogeneity assumption is relaxed for emerging market economies (2)



In the next section, I use commodity price indices from section 3.3.3 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 3.3.4.

Structural breaks Previous studies discuss that estimates of the output gap from different methods can be susceptible to accounting for structural breaks (Perron and Wada, 2016; Kamber et al., 2018). 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 3-B.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.

3.4 Model assessment

3.4.1 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 (Camba-Mendez and Rodriguez-Palenzuela, 2003; Álvarez and Correa-López, 2020). 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

$$\pi_{t+m}^m = \alpha + \sum_{i=1}^{n} \beta_i \pi_{t-i}^1 + \sum_{j=1}^{h} \gamma_j y_{t-j} + e_{t+m}, \tag{3-D.13}$$

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 by using ordinary least squares (OLS).

The estimation of equation 3-D.13 and the inflation forecasting process are explained below. To forecast inflation (out-of-sample data) for each quarter, I use the estimates obtained

[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.

from equation 3-D.13 (in-sample data). To estimate equation 3-D.13, 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 3-D.13. Then, I use these estimates for the forty-eight-quarter-ahead forecast of inflation at 2006Q1, 2006Q2, 2006Q3, 2006Q4 to 2018Q1.

I consider equation 3-D.13 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 3.3.4) 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:

$$MSFE = \frac{(i\hat{n}f - inf)_t^2 + ... + (i\hat{n}f - inf)_{t-48}^2}{49}. \tag{3-D.14}$$

After using these specifications to forecast inflation, I use equation 3-D.14 to save the MSFEs from each regression. Table 3-3 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.

3.4.2 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 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

$$|DM| > z_{\alpha/2}, \tag{3-D.15}$$

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

Table 3-3: Mean squared forecasting error in equation 3-D.13

	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.

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 3-4 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 3.3.4. 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 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

Table 3-4: 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.

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 3-D.13 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 3-D.13 (model 4), and BP-filtered output with past inflation (model 5). Lastly, I assume equation 3-D.13 without the output gap to forecast inflation; this is referred to as an autoregressive model (AR) (model 6). Table 3-A.2 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.

3.5 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 et al., 2000; Smets, 2002; Walsh, 2003; Svensson, 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, 2008b). 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.

3-A Appendix

Table 3-A.1: 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 3-A.2: 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.

Figure 3-A.1: Output trend and output for advanced economies

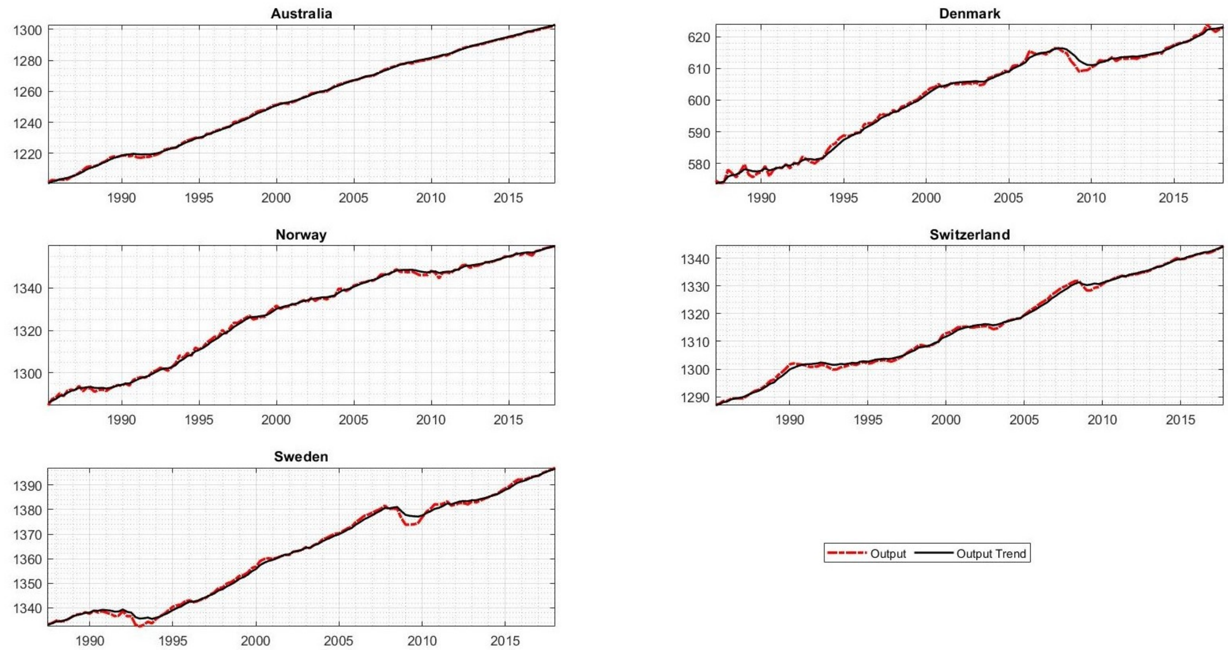


Figure 3-A.2: Output trends and output for emerging economies (1)

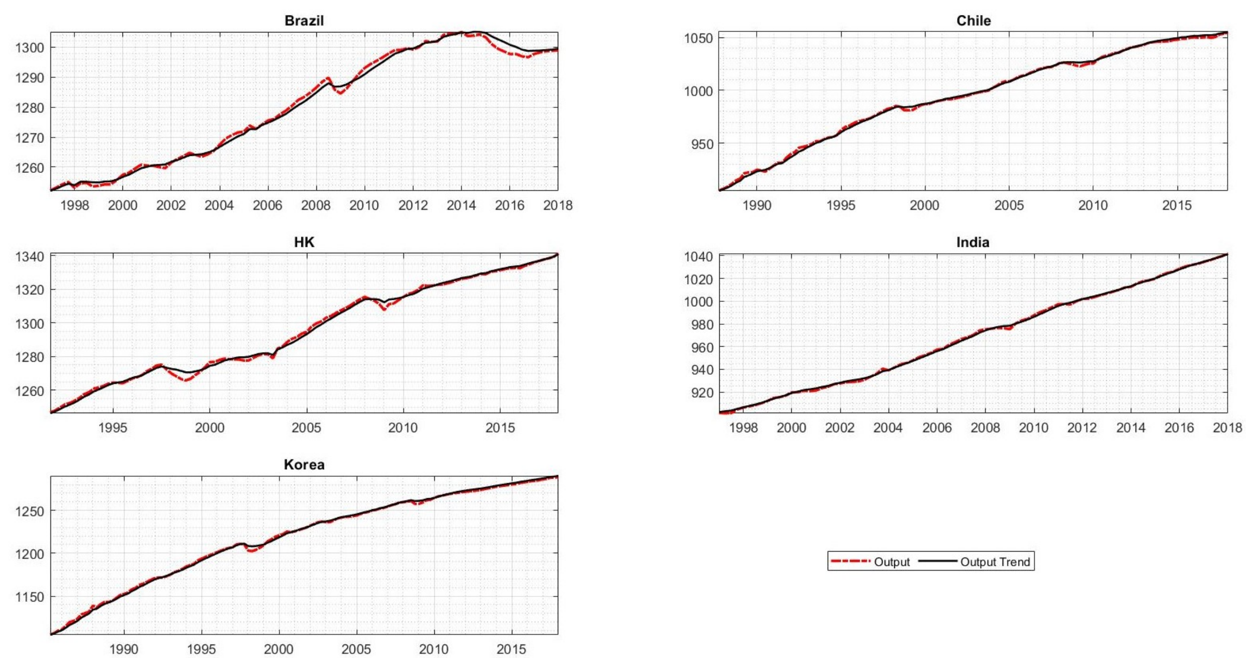


Figure 3-A.3: Output trends and output for emerging economies (2)

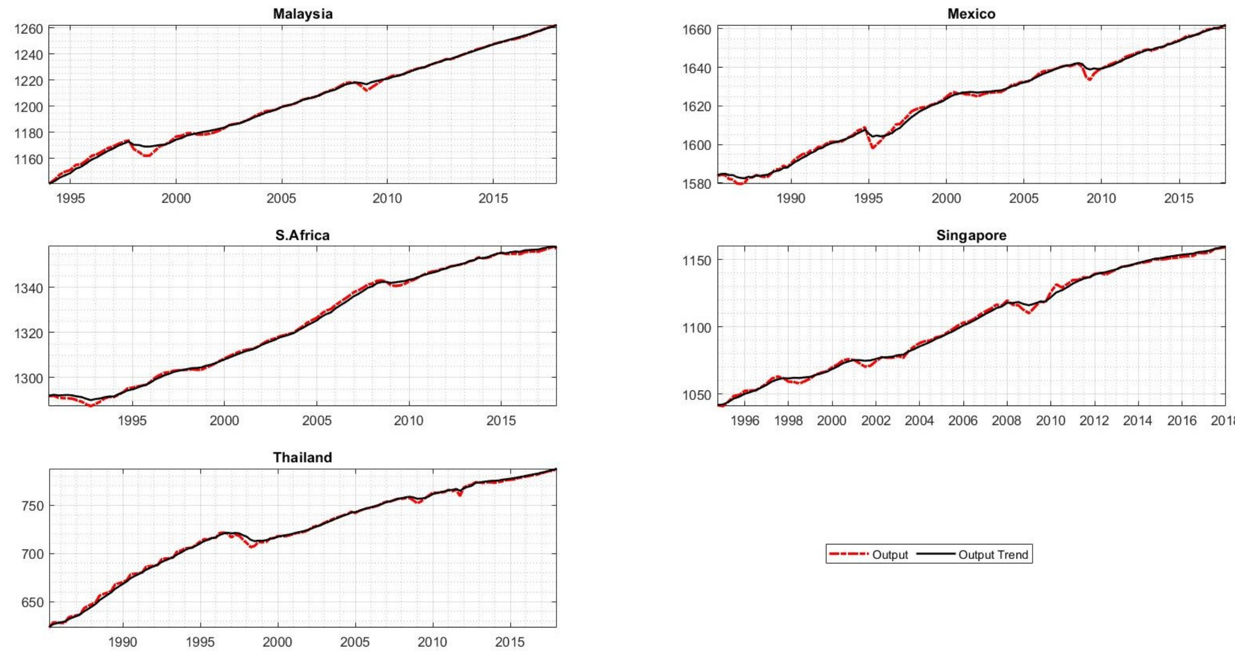


Figure 3-A.4: Robustness checks on the output gap for advanced economies

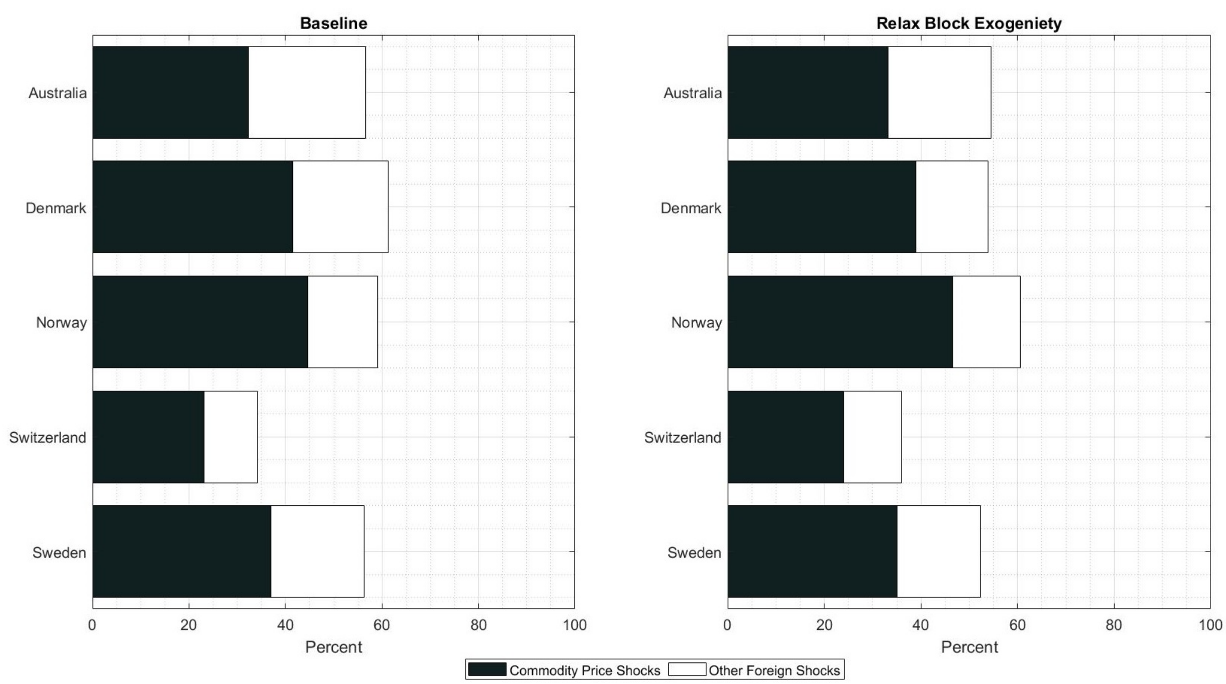


Figure 3-A.5: Robustness checks on the output gap for emerging economies (1)

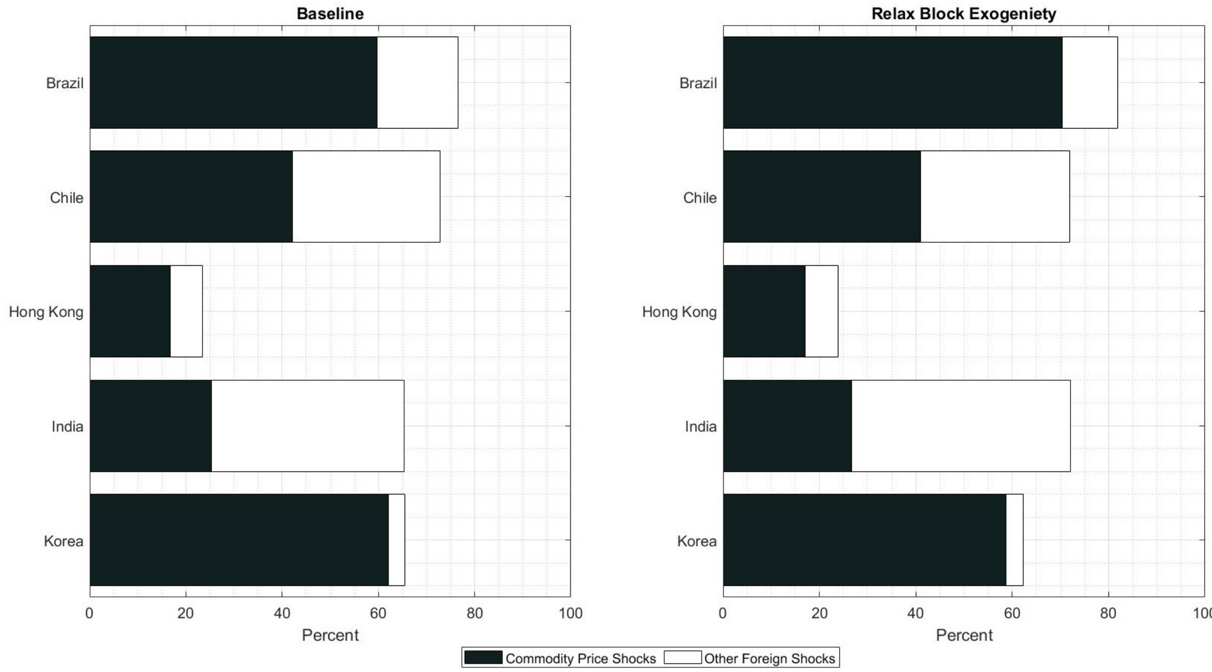


Figure 3-A.6: Robustness checks on the output gap for emerging economies (2)

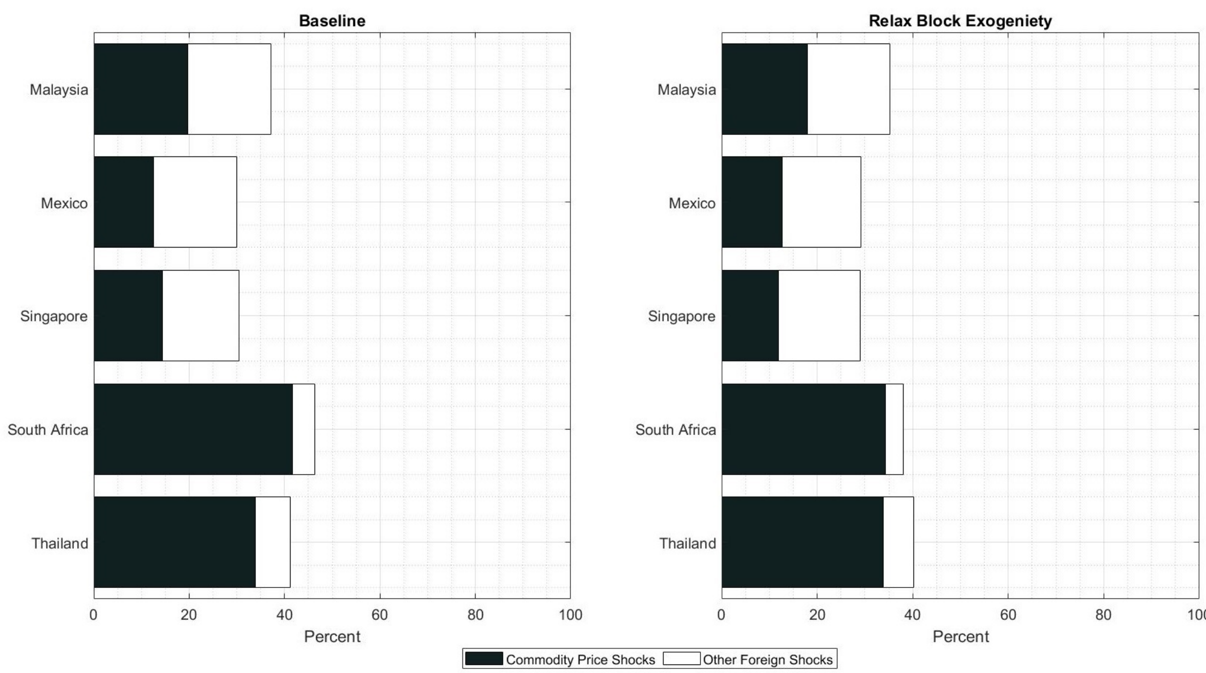


Figure 3-A.7: Robustness checks on the output trend for advanced economies

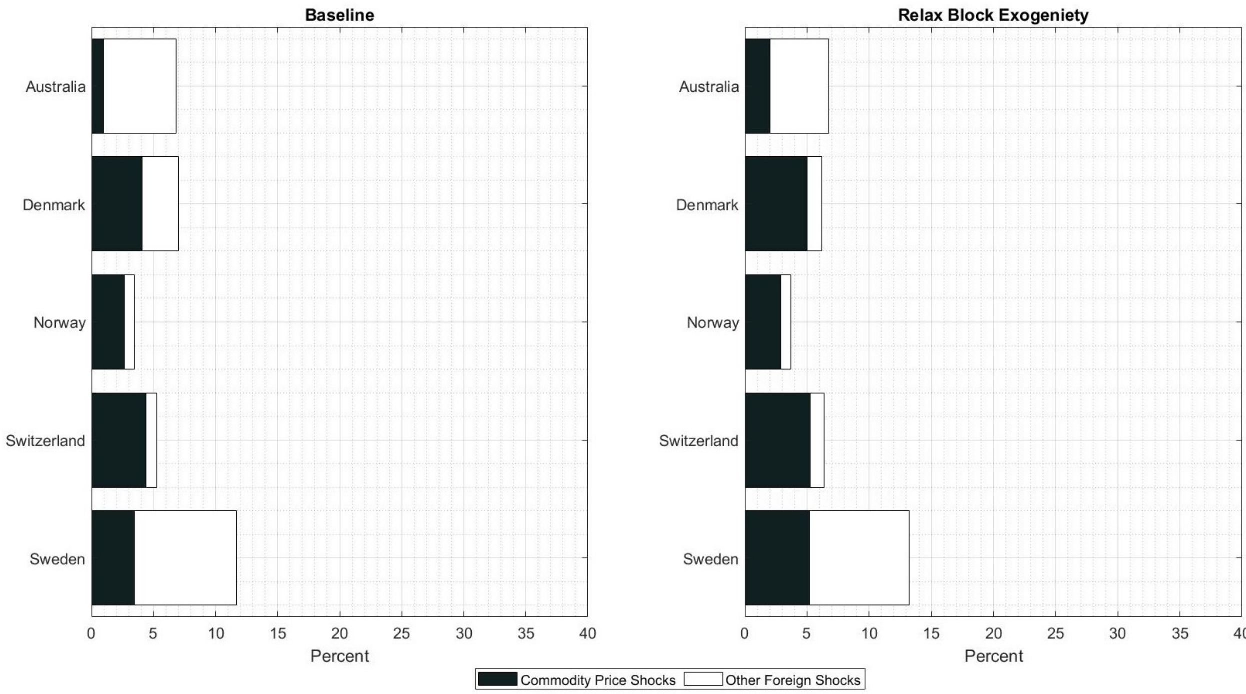


Figure 3-A.8: Robustness checks on the output trend for emerging economies (1)

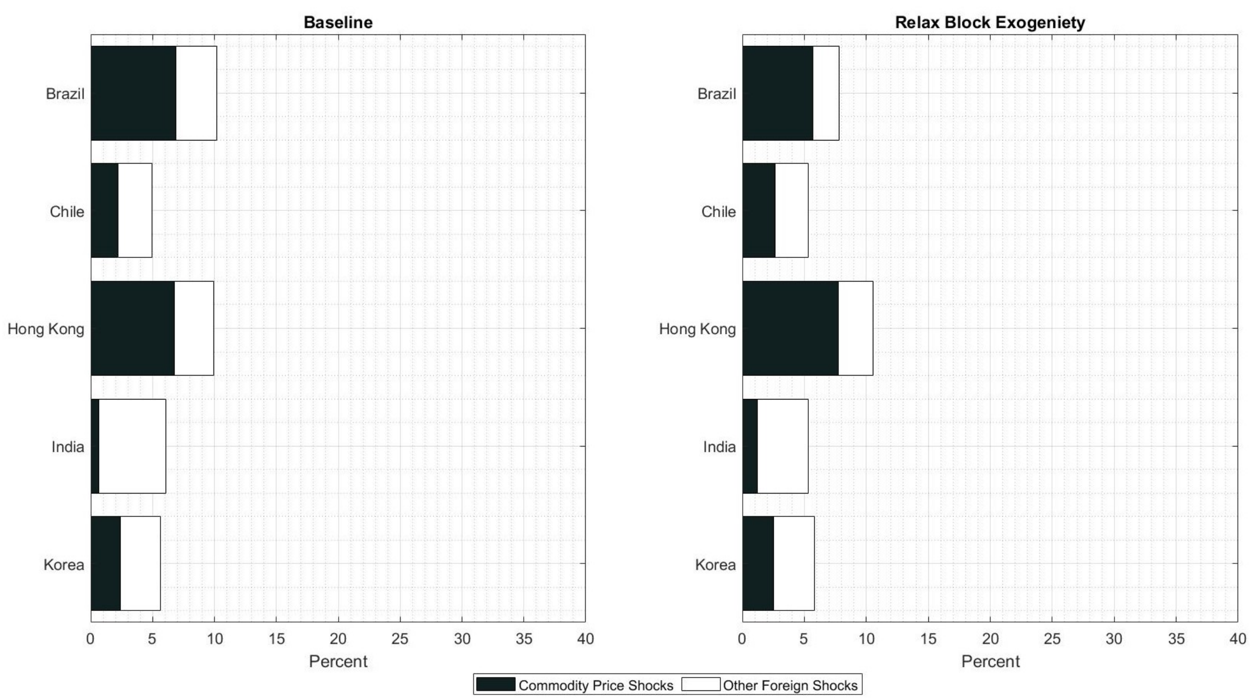
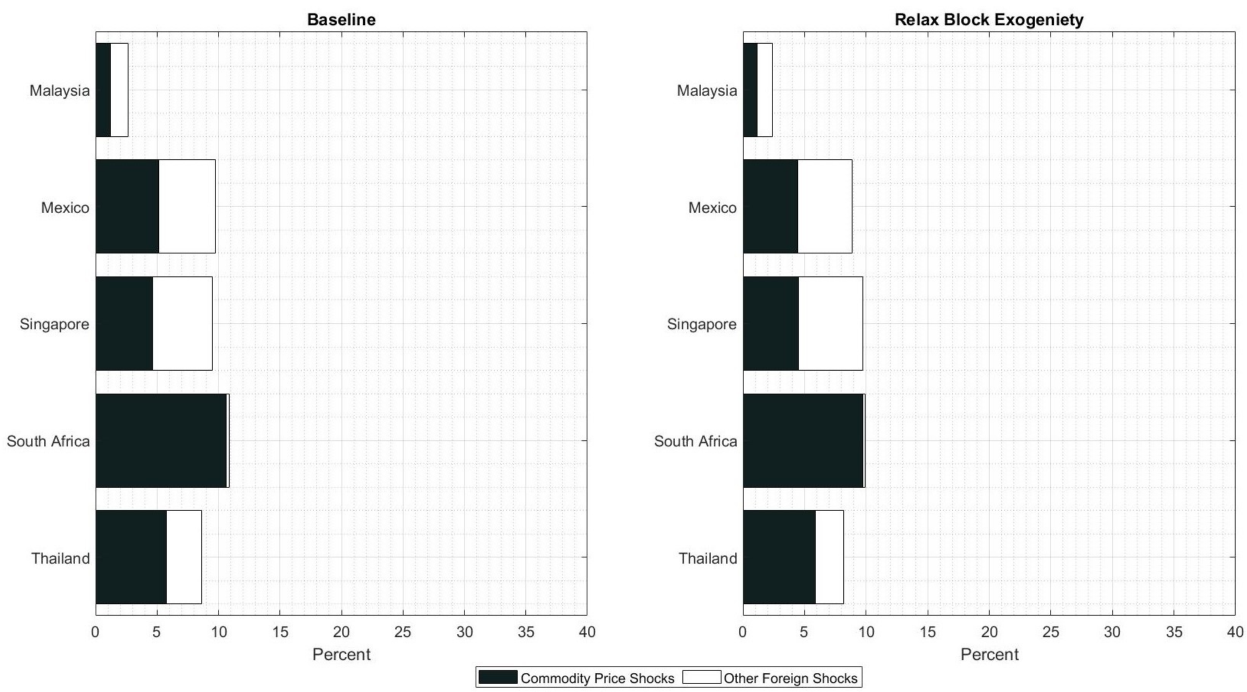


Figure 3-A.9: Robustness checks on the output trend for emerging economies (2)



Appendix B

Output gap computation In this section, I briefly explain how the output gap is computed in equation 3-B.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 3-B.3 into equations 3-B.4 and 3-B.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 3-B.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,

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

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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