The Relationship Between Commodity Prices and Australia's Gross Domestic Income

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Statement of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no material previously published or written by another person. Nor does it contain any material which has been accepted for the award of any other degree or diploma at the University of Sydney or at any other educational institution, except where due acknowledgment is made in this thesis.

Any contributions made to the research by others with whom I have had the benefit of working at the University of Sydney is explicitly acknowledged.

I also declare that the intellectual content of this study is the product of my own work and research, except to the extent that assistance from others in the project's conception and design is acknowledged.

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5 November 2022

Acknowledgments

I would like to thank my supervisors, Dr. Luke Hartigan and Dr. Mariano Kulish who have selflessly devoted hours of their own time over the past year guiding me through this thesis. The insights and recommendations they have offered have been crucial to the formation of my work, and I can say without a doubt this would not have been possible without both of them.
I would also like to extend my thanks to the broader USYD School of Economics teaching staff for taking the time to provide invaluable feedback on my thesis proposal.

Abstract:

Commodities dominate Australia's export composition. To this effect, there is a plausible relationship between commodity prices and the prosperity of Australians. Gross domestic income is chosen as a proxy for prosperity given it is better able to capture purchasing power than gross domestic product in the Australian context. Using a discrete wavelet transformation, the commodity price series is decomposed into a trend and cycle component. Following, I run a series of structural vector autoregressions for the period 1985:Q4 to 2019:Q4, as well as two sub-samples, pre and post mid-2003, in view of the increase in price and variance of commodity prices at this time. I find that both the trend and cycle components of commodity prices meaningfully impact GDI primarily via gross operating surplus, while GDP is unaffected. Although a shock to the cycle component of the commodity price series has a larger effect on GDI when compared to the trend, the impact of the trend is far more persistent. Further, for the pre mid-2003 sub-sample, commodity price changes have no discernable impact on GDI, as opposed to the post mid-2003 sample where a noticeably strong relationship exists.

Contents

1. Introduction

Donald Horne (1964) was the first to call Australia 'the lucky country'. While Horne's description was meant as a disparaging characterisation of Australia's leadership, one enduring interpretation is that Australia is lucky in the sense that its prosperity is generated by the sheer luck of its natural endowments. But is this interpretation fair? Using Gross Domestic Income (GDI) as a proxy for prosperity, I define my research question as 'the extent to which commodity price changes predict Australia's Gross Domestic income'. I select GDI as the focal metric as it is a measure of purchasing power and is influenced to a greater extent than GDP by commodity price movements for commodity-exporting countries. This sensitivity to commodity prices is due to the fact that higher export prices for commodities will result in an increase in nominal export earnings, thus appreciating the terms of trade. Subsequently, purchasing power increases while the level of real output remains unchanged, a result that GDI can capture. Indeed, Kohli (2004) claims "Real GDP was found to underestimate the growth in real domestic income in a majority of the countries in our sample… due to the improvements in the terms of trade that these countries have experienced" (Kohli, 2004, p. 102). While in theory GDI and GDP should be equal, Australian GDI and GDP are not perfectly correlated (Figures 1 and 2). It is thus expected that GDI will demonstrate a stronger response to commodity price shocks, than GDP, a claim which warrants a comparison between the two throughout the forthcoming analysis. GDI, is, however, a conglomeration of its four component elements. The first and largest of these is the compensation of employees, which accounts for the total remuneration, in cash or in kind, payable by an enterprise to an employee in return for work done by the latter during the accounting period (wages and salaries). The second component of GDI is gross operating surplus, which is the income from [the] production of corporate enterprises and is the second largest in value. The third is gross mixed income which is the income from the production of unincorporated enterprises (such as sole traders) and is on average the smallest in value. The fourth component of GDI is taxes less subsidies on production and imports. Taxes encompass those that are payable on goods and services, and taxes and duties on imports. Additional items included as taxes are those related to the payroll or workforce, recurrent taxes on land, buildings, or other structures, some business and professional licences, taxes on the use of fixed assets, taxes on pollution, and taxes on international financial transactions. Subsidies on the other hand encompass unrequited payments that government units make to resident producers or importers (Australian Bureau of Statistics, 2021). Given the capital intensity of commodity extraction, the response of gross operating surplus is of particular importance as it encapsulates the income earned on capital owned by large enterprises.

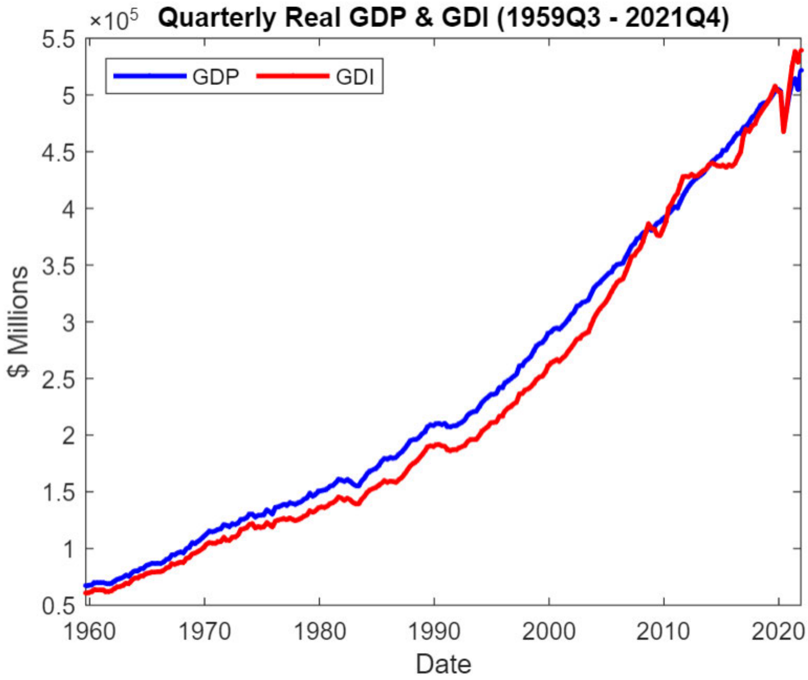


Figure 1

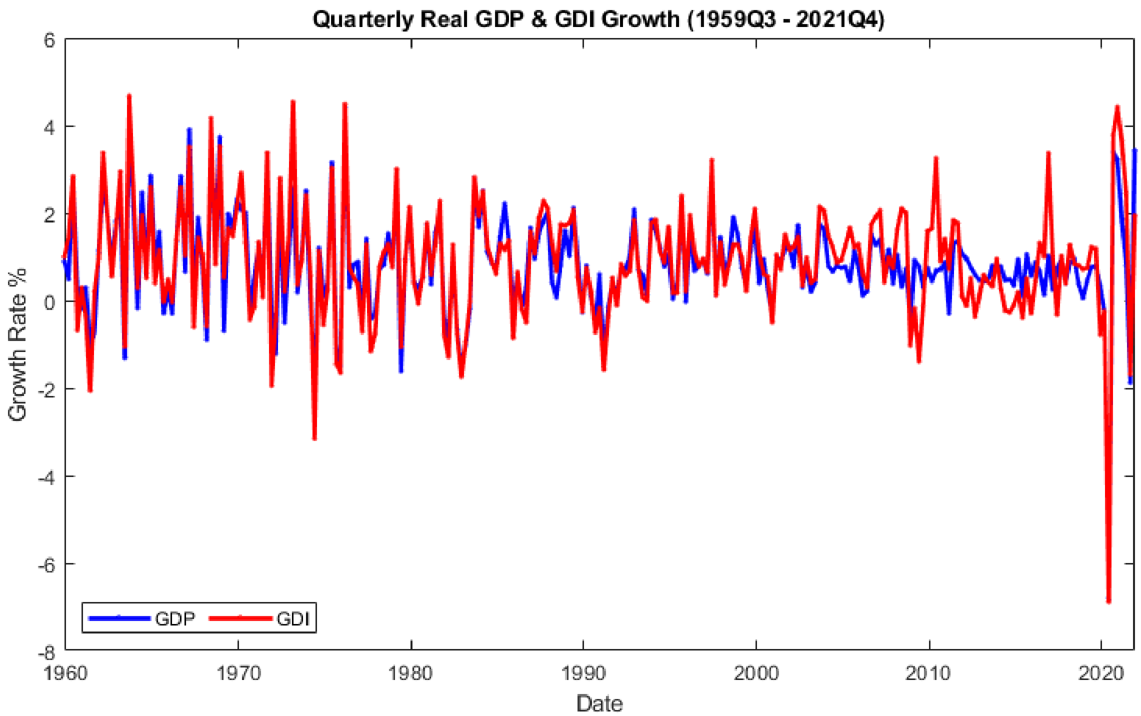


Figure 2

Broad data-based insights into the Australian economy validate a potential relationship between the focal variables proposed for study. The Reserve Bank of Australia (RBA) states "Australia is a relatively open, trade-exposed economy. This means that changes in other countries' demand for our goods and services can have significant implications for our economy" (Reserve Bank of Australia, n.d.). In the 2019-2020 financial year, Minerals and Fuels, Rural products, and Gold made up 67% of Australia's export value (Department of Foreign Affairs and Trade, 2021). Changes to demand (and prices) for commodities are then likely to have widespread economic consequences for Australia. Indeed, the rise in the Terms of Trade in the early 2010s generated by increased prices for Australian commodities caused increased investment into the mining sector, increased wages, increased profits, and increased government revenue, as well as decreased unemployment (Reserve Bank of Australia, n.d.; Gruen, 2011). An important aspect to consider when dealing with commodity prices is the differences in the permanent and transitory components of the series. In mid-2003 commodity prices saw a large and permanent increase in nominal value alongside increased volatility, as shown in Figure 3 (Kulish & Rees, 2017). As such, decomposing the analysis into pre and post mid-2003 samples, alongside a discussion of the permanent and transitory components of the commodity price series is likely to prove insightful.

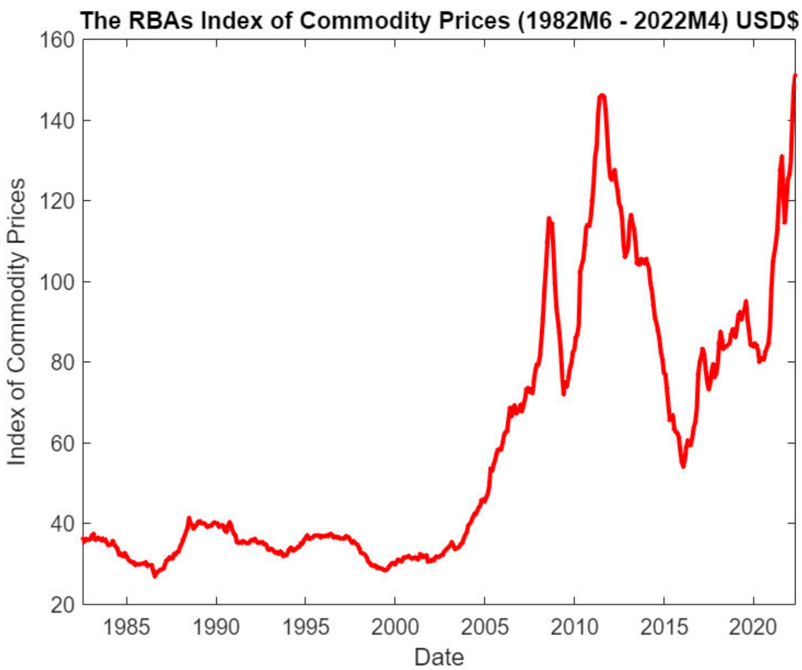


Figure 3

To complete the permanent and transitory decomposition of the commodity price series, I employ the RBAs index of commodity prices (ICP) series that has had the Discrete Wavelet Transform (DWT) applied to it. A non-parametric approach, DWT filters a series into different frequencies which can be labeled as a short-term, business cycle, medium-term, and long-term component, that can be subsequently aggregated to form the cycle and trend. To explore the relationships of interest, I use a recursive small macro model SVAR. An extension of the standard VAR model, the SVAR importantly allows for the isolation of purely exogenous shocks, thereby permitting the identification of the dynamic effects of interest.

The importance of the following discussion and subsequent results is two-fold. This thesis expands upon the scarce existing literature that explores the interactions of GDI within an Australian context. Specifically, the forthcoming analysis explores a key determinant of GDI for Australia and the scale to which GDI responds to relevant shocks. While contributing to the literature, it is perhaps the practical application of the results through policymaking, which provides them with the most importance. By understanding the persistence, degree, and avenue by which commodity prices influence Australia's GDI, policymakers are better able to manage the economy and mitigate risk through improved forecasts. Policymakers may also be better prepared to capture the gains to incomes resulting from commodity price shocks through the creation of taxation policies that target the component of GDI where the gains are concentrated.

This thesis will begin with a literature review exploring works on commodity prices, their features and role in the economy, GDI, and the various models I employ. I will then introduce the data I worked with and the models and their variations to which I apply this data. I will present the results for the whole sample, as well as both the pre and post mid-2003 sub-samples, before ending with a discussion and conclusion. I find that commodity prices meaningfully impact GDI, with the response of GDI differing to a shock to either the trend or cycle component of the ICP, as well as across sub-samples.

2. Literature Review

The relationship between commodity prices and the macroeconomy has long been explored in the literature. Notably, however, discussions on GDI are lacking but do exist, even if not to the magnitude of GDP. Importantly, the literature on the models I intend to use, both the discrete wavelet transform and SVAR is solid and in the case of the latter extends to the Australian context. Nevertheless, the opportunity for research is vast, meaning there remain many vacant avenues for exploration. To begin, Ge and Tang (2020) introduce the importance of understanding commodity prices and their impact on the broader economy stating commodities are an important factor within the economy given they are used "for industrial production and… [are] necessary consumption goods for daily life" (Ge & Tang, 2020, p. 1). They find a significant relationship between commodity prices and GDP. Specifically, they find for developed countries, commodity returns can predict GDP growth at the 1% significance level. That is, commodity booms and busts correspond tightly with the economic cycle. Ge and Tang's work also takes a different approach to the approach taken here by decomposing commodity price changes into supply and demand-driven shocks. Downes, Hanslow and Tulip (2014) have done extensive work specifically on Australia's mining boom. Their work provides foundational insight into the interaction of the Australian economy and its commodities sector. Importantly, they assert the mining boom resulted in a rise in living standards. Their findings include, by 2013, a rise in disposable income per capita of about 13%, an increase in real wages of 6%, and lowered unemployment by 1.25% compared to the counterfactual. Interestingly concerning domestic income and subsequently my research question, they struggle to define the extent to which the profits of commodity producers accrue to foreigners.

Kulish and Rees (2017) explore a highly relevant phenomenon in Australian commodity prices. They decompose the fluctuations in commodity prices into a permanent and a transitory component and conclude that the long-run level of Australia's commodity prices increased permanently by around 40% in mid-2003 and that the volatility of shocks "more than doubled" shortly after this period (Kulish & Rees, 2017, p. 352) . This significant finding in the behaviour and price level of Australian commodities is a crucial element to consider when modelling the impact of commodity price changes on Australia's GDI and is a guide for furthering the existing literature. Baffes and Kabundi (2021) delve deeper into the permanent and transitory distinction of commodity prices by applying an ideal band pass filter to a variety of commodity price series. They assert transitory shocks may originate from several sources, including recession, ad hoc policy measures, weather conditions, accidents, conflicts, and terrorist attacks. On the other hand, technology and policy shocks typically have a more permanent effect. They find permanent shocks have an upward trend for most industrial commodities and a downward trend for agricultural commodities. On average, though, permanent shocks account for less than half of price variability, with the remainder, 33% attributed to the medium-term price cycle, 17% to the business cycle, and only 4% due to purely short-term fluctuations. Dehn (2000) steps away from the permanent and transitory distinction of commodity shocks and pays significant heed to the broader policy implications of commodity price shocks. For governments of developing economies, he finds unforeseen shocks to commodity prices can complicate budgetary planning and make meeting debt targets challenging. For exporters, commodity price shocks increase cash flow variability and reduce the collateral value of inventories, both of which increase borrowing costs. The author goes on to note five key policy errors that lead to a failure to capture the gains to incomes as generated by positive commodity price shocks in primary producing developing countries. The first is that the windfall is simply not saved, with the second error much similar in that when the windfall is saved, it is quickly spent. Third, windfall spending on capital projects typically occurs while the boom generated by the positive shock to commodity prices is still ongoing. This means domestic prices are still elevated, reducing their efficiency. Fourth, governments of developing countries often channel windfalls into low-return projects motivated by political rather than economic gain. Finally, governments typically exit the boom period with large fiscal deficits after attempting to capture the shock which must be financed by extracting taxes from the private sector post-boom. While tangential to Australia, these results still highlight pitfalls to be aware of.

The importance of GDI, while often ignored, is present in a small sample of the literature. Although there has been no direct exploration of the impact of commodity price changes on GDI, Macdonald (2010) investigates the evolution of GDI in OECD countries. Macdonald rationalises the use of GDI, stating it is a measure of purchasing power, and finds the change in the terms of trade is the most significant variable influencing GDI in developed countries. The significant influence of commodity price shocks on the terms of trade in the Australian context thus indicates the ability of commodity prices to influence GDI. Confirming this sentiment, Macdonald concludes "When commodity prices weakened, real GDI per capita performed… poorly relative to real GDP per capita in Australia" (Macdonald, 2010, p. 511). Building upon this finding, Macdonald remarks that commodity price cycles have been a source of real income fluctuations but does not elaborate on this point, signalling a potential extension of the literature. The preliminary relationship Macdonald finds is of direct consequence to my research question. In defence of GDI as a metric for use over GDP, Kohli (2004) finds real GDP tends to underestimate the growth in real domestic incomes. While employing his own construction for real domestic incomes as opposed to GDI, his findings remain relevant. For Australia specifically, real GDP underestimated growth in real domestic income in the period 1980–1996, if only marginally, due presumably to the appreciation in the terms of trade. The author rationalises, however, that this small discrepancy is not trivial when discussing the value of entire economies. The literature review thus far, while useful, has not covered the empirical strategy used in dissecting the focal relationship.

To extract the permanent and transitory elements of the commodity price series, I choose to employ the DWT. Matthes, Lubik and Verona (2019) decompose various US macroeconomic series using the DWT. They state the DWT separates the original series into different time series components, with these representing fluctuations within a specific frequency band. They identify four groups in their paper. The first is the short-term which captures high-frequency fluctuations of two years or less. The next group they identify is the business cycle, which captures fluctuations at frequencies of between 2 and 8 years. Medium-term fluctuations cover frequencies up to 32 years, while long-term fluctuations are those frequencies in excess of 32 years. They find this approach performs similarly to the one and two-sided Haar and Daubechies filters while performing significantly differently to Christiano and Fitzgerald, and Hodrick-Prescott filters. Canova (2019) comments on the DWT, stating it has some advantages over bandpass filters as they work in the time domain, and their MA representation is finite. He goes on to claim the smaller approximation error of the wavelet transform means it performs better than bandpass filters when extracting the transitory and gap components of an economic series simultaneously. He also claims that commonly used unobserved components models are "competitive only in terms of real time MSE", and for all other statistics, are typically inferior to other decomposition methods (Canova, 2019, p. 16). A different type of model is, however, necessary to capture the focal relationship explored in this thesis. An SVAR model specification is the best candidate for this purpose. The work of Dungey and Pagan (2009) provides an example of the construction of an SVAR for a small open economy - Australia. They state that the SVAR model is a useful tool for analysing the macroeconomy given its ability to establish empirical relationships in the framework of theoretical understandings. Their paper works with both permanent and transitory shocks, providing initial intuition regarding the process for integrating these shocks into my model. An aside mentioned within the paper is that rational expectations may not be empirically supported within empirical models due to complex dynamics and the abundance of variables influencing focal variables. This discussion of existing literature thus serves to inform the theoretical validity of my research question and provide guidance on the core conceptual issues to note and further develop throughout my thesis.

3. Methods and Procedures

3.1 Data

The primary data set I employ to track the level of commodity prices is the RBA's monthly index of commodity prices. I chose this dataset as the RBA states "The ICP is intended to provide a timely indicator of the prices received by Australian commodity exporters" (Reserve Bank of Australia, 2013, p. 23). Being an index it captures a desirable property whereby commodities are weighted by their importance in terms of export value. Figure 4 highlights this fact, with the index closely tracking the value of Australia's two most important commodities, iron, and coal, which together accounted for a third of all of Australia's exports in 2020 (Department of Foreign Affairs and Trade, 2021). Using an index will allow me to include the movements of a multitude of commodity price series of importance to Australia without having to work with these series individually. This is inclusive of energy prices which are implicit in the index with crude oil making up 2.7% of the index's value, and LNG 14.3% (Reserve Bank of Australia, 2022). The ICP, is, however, a monthly series, while the rest of the series used in this thesis are quarterly. As such, once all manipulations to the ICP were complete, I averaged it over the three months that compose a quarter. While this approach leads to a potential loss of information, it is both easily understood, and implemented, and makes some attempt to include the entirety of the information contained in the series. I proceed with the first difference of the ICP and its trend component to ensure stationarity. The cycle component does not require differencing.

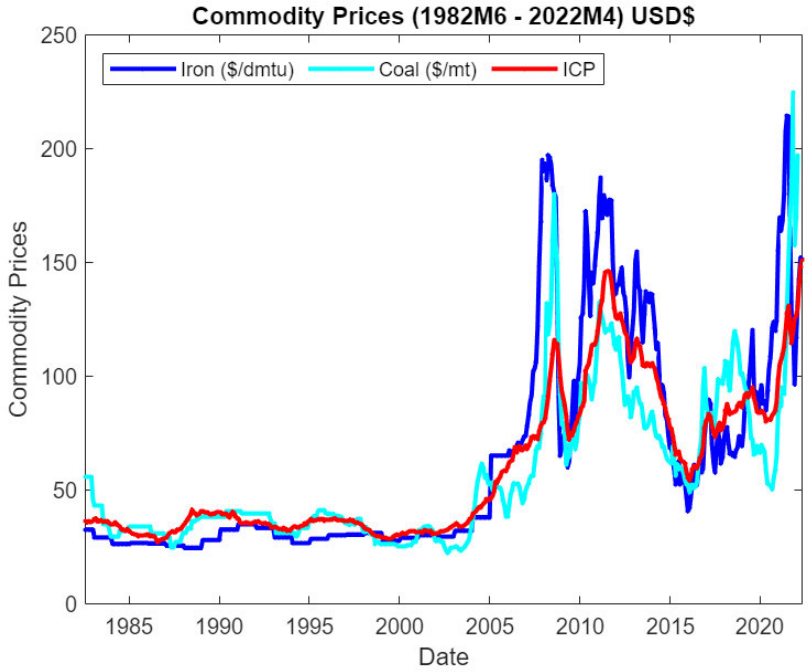


Figure 4

To capture global demand, I use the seasonally adjusted chained volume measure of US GDP as sourced from the FRED database. The US being the largest economy globally is a satisfactory proxy for global demand trends. For GDI and GDP, I use ABS seasonally adjusted chain volume measures. For the component elements of GDI, compensation of employees (COE), gross operating surplus (GOS), gross mixed income (GMI), and taxes less subsidies on production and imports (TLS), I use the seasonally adjusted original series. The ABS does not provide chained volume measures for these series. As such, I manually apply the ABS chain price index for GDP to each series to construct the series in real terms and remove the effects of price changes over time. I express these series in growth rates to ensure stationarity. The chain price index being the shortest dataset sets the sample size for the forthcoming analysis. The first data entry is 1985:Q4. I prematurely end my analysis in 2019:Q4 to remove the complexities involved with working with Covid-19 pandemic-related data. Important to note, as shown in Figure 3 and defined by Kulish and Rees (2017), commodity prices saw a large and permanent increase in mid-2003. This finding rationalises the splitting of the sample into pre and post mid-2003 sub-samples for analysis going forward.

3.2 Models

Discrete Wavelet Transform

To pull the trend and cycle components from the commodity price series, I employ the discrete wavelet transform. As stated by Matthes et al., (2019) DWT decomposes an economic series into a trend, a cycle, and a noise component. The approach of a DWT is similar to the application of a Bandpass filter, in that the series is filtered based on frequency. Following the specification in Matthes et al., (2019), any economic series may be decomposed as

$$X_t = \sum_{j=1}^{J} D_{j,t} + S_{J,t}$$

In which X_t is the economic series of interest, $D_{j,\,t}$ are the wavelet coefficients at scale j, and $S_{J,\,t}$ is the scaling coefficient. The latter two coefficients are defined as:

$$D_{j,t} = \frac{1}{2^j}\left(\sum_{i=0}^{2^{j-1}-1} X_{t-i} - \sum_{i=2^{j-1}}^{2^{j-1}} X_{t-i}\right)$$

$$S_{J,t} = \frac{1}{2^J}\sum_{i=0}^{2^J-1} X_{t-i}$$

The wavelet coefficients as interpreted by Matthes et al., (2019) are the components of the economic series with different levels of persistence across time, operating at different frequencies. The scaling coefficient is the low-frequency trend of the series. As j increases, the decomposition captures lower frequency fluctuations in the series, i.e., more persistent cycles. It is thus possible to decompose the ICP into four components. Summing the results of scale coefficients 1 and 2 for monthly data produces the short-term component which captures fluctuations of two years or less. Summing the results of scale coefficients 3 and 4 produces the business cycle which captures persistent cycles of between 2 and 8 years. The medium-term component captures fluctuations of up to 32 years by summing the results of scaling coefficients 5 and 6. Finally, the long-term component, which captures fluctuations in excess of 32 years, uses scale coefficient S. To pull the cycle and trend from the commodity price series, I combine the short-term and business cycle components to form the cycle, and the medium-term and long-term components to form the trend (Figure 5). This approach corresponds to definitions of trends and cycles as constructed using parameter methods.

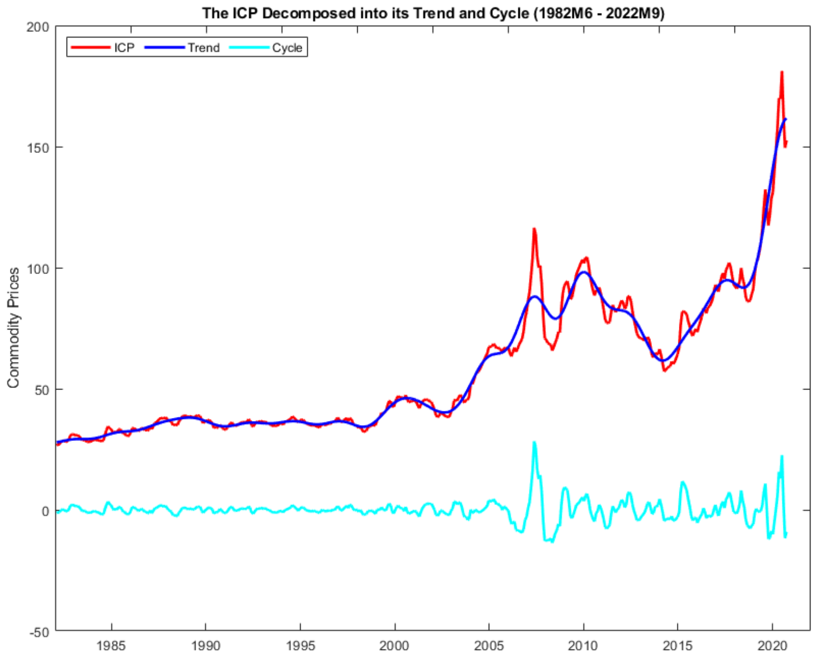


Figure 5

With a finite amount of data, all filters generate distortions and leakages over other frequencies (Canova, 2019). Further, being nonparametric, the DWT does not provide any structure or method for interpreting the results obtained. Despite these criticisms, the DWT remains a strong candidate for the decomposition of the commodity price series as other choices including unobserved components models and the Butterworth filter proved problematic and were unable to adequately decompose the series. Moreover, Matthes et al., (2019) find the DWT approach to perform relatively well when matched against other filter types.

SVAR

To explore the focal relationship proposed in this thesis, I employ an SVAR model. An SVAR is an extension of the standard VAR model in which the current value of a variable is explained by its own lags, the current values of the other variables in the system, and their lags. It builds upon the standard VAR model by postulating that structural shocks induce unanticipated movements in the variables. This feature is central to the rationale for choosing to employ an SVAR model. The identification of the structural model allows for an understanding of the dynamic effect of purely exogenous shocks. This is important given the endogenous nature of GDI and commodity prices. With regard to the research question, it is not unlikely that commodity-extracting enterprises invest in capital in response to past shocks, endogenously increasing exposure to current shocks. Alternatively, commodity-extracting enterprises may respond speculatively to unrealised commodity price shocks given past shocks by expanding employment or encouraging investment in capital, which again increases the exposure of GDI to current shocks. This is not the effect that this thesis seeks to explore, and the one which the standard VAR answers. Rather, this thesis seeks to understand the impact of a one-time exogenous shock to commodity prices on GDI and its component elements.

Given the correlation between the shocks due to the contemporaneous correlations between the variables in a standard VAR, to recover the structural shocks the SVAR permits each variable in the system to depend on the contemporaneous values of the other variables. This condition, however, creates a new problem, whereby structural (simultaneous) equations must be estimated, which requires restrictions. This process of identification involves restrictions on the contemporaneous impacts of the variables across the model, as well as specifying the shocks as being uncorrelated (Ouliaris et al., 2018). The restrictions I employ for my SVARs looking at GDI and GDP follow that of the Recursive Small Macro Model set out in Ouliaris, Pagan and Restrepo (2018). The recursive structure defines a lower-triangular matrix, A_0, and the structural shocks as being uncorrelated via matrix B. These two restrictions suggest the numerical method for estimating the recursive system is the Cholesky decomposition. This is to say, the variables further up the matrix contemporaneously influence those below it, but the reverse is not true. I order the more ‘exogenous’ internationally influenced variables (the ICP and its decomposition, and US GDP) above the domestic variables (GDI, GDP, and the components of GDI). Broadly, I run the SVAR:

$$A_0 z_t = A_1 z_{t-1} + \ldots + A_p z_{t-p} + B\eta_t$$

With restriction matrices:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 & 0 \\ \dots & \dots & 0 & 0 \\ \dots & \dots & \dots & 0 \\ \dots & \dots & \dots & a_{0,\text{mn}} \end{bmatrix} \quad B = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \sigma_m \end{bmatrix}$$

A complete specification of the SVARs I run is available in appendix A.2. The AIC indicated 2 lags were optimal for my baseline models, SVAR 1 and 2. Subsequently, I run all the following models with 2 lags for the sake of comparison to this baseline. As a robustness check, I re-run the SVARs that include the components of GDI and specify the component elements as having no contemporaneous relationship. The p-value for the over-identified restriction for the model which does not decompose the ICP is 0.22. That is, I fail to reject the null that the data supports this restriction. For the model over the whole sample which decomposes the ICP, the over-identified restriction has a p-value of 0.21. For the pre mid-2003 sample, the p-value is 0.04, meaning I reject the null that the data supports this restriction. For the post mid-2003 sample, the p-value is 0.12. While Lawson and Rees (2008) rationalsie this restriction and it is supported across the majority of samples, I leave it as a robustness check.

4. Results

4.1 Whole Sample (1985:Q4 - 2019:Q4)

Commodity Prices, Global Demand, and GDI/GDP (SVAR 1 & 2)

To begin, I present the key finding of the 3 variable SVAR, both with GDI and GDP in growth rates. Within the IRFs the suffix G signifies growth rates, while the suffixes T and C are the trend and cycle respectively. The dashed lines are representative of a 95% confidence interval.

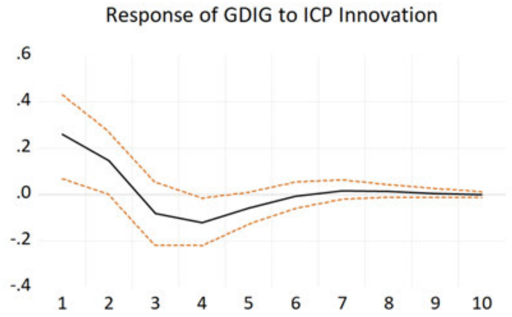


Figure 6 - Impulse response of GDI growth to a one standard deviation shock to the ICP

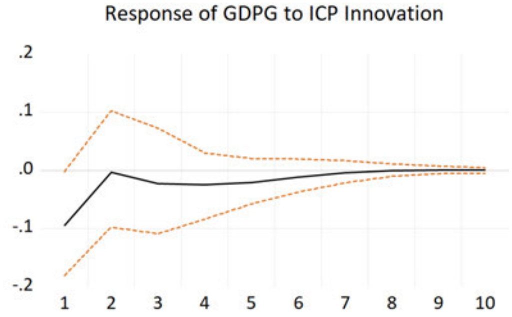


Figure 7 - Impulse response of GDP growth to a one standard deviation shock to the ICP

In response to a one standard deviation shock to the ICP, GDI growth is shown to increase by around 30% of a standard deviation, before briefly turning negative in the 4th period post the shock. This finding is interesting when contrasted with the response of GDP. In response to the same shock, GDP growth falls by 10% of a standard deviation in the first period post-shock, but, within a 95% confidence interval, has no response post this period. Both responses are transitory in nature. A variance decomposition shows that on average, commodity prices determine ~13.4% of GDI growth over 10 periods (See Appendix A.4 for variance decompositions). In comparison, the variance decomposition for GDP growth shows on average, commodity prices determine only ~2.6% of its value over 10 periods. These preliminary results are important in two ways. Foremostly, they highlight that a meaningful relationship between commodity prices and GDI does in fact exist. When commodity prices increase, GDI growth correspondingly increases, at least initially. Secondly, these results rationalise the choice to examine GDI as the focal variable over GDP. Indeed, the response of GDP to a commodity price shock is negligible. This response (or lack thereof) is likely due to the change in the terms of trade, which, ceteris paribus, does not change the real output of the economy as production is predetermined by technical factors (Reserve Bank of Australia, 2005). As such, GDP is unable to capture the change in incomes, or prosperity, generated by the rise in commodity prices within a commodity-exporting economy.

Commodity Prices, Global Demand, and the Components of GDI (SVAR 3)

I then run an SVAR with the component elements of GDI.

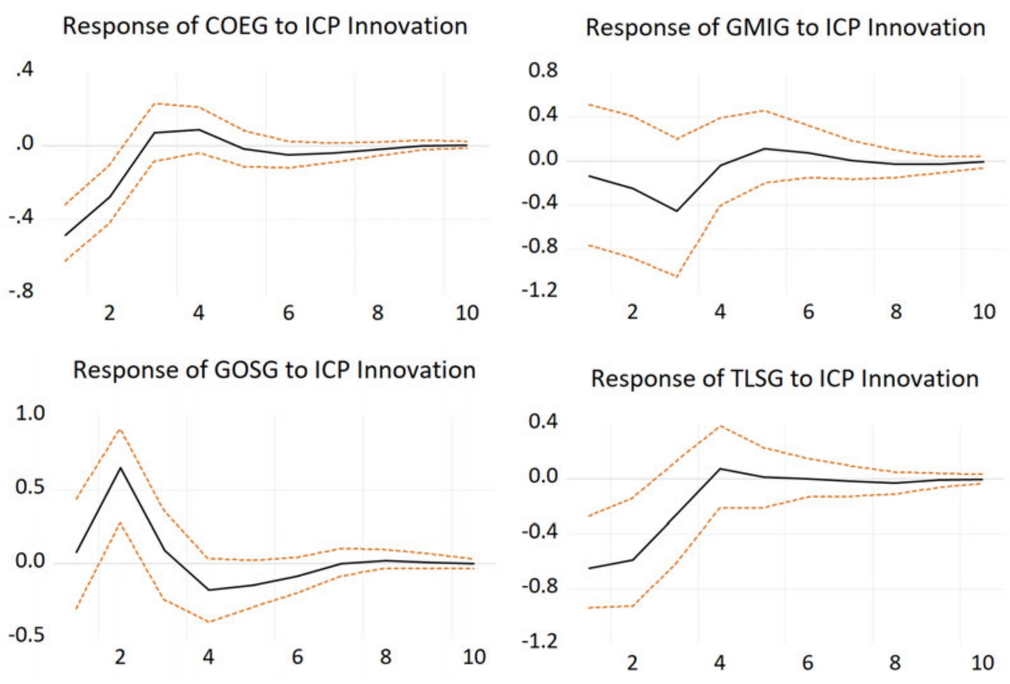
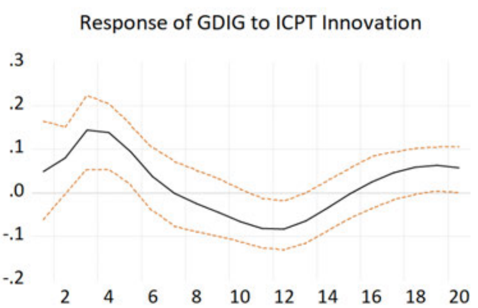


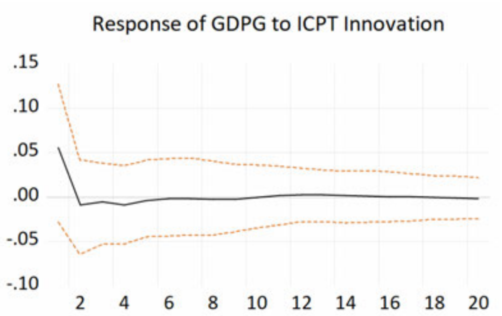
Figure 8 - Impulse responses of growth in COE, GOS, GMI, and TLS, to a one standard deviation shock to the ICP

The components of GDI do not respond uniformly to a one standard deviation shock to the ICP. COE and TLS growth responds negatively to the shock (-40% of a standard deviation and -60% of a standard deviation respectively). This result is perhaps unexpected at first glance. For the former, only 2% of Australia's total workforce is directly employed by the mining sector specifically (Das, 2022). It may also be the fact that higher input costs in the form of higher energy costs induce a need by employers to cut costs, which reduces the compensation of employees. For the latter, the inverse relation to the ICP shock is puzzling, but an explanation for the absence of a clear proportional movement to the shock potentially is the fact that as of 2017, 86% of Australian mining operations are foreign-owned, indicating earnings (and subsequent taxation) are flowing overseas (Aulby, 2017). Further, Das (2020), states "Large write-offs, depreciation, capital allowances and avenues for cross-border planning limit local tax receipts". As per Dungey and Pagan (2009), it may simply be a case where rational expectations are not met within the framework of an empirical model given the complex interactions of real-world data. Moving on, given a 95% confidence interval, GMI responds ambiguously, likely due to the wealth of sectors within the economy in which non-incorporated enterprises operate. Cardinally, gross operating surplus responds correspondingly to the shock to the ICP. A positive shock to the ICP results in a rise in GOS growth, peaking at an increase of 60% of a standard deviation in the second period. This is not surprising given some of Australia's largest and most influential enterprises are commodity extractors involved in mining and oil and gas. Additionally, commodity extraction is a highly capital-intensive industry that requires large economies of scale, only achievable by the largest corporate enterprise. Each response is, however, transitory, with the effect of the shock dissipating by the third or fourth period post shock. Throughout this analysis, one must recall the components of GDI are not of uniform value. A one standard deviation shift in a series as shown in the IRFs means larger changes in nominal dollar value for the growth of COE and GOS, for example, when compared to the growth of GMI and TLS. A variance decomposition reveals that on average, commodity prices determine ~27.8% of COE growth, ~13% of TLS growth, and ~9.4% of GOS growth over 10 periods. This is opposed to the attribution of only ~1.3% of the movement in GMI growth to the ICP shock. The results of these IRFs hold importance for a singular primary reason. Given GDI as a whole responds positively to the shock, it is likely that the majority of this gain is centred on the only component to respond positively, GOS. Over-identifying the restrictions for this SVAR by stipulating the component elements of GDI to have no contemporaneous impact upon one another yields similar results (see Appendix A.5)

Trend and Cycle Components of Commodity Prices, Global Demand, and GDI/GDP (SVAR 4 & 5)

I now re-run SVARs 1 and 2 with the decomposition of ICP into its trend and cycle component.





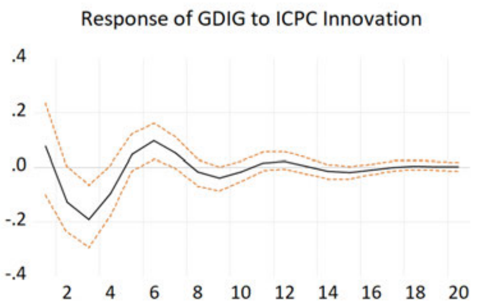


Figure 9 - Impulse responses of GDI growth to a one standard deviation shock to the trend and cycle components of the ICP

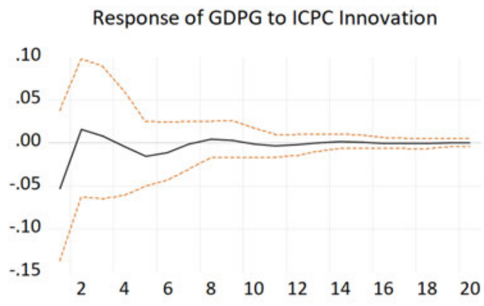


Figure 10 - Impulse response of GDP growth to a one standard deviation shock to the trend and cycle components of the ICP

The decomposition of the trend and cycle component of the ICP affirms the previous findings. GDI responds proportionally to the one standard deviation shock to the ICP, while GDP does not. In fact, with 95% confidence, GDP does not respond to a shock either to the trend or cycle of the commodity price series. The evolution of GDI growth in response to these two shocks closely follows the shock of the trend and cycle components of the ICP to themselves (see Appendix A.3). While both shocks appear cyclical in nature, the trend, as expected, is far more persistent. The impact of a shock to the cycle component of the ICP on GDI growth completely disappears within 20 periods (although with a 95% confidence interval, it disappears far earlier). Opposingly, the impact of the shock to the trend component of the ICP on GDI growth is still present after 20 periods. Interestingly, although far more transitory in nature, the impact of a shock to the cycle component results in larger deviations from the steady state level of growth. At its greatest effect, the cycle component of the ICP results in GDI growth falling by just under 20% of a standard deviation. This response is soon followed by an increase of 10% of a standard deviation above steady-state in period 6 post-shock. In contrast, the shock to the trend component of the ICP results in GDI growing at around 15% of a standard deviation above its steady-state level of growth in periods 3 and 4 at its peak. Following, GDI growth then falls to just under 10% of a standard deviation below steady-state in the 12th period. Analysing the variance decompositions for GDI growth confirms these findings. I find on average the trend component of commodity prices determines ~6.2% of GDI growth, and the cycle component determines a larger ~8.7% of GDI growth, over 10 periods. These SVARs thus reaffirm previous findings and additionally find that the response of GDI to the trend and cycle components of commodity prices are divergent. GDI is perhaps marginally influenced to a greater extent by the cycle component. Still, given its transitory nature, one could argue the trend component is more important to

GDI in the long run. Nevertheless, GDI is shown to proportionally evolve in line with decomposed shocks to the ICP.

Trend and Cycle Components of Commodity Prices, Global Demand, and the Components of GDI (SVAR 6)

Similarly, I re-run SVAR 3 with the decomposition of the ICP into its trend and cycle component.

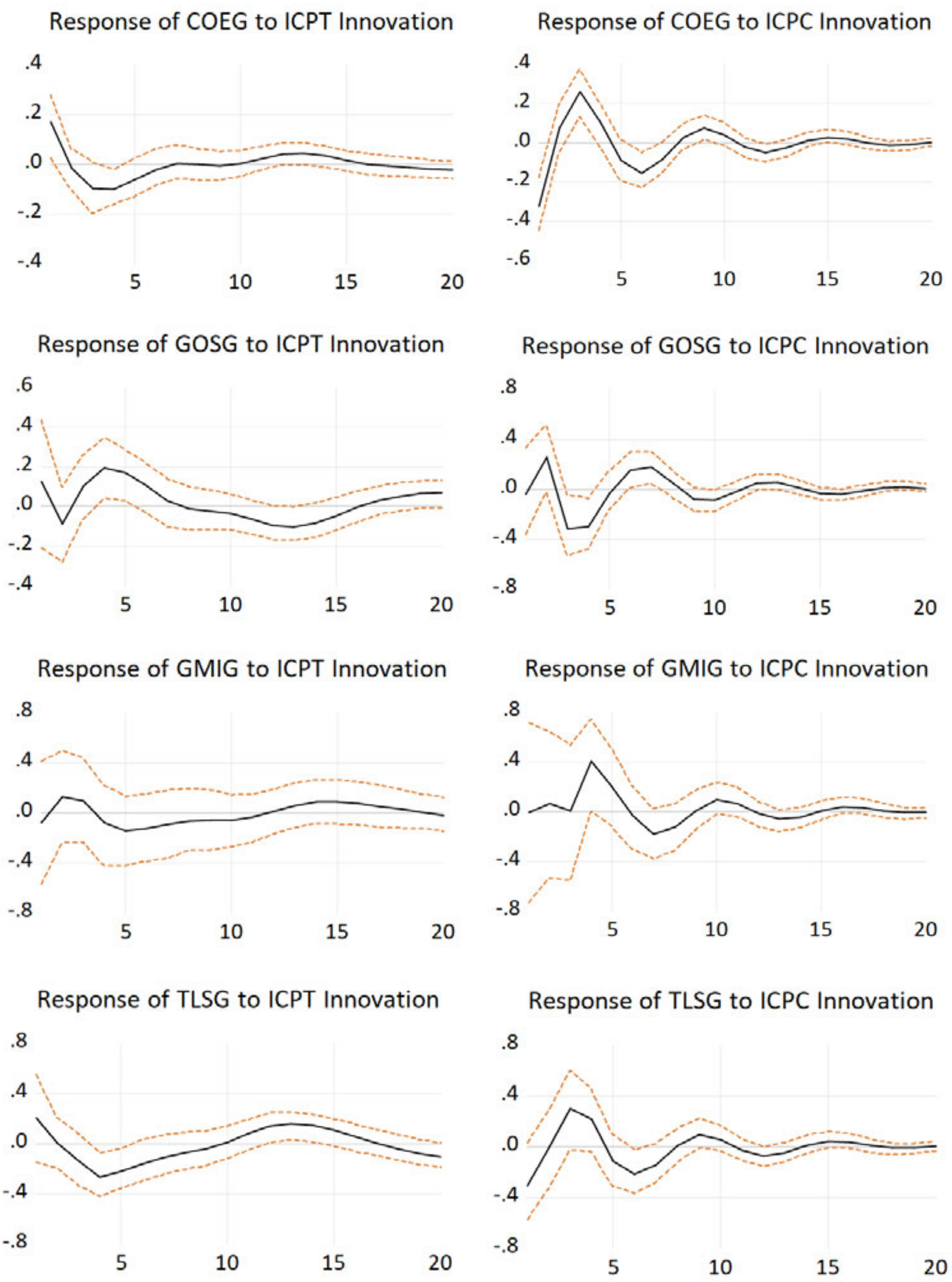


Figure 11 - Impulse responses of growth in COE, GOS, GMI, and TLS, to the trend and cycle components of the ICP

The component elements of GDI respond slightly differently in light of the trend and cycle decomposition of the commodity price series to previous findings. The shock to the trend component of the ICP generates more persistent responses from the component elements of GDI. Again, the impact of the shock to the cycle component is transitory, but the response exhibits greater amplitudes. Initially, in response to a shock to the trend component of the ICP, COE growth rises by 20% of a standard deviation above the steady-state, before falling by about 10% of a standard deviation in the 4th period. By the 6th period, however, COE growth returns to its steady-state level of growth. GOS growth initially appreciates in response to the shock, by 20% of a standard deviation, before marginally turning negative by 10% in period 13. TLS growth responds with growth below steady state, by 30% of a standard deviation in period 4, but this fall reverses by period 13 when TLS growth appreciates by just under 20% of a standard deviation. The shock to the trend component of the commodity price series does not significantly affect GMI growth. These results are somewhat expected. Given the expectation that commodity prices will remain high (the definition of a trend), commodity producers can commit to long-term investments by renegotiating higher wage contracts and seeking larger investments (Reserve Bank of Australia, 2005). The response of TLS growth may be attributed to a delay between the shock to the trend component of commodity prices and the collection period of taxation on production.

When looking at the response of the component elements of GDI to a one standard deviation shock to the cycle component of commodity prices, the results differ yet again. Initially, COE growth is negative, by 30% of a standard deviation, then by the 3rd period, appreciates by 20% of a standard deviation above steady-state. This cyclical response continues meaningfully until about the 15th period. GOS growth initially with 95% confidence in periods 3 and 4, responds negatively to the shock to the cycle component, falling by around 30% of a standard deviation below steady-state, before in the 6th and 7th periods, rising by 20% of a standard deviation. Much like COE growth, any meaningful response dissipates by the 15th period. GMI growth responds with positive growth, 40% of a standard deviation above steady-state, but with 95% confidence, this response only lasts a single period. TLS growth in response to the shock falls by 20% of a standard deviation in the 6th period, but much like the response to GMI, with 95% confidence, this response only lasts for one period. Interestingly, while growth in GOS tends to move more in line with the shock, growth in COE, GMI, and TLS appears to respond to the shock with a delay of roughly 2 periods (see

Appendix A.3). This delay may be the reason why COE and TLS growth seemingly responds inversely to the shock to the ICP in SVAR 3. Turning to the variance decomposition, I find on average the trend component of commodity prices determines ~4.3% of COE growth, and the cycle component ~17.5%, over 10 periods. For GOS growth, I find on average the trend component determines ~1.8% of growth, while the cycle component on average determines ~5.1% of growth over 10 periods. On average, the model attributes ~0.3% of GMI growth to the trend component, and ~0.8% to the cycle component, over 10 periods. Finally, I find the trend component determines ~2.6% of TLS growth, while the cycle determines ~4% of growth on average over 10 periods. The model thus again attributes more of the movement across key variables to the cycle, as opposed to the trend component of commodity prices. The decomposition of the commodity price series, therefore, suggests that the majority of the impact upon GDI attributed to changes in commodity prices stems from the COE and GOS component elements. As before, the over-identified restriction for this SVAR yields similar results.

4.2 Pre mid-2003 Sample (1985:Q4 - 2003:Q2)

Trend and Cycle Components of Commodity Prices, Global Demand, and GDI/GDP (SVAR 7 & 8)

As a robustness check, I split my sample into two smaller sub-samples, both pre and post mid-2003. I begin with the 'pre' sub-sample.

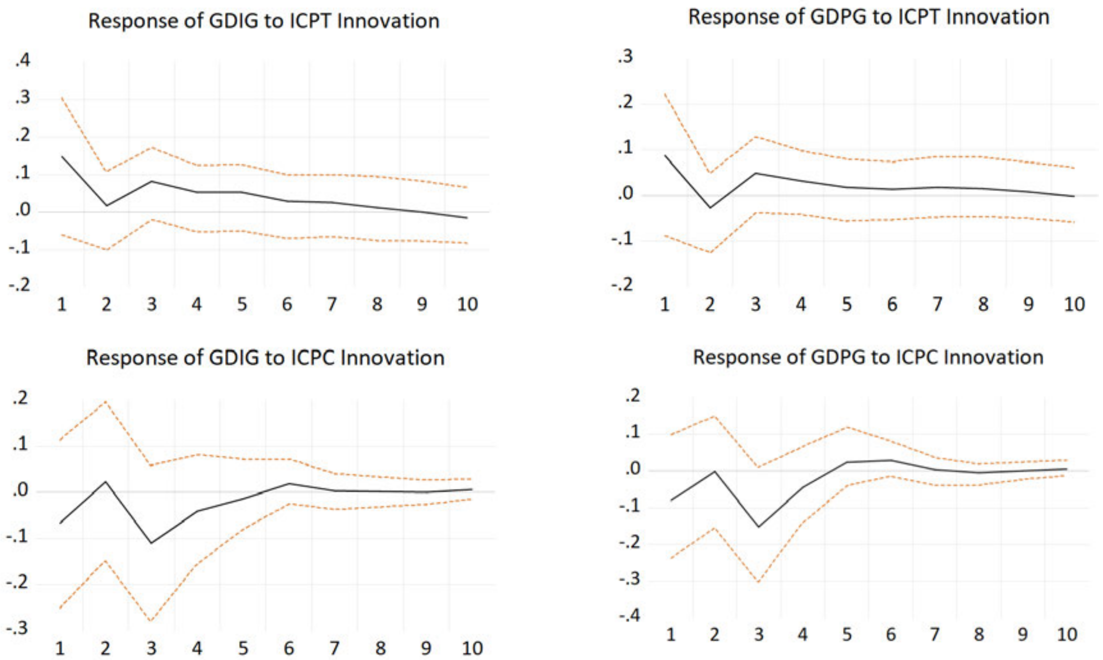


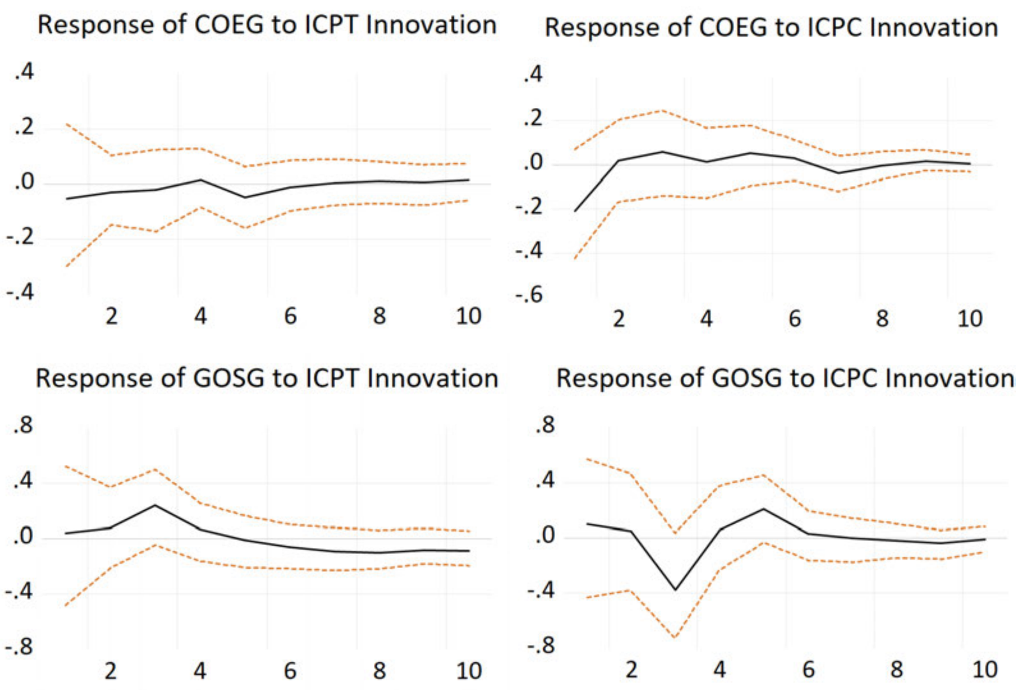
Figure 12 - Impulse responses of GDI growth to a one standard deviation shock to the trend and cycle components of the ICP

Figure 13 - Impulse response of GDP growth to a one standard deviation shock to the trend and cycle components of the ICP

For the pre mid-2003 sample, a one standard deviation shock to both the trend and cycle components of commodity prices have no impact on GDI or GDP growth. This is an unusual discovery when contrasted with the findings of SVAR 4, in which GDI is meaningfully impacted by both components of the ICP. One obvious reason for why this may be is shown in Figure 5. Pre mid-2003, both the trend and cycle components of the ICP show limited variance. It could thus be the case that the displayed variation in the data is not enough to induce a meaningful change in GDI. Put differently, the gains (or losses) of commodity prices in this sample period were not significant enough to induce a material change in the terms of trade for Australia, which would subsequently pass through to GDI,

Trend and Cycle Components of Commodity Prices, Global Demand, and the Components of GDI (SVAR 9)

Presenting the component elements of the GDI.



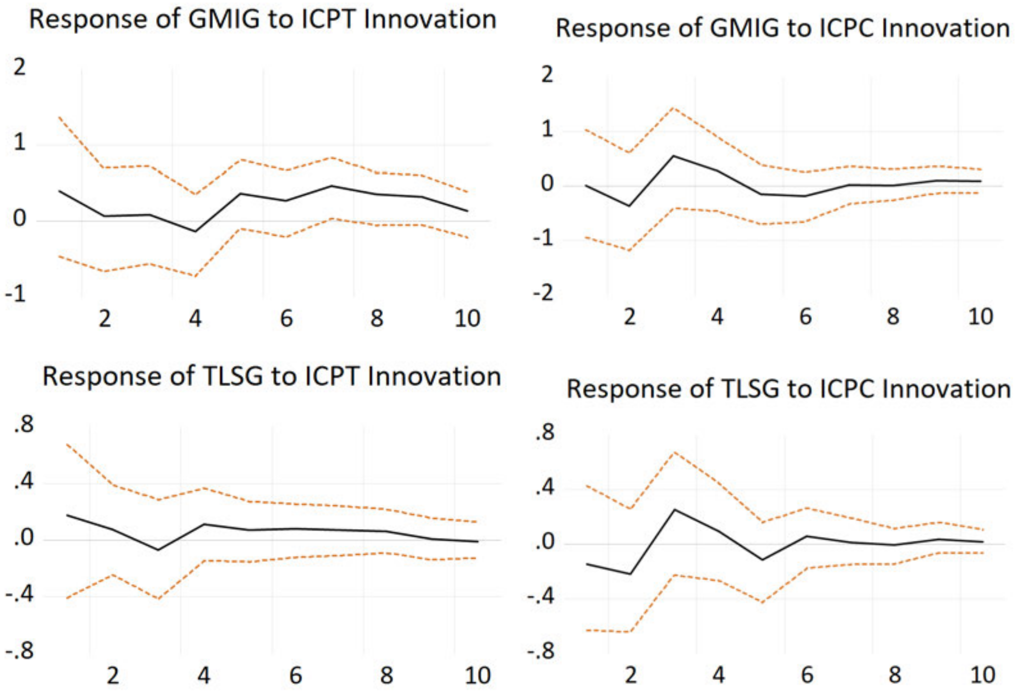


Figure 14 - Impulse responses of growth in COE, GOS, GMI, and TLS, to the trend and cycle components of the ICP

Given the findings of SVAR 7, the results presented here are not surprising. For the pre mid-2003 sub-sample, the component elements of GDI do not respond to a one standard deviation shock to either the trend or cycle component of the ICP. Again this is likely due to the minimally varying data employed within this sub-sample. Using the over-identified restrictions yields a broadly similar story, although the response of GMI growth to a one standard deviation shock to the trend component of the ICP briefly yields positive growth above steady-state in the 7th period post the shock. This restriction is not statistically significant.

4.3 Post mid-2003 Sample (2003:Q3 - 2019:Q4)

Trend and Cycle Components of Commodity Prices, Global Demand, and GDI/GDP (SVAR 10 & 11)

The final set of SVARs I examine are for the post mid-2003 sub-sample.

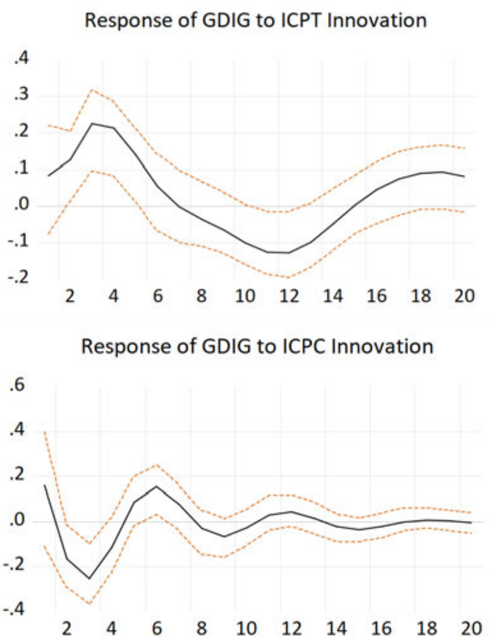


Figure 15 - Impulse responses of GDI growth to a one standard deviation shock to the trend and cycle components of the ICP

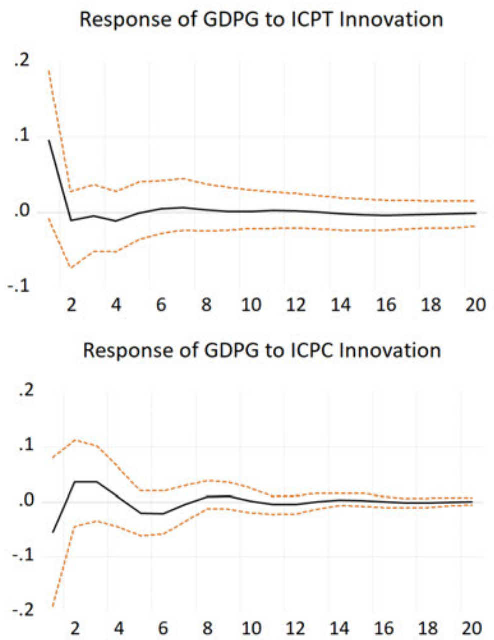


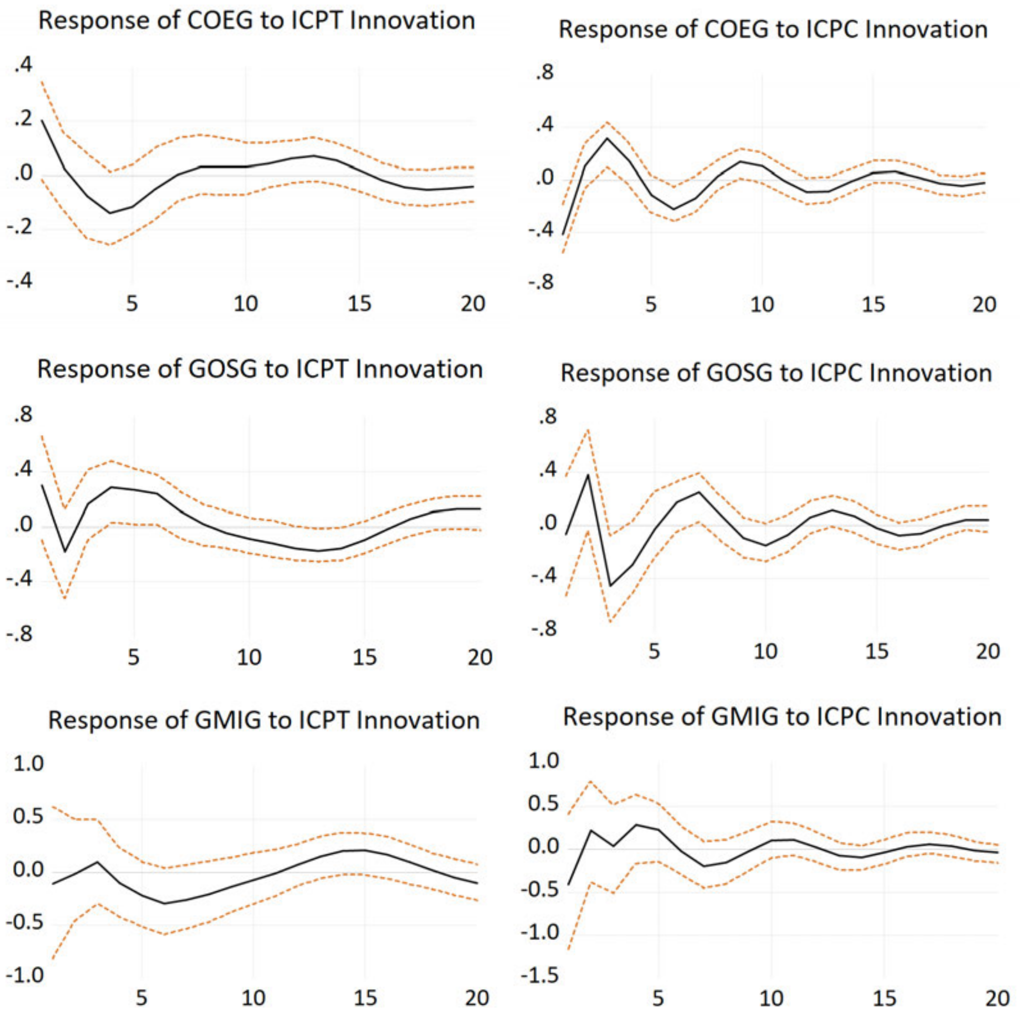
Figure 16 - Impulse response of GDP growth to a one standard deviation shock to the trend and cycle components of the ICP

The presented SVARs appear more alike to SVARs 4 and 5. GDI is responsive to a one standard deviation shock to both the trend and cycle components of the ICP, while GDP is not. As recorded by Kulish and Rees (2017), a stark difference between this sample and the pre mid-2003 sample is that commodity prices saw an appreciation in price, with the volatility of prices also doubling. This finding could signal that the majority of the influence of the ICP on GDI stems from the post mid-2003 period. Although SVAR 10 looks similar to SVAR 4, the magnitude of movement in response to the various shocks is larger. In response to a one standard deviation shock to the trend component of the ICP, GDI growth peaks at just above 20% of a standard deviation above the steady state-level of growth in periods 3 and 4 post-shock. GDI growth then becomes negative, in the 11th and 12th periods, bottoming out at just above 10% of a standard deviation below the steady-state. Alternatively, in response to a one standard deviation shock to the cycle component of the ICP, GDI growth follows the path of the shock, which becomes negative early on, bottoming out at a little more than 20% of a standard deviation below steady-state. It then turns positive around period 6 at just under 20% of a standard deviation above its steady-state level. These amplitudes are greater than those exhibited in SVAR 4. A variance decomposition for the growth of GDI for this sub-sample affirms a stronger response to the shock than when compared to the whole sample. I find on average the trend component of commodity prices determines ~14.8% of

GDI growth, and the cycle component determines ~18.1% of GDI growth, over 10 periods. Thus for the post mid-2003 sample, the model attributes far more of the variation in GDI growth to both the trend and cycle components of the commodity price series. This suggests that for the whole sample, the movement in GDI as a result of commodity price changes mostly derives from the post mid-2003 period, with the pre mid-2003 sample mediating the results.

Trend and Cycle Components of Commodity Prices, Global Demand, and the Components of GDI (SVAR 12)

The final SVAR I present employs the component elements of GDI for the post mid-2003 sample.



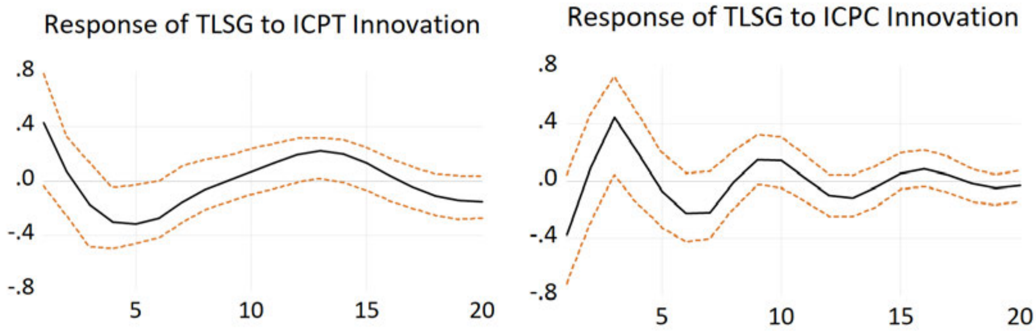


Figure 17 - Impulse responses of growth in COE, GOS, GMI, and TLS, to the trend and cycle components of the ICP

Again, these results are similar to those of the whole sample (SVAR 6), but the magnitudes are larger. Interestingly, the one standard deviation shock to the trend component of the ICP now does not have a statistically significant effect on COE growth. GOS growth peaks at around 30% of a standard deviation above its steady-state level in periods 4 and 5. Then in periods 12 and 13, GOS growth is below steady-state by 20% of a standard deviation. TLS growth initially in periods 4 and 5 falls below its steady-state level by just under 40% of a standard deviation. This fall is then followed by a rise above steady-state in period 13 of 20%. With regards to the one standard deviation shock to the cycle component of the ICP, growth in COE, GOS, and TLS are meaningfully impacted with 95% confidence. COE growth is initially negative at 40% of a standard deviation below steady-state, before reversing and rising just below 40% of a standard deviation above steady-state in period 3. GOS growth with 95% confidence initially falls just above 40% of a standard deviation below its steady-state in period 3, but by period 7, appreciates by about 20% of a standard deviation above its steady-state. The only certain reaction of TLS growth with 95% confidence is in period 3, where it rises 40% of a standard deviation above the steady-state. Again, growth in GOS seems to mirror the evolution of the shock to the cycle component of commodity prices. Growth in COE and TLS reacts with an apparent delay of roughly 2 periods, which appears as these series reacting seemingly inversely to the shock. On average I find the trend component of commodity prices determines ~6.7% of GOS growth and ~8.5% of TLS growth over 10 periods. Alternatively, on average I find the cycle determines ~29.8% of COE growth, ~9.7% of GOS growth, and ~8.7% of TLS growth over 10 periods. For the comparable variance decompositions of SVAR 6, this model attributes a greater share of the movement to the commodity price series. This affirms the previous finding that the majority of the influence of commodity prices on GDI stems from the post mid-2003 sample, likely due to the large appreciation and greater variance of commodity prices in this period. The over-identified restriction produces similar results.

4.4 Robustness

The presented results across all models are robust, with a broadly similar narrative told for various manipulations of the models. To this effect, the results of the robustness checks conducted for each SVAR are available in Appendix A.5. To begin, I choose to re-order the shocks. Given the recursive SVAR structure, it is plausible that rearranging the shocks to the system can produce different results. However, I find this manipulation to have a limited impact on the key findings. Particularly, whether I arrange US GDP above or below the decomposed ICP series has no real implication for the results. Choosing to arrange the cycle component over the trend similarly does not meaningfully change the results. As an extreme, arranging the focal variable (GDI, GDP, and the components of GDI) above all other variables does at times have a minor influence on specific conclusions, but the broad movements of the IRFs remain similar. I further change the lag structure of the SVAR by halving and doubling the lags (1 and 4 lags). This manipulation again did not materially change the results, although 1 lag would lead to a loss of information in the IRFs, while 4 would produce noticeably more movement. As mentioned previously, the over-identified restrictions for the SVARs examining the component elements of GDI produced near exact conclusions.

5. Discussion and Conclusion

In this thesis, I seek to establish the relationship between commodity prices and Australian prosperity. Through a decomposition of the RBAs index of commodity prices via the discrete wavelet transform, I ran multiple SVARs with the commodity price series, its permanent and transitory components, global demand, GDI, GDP, and the component elements of GDI. I did so for the period 1985:Q4 to 2019:Q4, as well as two sub-samples, pre and post mid-2003. I find that GDI is meaningfully and correspondingly influenced by commodity prices while GDP is not. That is, for an appreciation in commodity prices, GDI rises, and vice versa. While both the trend and cycle components of the commodity price series impact GDI, GDI responds more strongly to evolutions in the cycle component, although these are far more transitory in nature than evolutions in the trend. Further, while changes to commodity prices influence all components of GDI in some way, gains are concentrated in gross operating surplus. Finally, splitting my sample into two smaller periods for analysis, both pre and post a large rise in the value and variance of commodity prices, yields interesting results. Pre mid-2003 there is no meaningful relationship between commodity prices and GDI, while the relationship post mid-2003 is exceptionally strong.

These findings reveal important relationships for consideration. The clear distinction between the response of GDI and GDP, especially in the more recent post mid-2003 period suggests GDI is a crucial yet under-represented macroeconomic metric to study in the Australian context. In periods where the variance of commodity prices is especially volatile, the choice to employ GDI when studying the Australian economy is advantageous. For policymakers, these findings suggest capturing gains to GDI generated by the cycle may yield greater benefits than those of the trend. Conversely, policy that attempts to mediate the response of GDI in relation to the trend component of commodity prices is likely to be more effective than a response to the cycle, given the trend has far more persistence. Perhaps of greatest utility in regard to policy is understanding where the gains of GDI are concentrated. Knowing gains to both the trend and cycle component of the commodity price series are concentrated in gross operating surplus may suggest that something akin to a resource super profits tax would be beneficial. Such a policy could save the windfall gains to GDI attributed to a rise in commodity prices. The case for this policy is strong. As stated previously, 86% of Australian mining operations are foreign-owned. Much of the profit generated without change to either output or investment is flowing overseas despite the fact that officially, Australians own the very resources generating these super profits (Department of Industry, Science and Resources, n.d.). A super profits tax would allow Australians to benefit from the rise in prices by shifting some of the gains from gross operating surplus to taxes less subsidies on production and imports. As noted by Dehn (2000), policymakers should responsibly and strategically invest the windfall in high-return projects post the commodity shock induced boom period. While discussions on the details of such a policy are far too broad for this thesis, the tax should only apply to those profits generated above the steady-state level of commodity prices.

The opportunities for further research remain vast. For one, conducting this same research in future periods of commodity price moderation may yield different results, as suggested by the comparison between the pre and post mid-2003 samples. Further, employing a mixed-frequency SVAR to reconcile the monthly ICP data with quarterly GDI and GDP data could aid in the robustness of the results. Additionally, the inclusion of other price series for the sources of income for other industries of importance to Australia could prove useful. By including these different price series and comparing them to the impact of commodity prices, it would be possible to gauge the relative importance of commodities on Australia's prosperity. Moreover, running the same SVARs over a variety of commodity-exporting (such as Canada and Norway) and non-commodity-exporting countries (such as France and Japan) could help to further reveal the importance of GDI. By comparing the response of GDI and GDP to commodity price shocks in these economies alongside a discussion of the terms of trade, the importance of GDI in commodity-exporting economies may be better understood.

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Appendix

A.1 Data Sources

Data	Reference	Series ID	Frequency	Sample Period
Index of Commodity Prices	Reserve Bank of Australia. (2022). *Commodity Prices - I2* (April 2022) [Data set]. https://www rba.gov.au/statistics/frequency/commodity-prices/2022/	GRCPAIAD	Monthly	1982:M7 - 2022:M4
US Gross Domestic Product	Federal Reserve Economic Data. (2022). Real Gross Domestic Product (October 2022) [Data set]. https://fred.stlouisfed.org/series/GDPC1	GDPC1	Quarterly	1947:Q1 - 2022:Q2
Australian Gross Domestic Income	Australian Bureau of Statistics. (2021). Australian National Accounts: National Income, Expenditure and Product (December 2021) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021	A2304410X	Quarterly	1959:Q4 - 2021:Q4
Australian Gross Domestic Product	Australian Bureau of Statistics. (2021). Australian National Accounts: National Income, Expenditure and Product. Table 1. Key National Accounts Aggregates (December 2021) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021	A2304402X	Quarterly	1959:Q4 - 2021:Q4
Australian Compensation of Employees	Australian Bureau of Statistics. (2021). 5206.0 Australian National Accounts: National Income, Expenditure and Product. Table 11. National Income Account, Current prices (December 2021) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021	A2303359K	Quarterly	1959:Q4 - 2021:Q4
Australian Gross Operating Surplus	Australian Bureau of Statistics. (2021). 5206.0 Australian National Accounts: National Income, Expenditure and Product. Table 11. National Income Account, Current prices (December 2021) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021	A2303375K	Quarterly	1959:Q4 - 2021:Q4
Australian Gross Mixed Income	Australian Bureau of Statistics. (2021). 5206.0 Australian National Accounts: National Income, Expenditure and Product. Table 11. National Income Account, Current prices (December 2021) [Data set].	A2303377R	Quarterly	1959:Q4 - 2021:Q4

	https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021			
Australian Taxes Less Subsidies on Production and Imports	Australian Bureau of Statistics. (2021). 5206.0 Australian National Accounts: National Income, Expenditure and Product. Table 11. National Income Account, Current prices (December 2021) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/dec-2021	A2302831K	Quarterly	1959:Q4 - 2021:Q4
Chain Price Index	Australian Bureau of Statistics. (2022). 5206.0 Australian National Accounts: National Income, Expenditure and Product. Table 4. Expenditure on Gross Domestic Product (GDP), Chain price indexes (March 2022) [Data set]. https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-national-income-expenditure-and-product/mar-2022	A2303862V	Quarterly	1985:Q3 - 2022:Q1

A.2 Models

SVAR 1 & 2

$$A_0 z_t = A_1 z_{t-1} + \ldots + A_p z_{t-p} + B\eta_t$$

With restriction matrices:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 \\ a_{0,21} & a_{0,22} & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} \end{bmatrix} \quad B = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix}$$

And where:

$$z_t = \begin{bmatrix} \kappa_t \\ d_t \\ g_t \end{bmatrix}, z_t = \begin{bmatrix} \kappa_t \\ d_t \\ y_t \end{bmatrix} \quad A_i = \begin{bmatrix} a_{i,11} & a_{i,12} & a_{i,13} \\ a_{i,21} & a_{i,22} & a_{i,23} \\ a_{i,31} & a_{i,32} & a_{i,33} \end{bmatrix} \quad \eta_t = \begin{bmatrix} \varepsilon_{\kappa_t} \\ \varepsilon_{d_t} \\ \varepsilon_{g_t} \end{bmatrix}, \eta_t = \begin{bmatrix} \varepsilon_{\kappa_t} \\ \varepsilon_{d_t} \\ \varepsilon_{y_t} \end{bmatrix}$$

In which κ is the commodity price series, *d* is global demand, *g* is GDI, and *y* is GDP.

SVAR 3

$$A_0 z_t = A_1 z_{t-1} + \ldots + A_p z_{t-p} + B\eta_t$$

With restriction matrices:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 & 0 & 0 & 0 \\ a_{0,21} & a_{0,22} & 0 & 0 & 0 & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} & 0 & 0 & 0 \\ a_{0,41} & a_{0,42} & a_{0,43} & a_{0,44} & 0 & 0 \\ a_{0,51} & a_{0,52} & a_{0,53} & a_{0,54} & a_{0,55} & 0 \\ a_{0,61} & a_{0,62} & a_{0,63} & a_{0,64} & a_{0,65} & a_{0,66} \end{bmatrix} \quad B = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_6 \end{bmatrix}$$

And where:

$$z_t = \begin{bmatrix} \kappa_t \\ d_t \\ e_t \\ s_t \\ m_t \\ t_t \end{bmatrix} \quad A_i = \begin{bmatrix} a_{i,11} & a_{i,12} & a_{i,13} & a_{i,14} & a_{i,15} & a_{i,16} \\ a_{i,21} & a_{i,22} & a_{i,23} & a_{i,24} & a_{i,25} & a_{i,26} \\ a_{i,31} & a_{i,32} & a_{i,33} & a_{i,34} & a_{i,35} & a_{i,36} \\ a_{i,41} & a_{i,42} & a_{i,43} & a_{i,44} & a_{i,45} & a_{i,46} \\ a_{i,51} & a_{i,52} & a_{i,53} & a_{i,54} & a_{i,55} & a_{i,56} \\ a_{i,61} & a_{i,62} & a_{i,63} & a_{i,64} & a_{i,65} & a_{i,66} \end{bmatrix} \quad \eta_t = \begin{bmatrix} \varepsilon_{\kappa_t} \\ \varepsilon_{d_t} \\ \varepsilon_{e_t} \\ \varepsilon_{s_t} \\ \varepsilon_{m_t} \\ \varepsilon_{t_t} \end{bmatrix}$$

In which e is the compensation of employees, s is gross operating surplus, m is gross mixed income, and t is taxes less subsidies of production and imports.

As a robustness check, I re-run the SVAR and specify the component elements of GDI as having no contemporaneous relationship. Where:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 & 0 & 0 & 0 \\ a_{0,21} & a_{0,22} & 0 & 0 & 0 & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} & 0 & 0 & 0 \\ a_{0,41} & a_{0,42} & 0 & a_{0,44} & 0 & 0 \\ a_{0,51} & a_{0,52} & 0 & 0 & a_{0,55} & 0 \\ a_{0,61} & a_{0,62} & 0 & 0 & 0 & a_{0,66} \end{bmatrix}$$

SVAR 4, 5, 7, 8, 10 & 11

$$A_0 z_t = A_1 z_{t-1} + \ldots + A_p z_{t-p} + B\eta_t$$

With restriction matrices:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 & 0 \\ a_{0,21} & a_{0,22} & 0 & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} & 0 \\ a_{0,41} & a_{0,42} & a_{0,43} & a_{0,44} \end{bmatrix} \quad B = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 \\ 0 & 0 & \sigma_3 & 0 \\ 0 & 0 & 0 & \sigma_4 \end{bmatrix}$$

And where:

$$z_t = \begin{bmatrix} \tau_t \\ c_t \\ d_t \\ g_t \end{bmatrix}, z_t = \begin{bmatrix} \tau_t \\ c_t \\ d_t \\ y_t \end{bmatrix} \quad \eta_t = \begin{bmatrix} \varepsilon_{\tau_t} \\ \varepsilon_{c_t} \\ \varepsilon_{d_t} \\ \varepsilon_{i_t} \end{bmatrix}, \eta_t = \begin{bmatrix} \varepsilon_{\tau_t} \\ \varepsilon_{c_t} \\ \varepsilon_{d_t} \\ \varepsilon_{y_t} \end{bmatrix}$$

In which τ is the trend component of the commodity price series, and *c* is the cycle component.

SVAR 6, 9 & 12

$$A_0 z_t = A_1 z_{t-1} + \ldots + A_p z_{t-p} + B\eta_t$$

With restriction matrices:

$$A_0 = \begin{bmatrix} a_{0,11} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{0,21} & a_{0,22} & 0 & 0 & 0 & 0 & 0 \\ a_{0,31} & a_{0,32} & a_{0,33} & 0 & 0 & 0 & 0 \\ a_{0,41} & a_{0,42} & a_{0,43} & a_{0,44} & 0 & 0 & 0 \\ a_{0,51} & a_{0,52} & a_{0,53} & a_{0,54} & a_{0,55} & 0 & 0 \\ a_{0,61} & a_{0,62} & a_{0,63} & a_{0,64} & a_{0,65} & a_{0,66} & 0 \\ a_{0,71} & a_{0,72} & a_{0,73} & a_{0,74} & a_{0,75} & a_{0,76} & a_{0,77} \end{bmatrix} \quad B = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_7 \end{bmatrix}$$

And where:

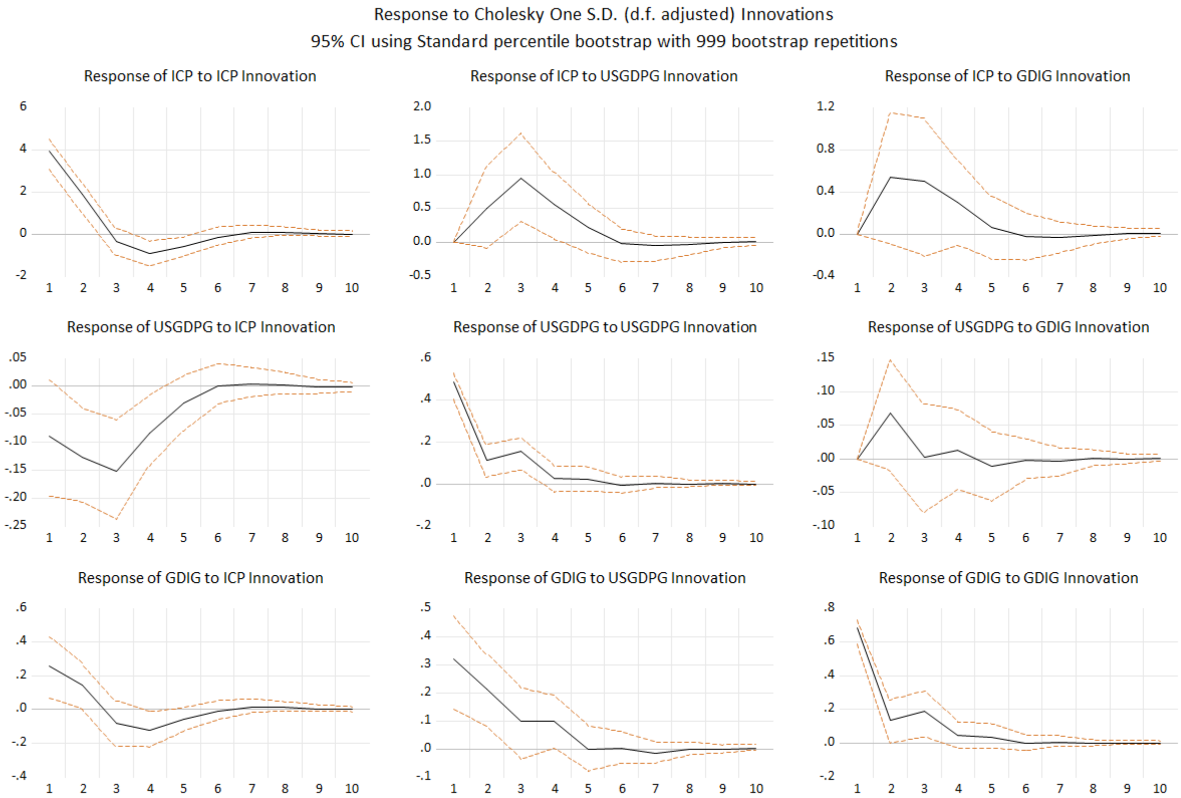
$$z_t = \begin{bmatrix} \tau_t \\ c_t \\ d_t \\ e_t \\ s_t \\ m_i \\ t_s \end{bmatrix} \quad A_i = \begin{bmatrix} a_{i,11} & a_{i,12} & a_{i,13} & a_{i,14} & a_{i,15} & a_{i,16} & a_{i,17} \\ a_{i,21} & a_{i,22} & a_{i,23} & a_{i,24} & a_{i,25} & a_{i,26} & a_{i,27} \\ a_{i,31} & a_{i,32} & a_{i,33} & a_{i,34} & a_{i,35} & a_{i,36} & a_{i,37} \\ a_{i,41} & a_{i,42} & a_{i,43} & a_{i,44} & a_{i,45} & a_{i,46} & a_{i,47} \\ a_{i,51} & a_{i,52} & a_{i,53} & a_{i,54} & a_{i,55} & a_{i,56} & a_{i,57} \\ a_{i,61} & a_{i,62} & a_{i,63} & a_{i,64} & a_{i,65} & a_{i,66} & a_{i,67} \\ a_{i,71} & a_{i,72} & a_{i,73} & a_{i,74} & a_{i,75} & a_{i,76} & a_{i,77} \end{bmatrix} \quad \eta_t = \begin{bmatrix} \varepsilon_{\tau_t} \\ \varepsilon_{c_t} \\ \varepsilon_{d_t} \\ \varepsilon_{e_t} \\ \varepsilon_{s_t} \\ \varepsilon_{m_t} \\ \varepsilon_{t_t} \end{bmatrix}$$

Again, I re-run these SVARs and specify the component elements of GDI as having no contemporaneous relationship. Where:

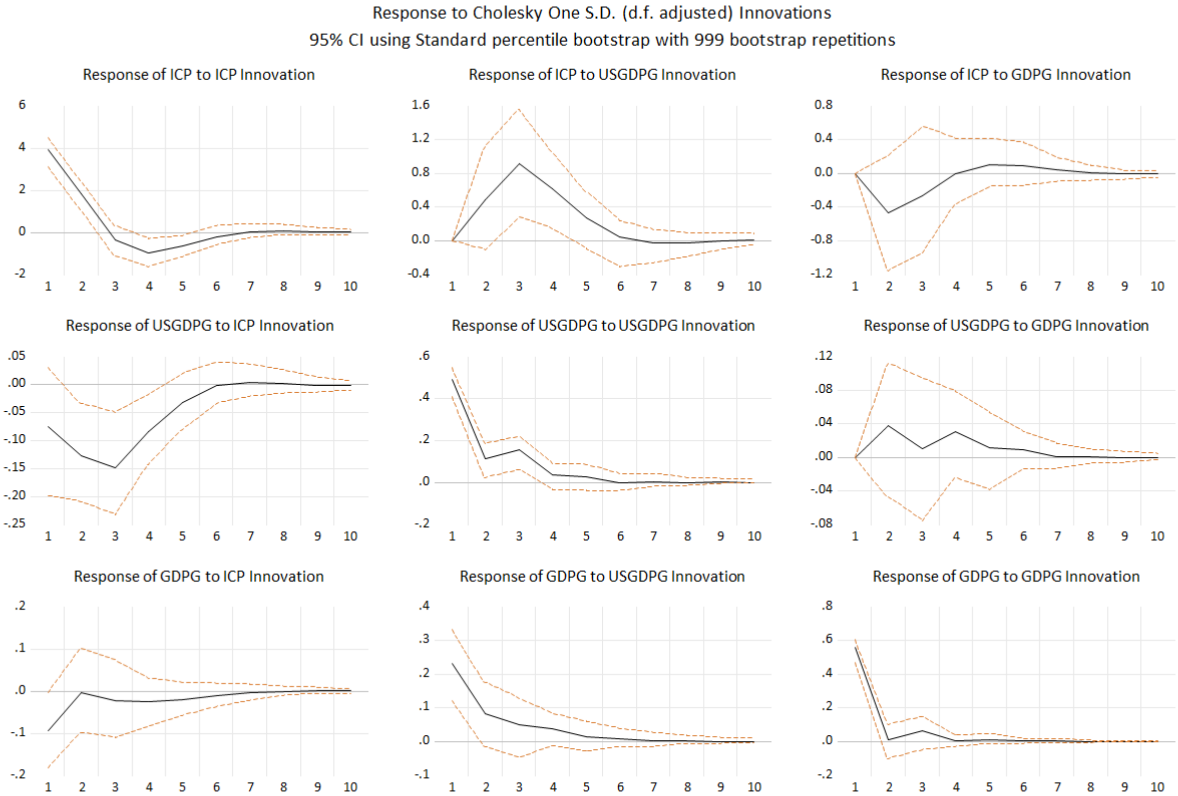
$$A_0 = \begin{bmatrix} a_{i,11} & a_{i,11} & 0 & 0 & 0 & 0 & 0 \\ a_{i,21} & a_{i,22} & 0 & 0 & 0 & 0 & 0 \\ a_{i,31} & a_{i,32} & a_{i,33} & 0 & 0 & 0 & 0 \\ a_{i,41} & a_{i,42} & a_{i,43} & a_{0,44} & 0 & 0 & 0 \\ a_{i,51} & a_{i,52} & a_{i,53} & 0 & a_{0,55} & 0 & 0 \\ a_{i,61} & a_{i,62} & a_{i,63} & 0 & 0 & a_{0,66} & 0 \\ a_{i,71} & a_{i,72} & a_{i,73} & 0 & 0 & 0 & a_{0,77} \end{bmatrix}$$

A.3 Full IRFs

SVAR 1



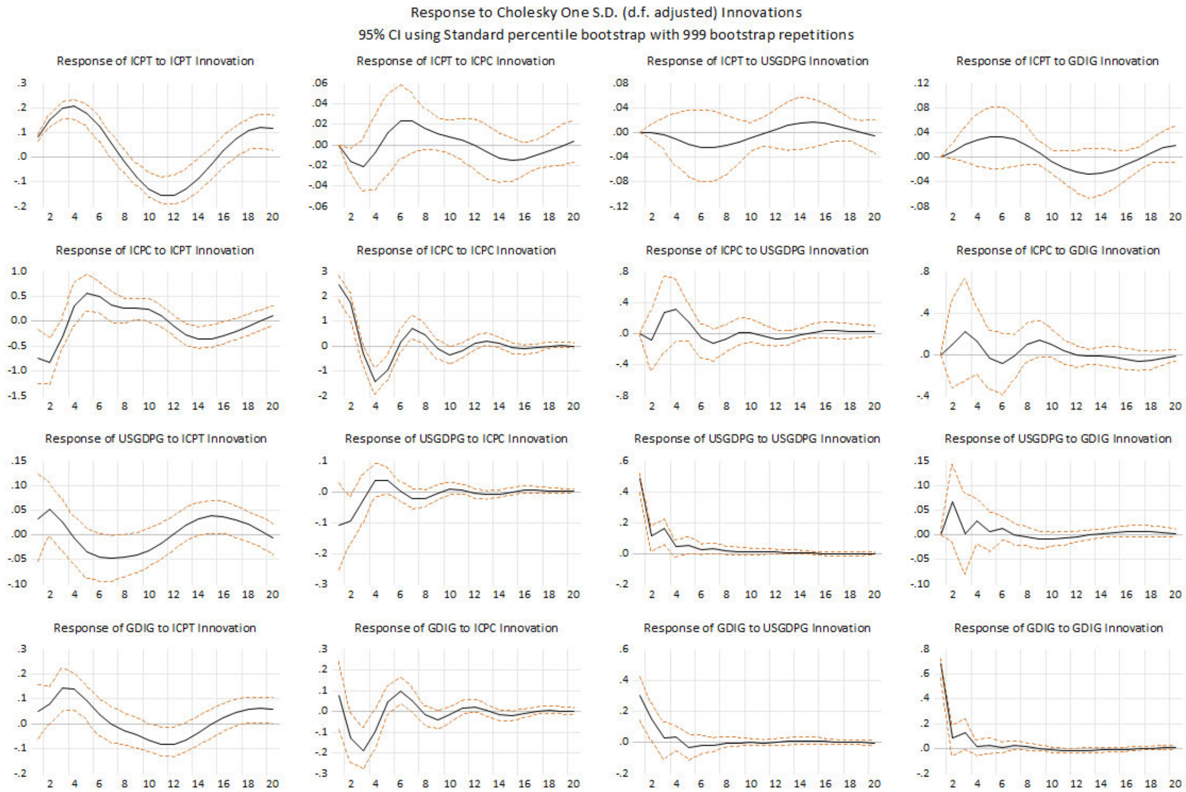
SVAR 2


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICP to ICP Innovation
Response of ICP to USGDPG Innovation
Response of ICP to GDPG Innovation
Response of USGDPG to ICP Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to GDPG Innovation
Response of GDPG to ICP Innovation
Response of GDPG to USGDPG Innovation
Response of GDPG to GDPG Innovation

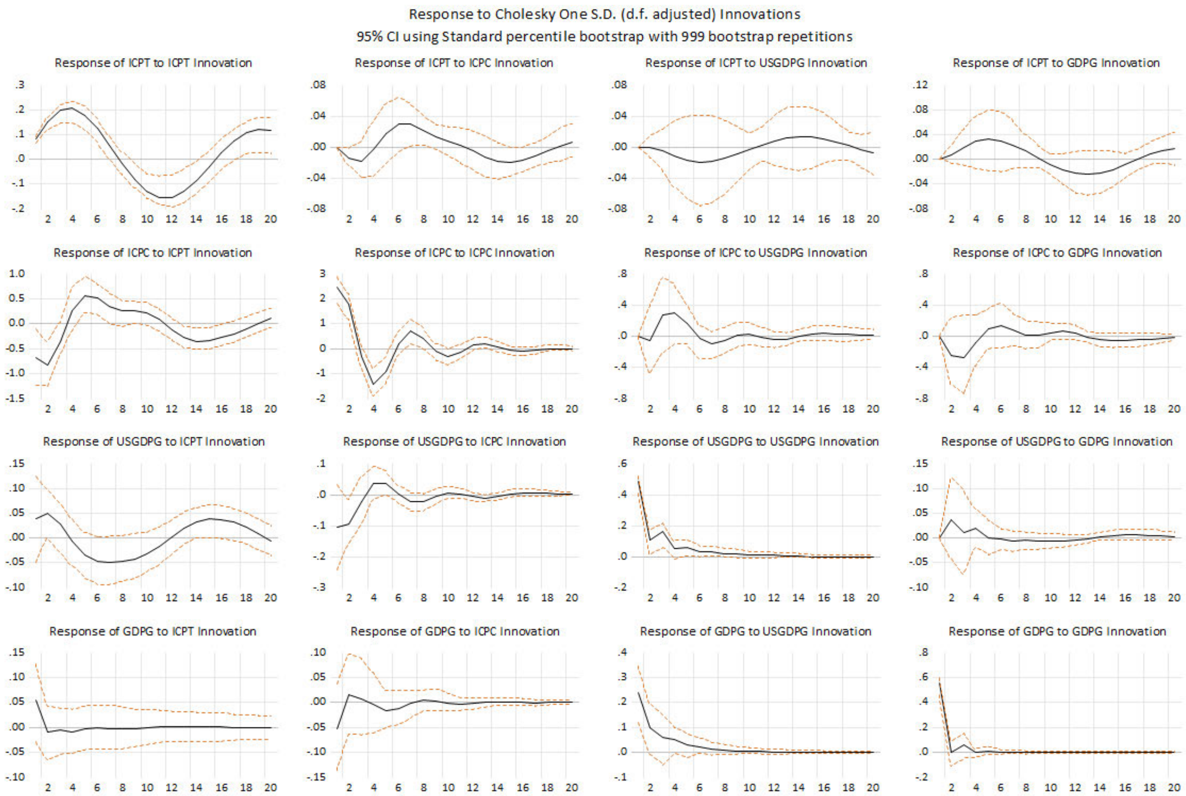
SVAR 3


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions

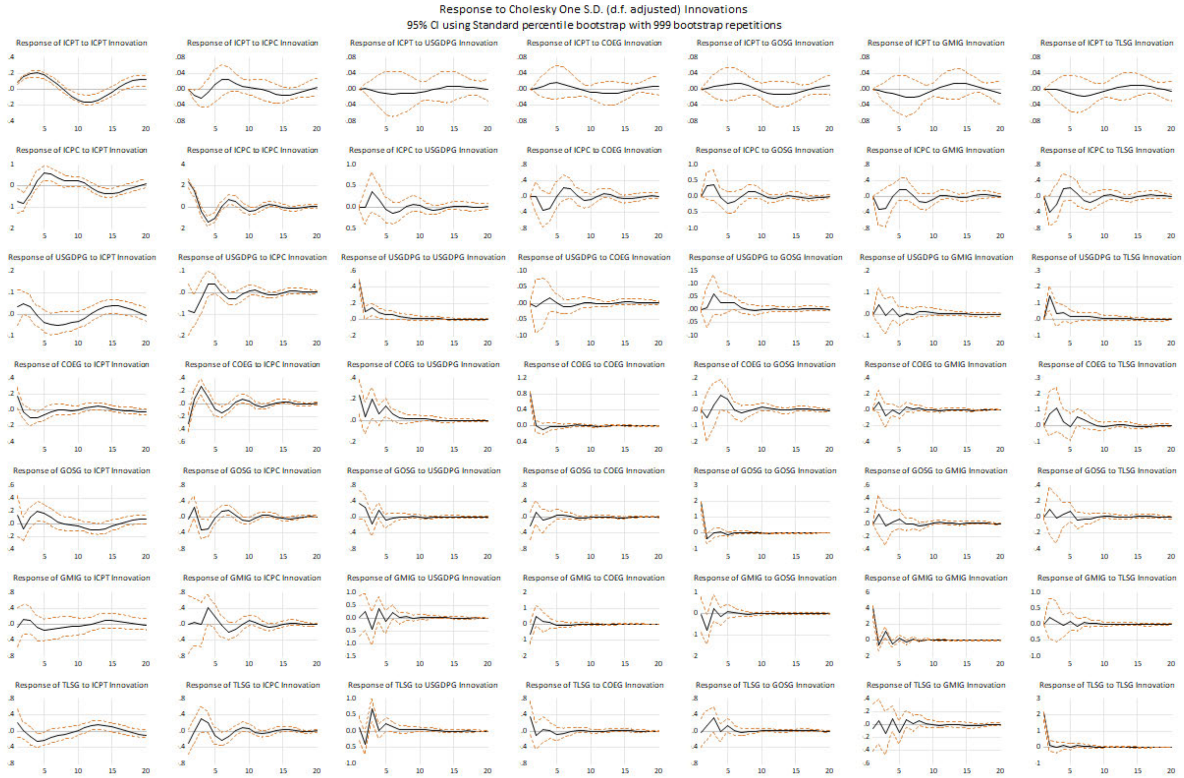
SVAR 4


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICPT to ICPT Innovation
Response of ICPT to ICPC Innovation
Response of ICPT to USGDPG Innovation
Response of ICPT to GDIG Innovation
Response of ICPC to ICPT Innovation
Response of ICPC to ICPC Innovation
Response of ICPC to USGDPG Innovation
Response of ICPC to GDIG Innovation
Response of USGDPG to ICPT Innovation
Response of USGDPG to ICPC Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to GDIG Innovation
Response of GDIG to ICPT Innovation
Response of GDIG to ICPC Innovation
Response of GDIG to USGDPG Innovation
Response of GDIG to GDIG Innovation

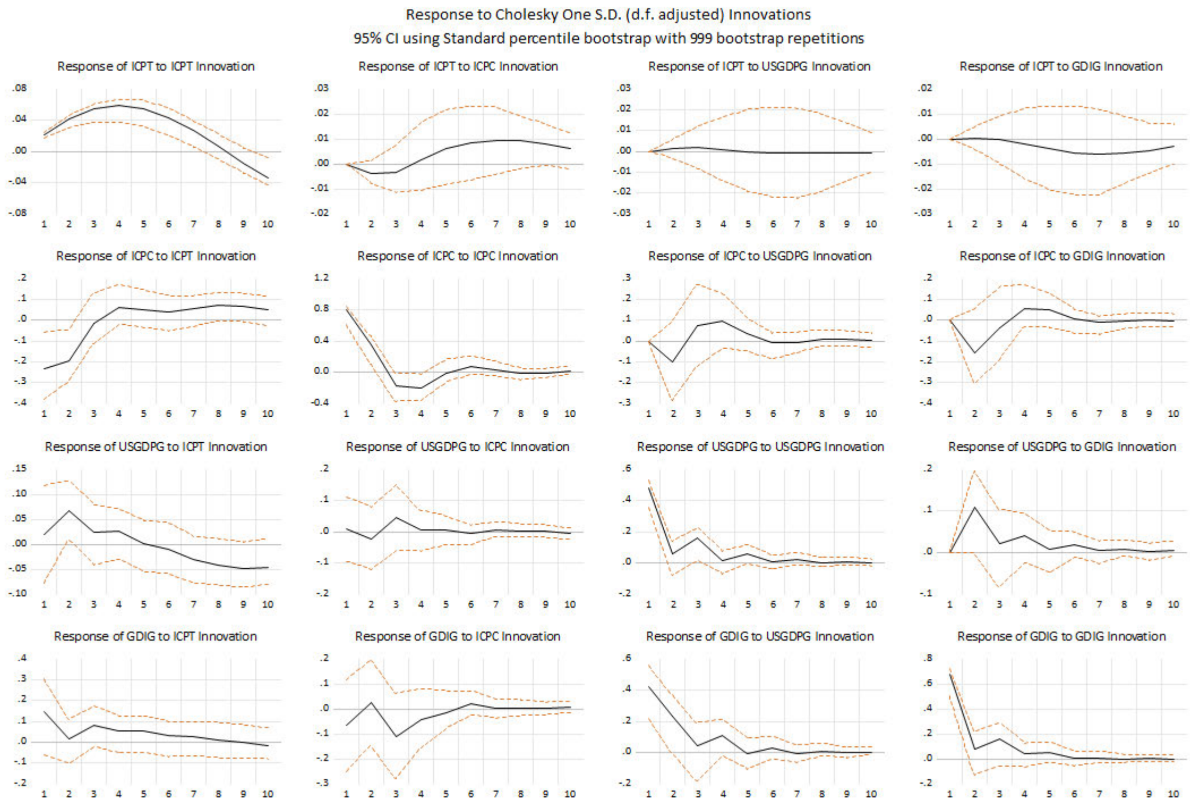
SVAR 5


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICPT to ICPT Innovation
Response of ICPT to ICPC Innovation
Response of ICPT to USGDPG Innovation
Response of ICPT to GDPG Innovation
Response of ICPC to ICPT Innovation
Response of ICPC to ICPC Innovation
Response of ICPC to USGDPG Innovation
Response of ICPC to GDPG Innovation
Response of USGDPG to ICPT Innovation
Response of USGDPG to ICPC Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to GDPG Innovation
Response of GDPG to ICPT Innovation
Response of GDPG to ICPC Innovation
Response of GDPG to USGDPG Innovation
Response of GDPG to GDPG Innovation

SVAR 6


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions

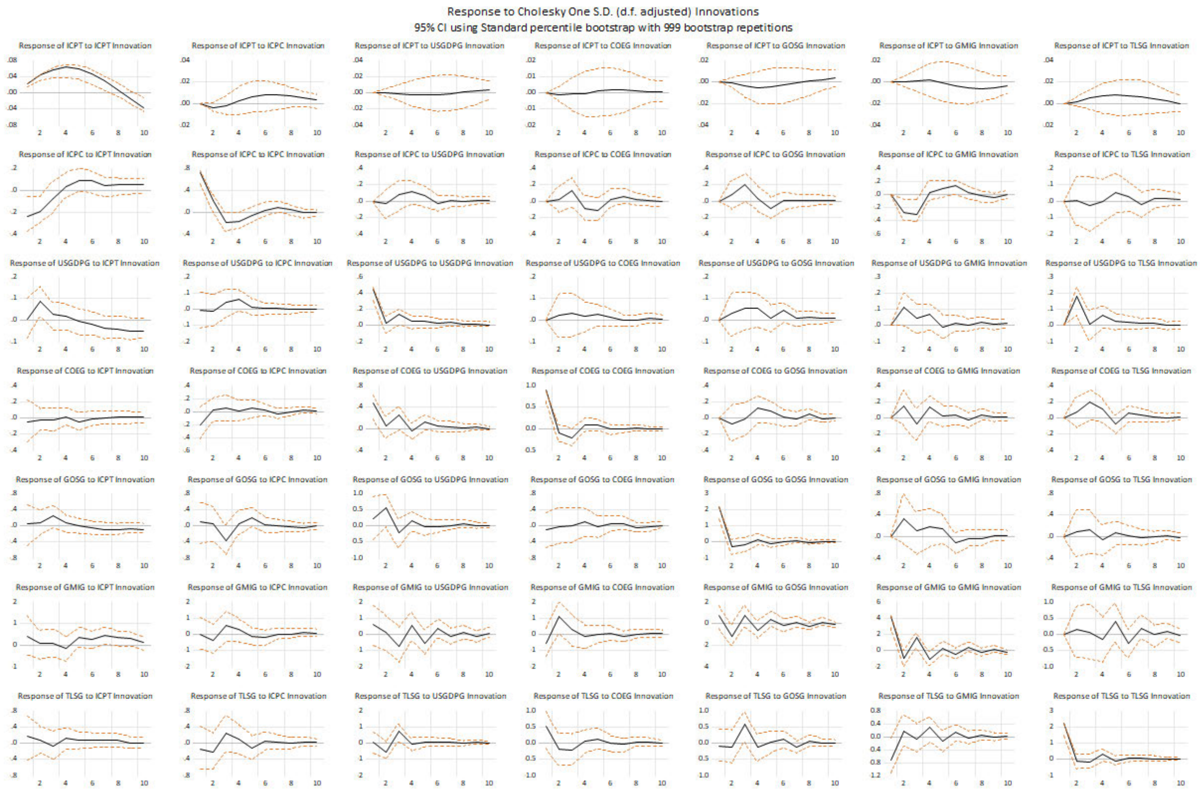
SVAR 7


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICPT to ICPT Innovation
Response of ICPT to ICPC Innovation
Response of ICPT to USGDPG Innovation
Response of ICPT to GDIG Innovation
Response of ICPC to ICPT Innovation
Response of ICPC to ICPC Innovation
Response of ICPC to USGDPG Innovation
Response of ICPC to GDIG Innovation
Response of USGDPG to ICPT Innovation
Response of USGDPG to ICPC Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to GDIG Innovation
Response of GDIG to ICPT Innovation
Response of GDIG to ICPC Innovation
Response of GDIG to USGDPG Innovation
Response of GDIG to GDIG Innovation

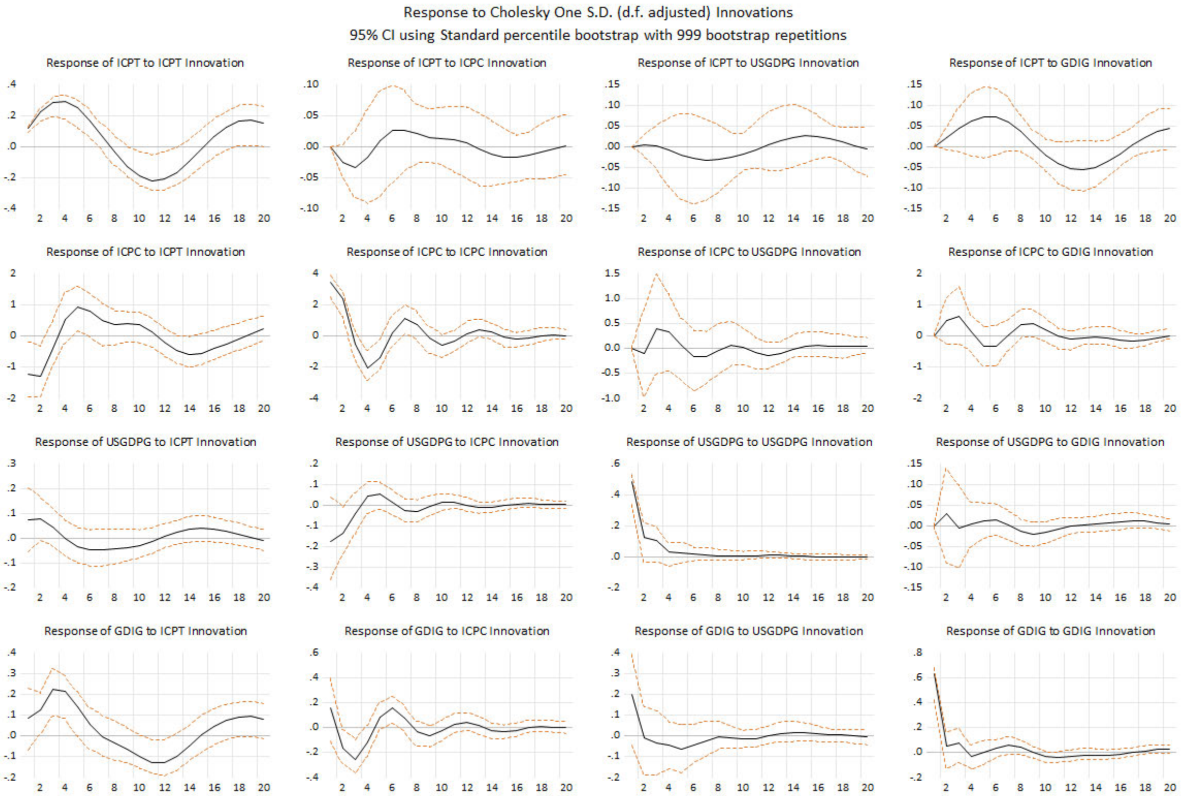
SVAR 8


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICPT to ICPT Innovation
Response of ICPT to ICPC Innovation
Response of ICPT to USGDPG Innovation
Response of ICPT to GDPG Innovation
Response of ICPC to ICPT Innovation
Response of ICPC to ICPC Innovation
Response of ICPC to USGDPG Innovation
Response of ICPC to GDPG Innovation
Response of USGDPG to ICPT Innovation
Response of USGDPG to ICPC Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to GDPG Innovation
Response of GDPG to ICPT Innovation
Response of GDPG to ICPC Innovation
Response of GDPG to USGDPG Innovation
Response of GDPG to GDPG Innovation

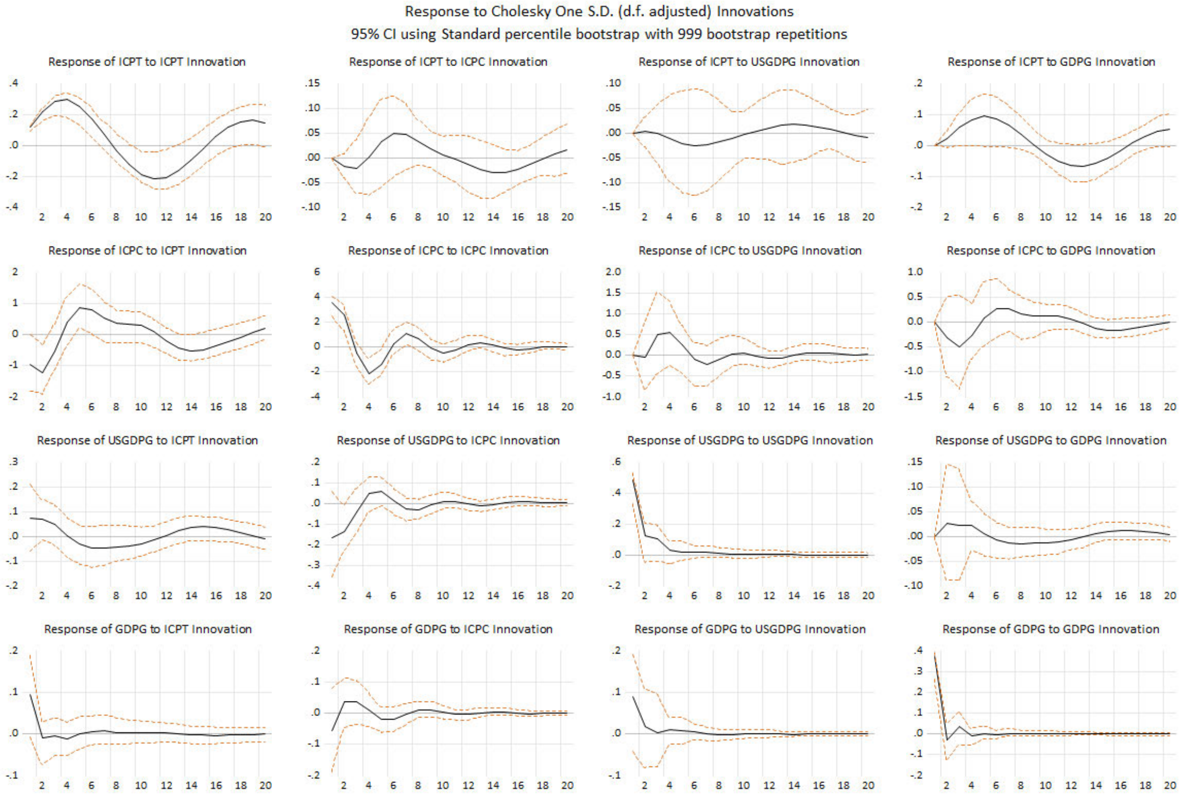
SVAR 9


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions

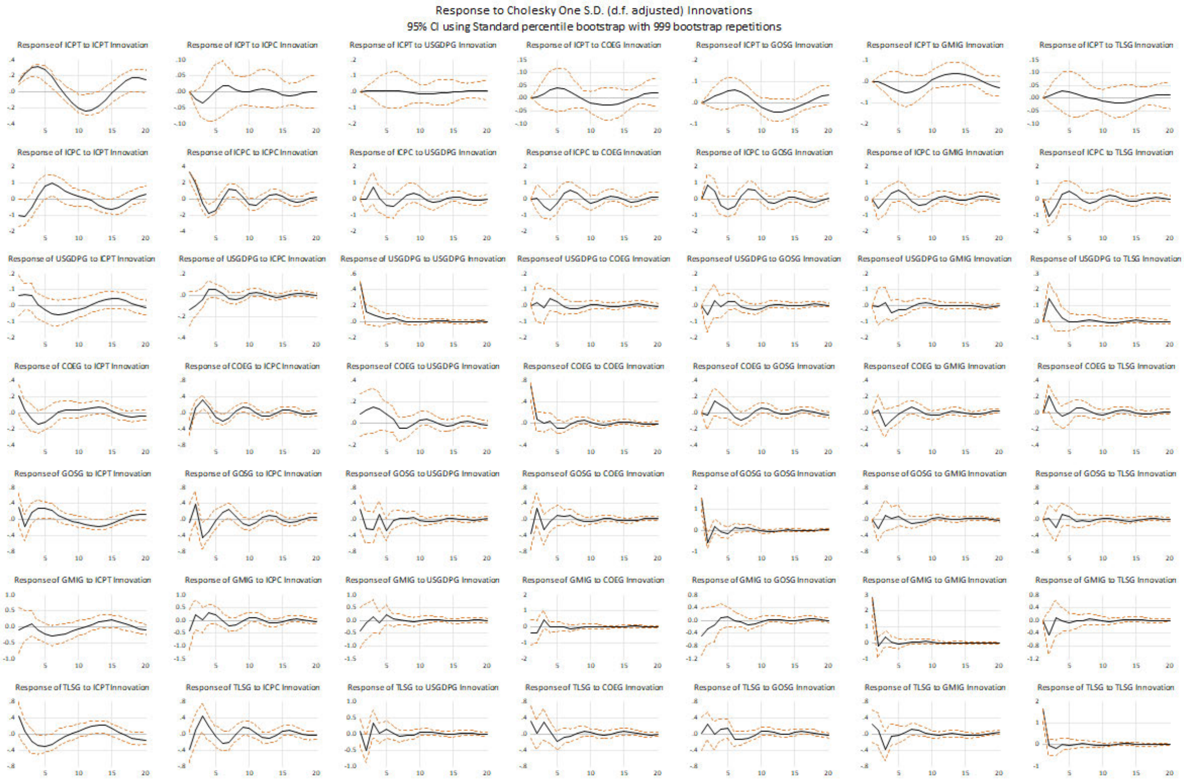
SVAR 10



SVAR 11



SVAR 12


Response to Cholesky One S.D. (d.f. adjusted) Innovations
95% CI using Standard percentile bootstrap with 999 bootstrap repetitions
Response of ICPT to ICPT Innovation
Response of ICPT to ICPC Innovation
Response of ICPT to USGDPG Innovation
Response of ICPT to COEG Innovation
Response of ICPT to GOSG Innovation
Response of ICPT to GMIG Innovation
Response of ICPT to TLSG Innovation
Response of ICPC to ICPT Innovation
Response of ICPC to ICPC Innovation
Response of ICPC to USGDPG Innovation
Response of ICPC to COEG Innovation
Response of ICPC to GOSG Innovation
Response of ICPC to GMIG Innovation
Response of ICPC to TLSG Innovation
Response of USGDPG to ICPT Innovation
Response of USGDPG to ICPC Innovation
Response of USGDPG to USGDPG Innovation
Response of USGDPG to COEG Innovation
Response of USGDPG to GOSG Innovation
Response of USGDPG to GMIG Innovation
Response of USGDPG to TLSG Innovation
Response of COEG to ICPT Innovation
Response of COEG to ICPC Innovation
Response of COEG to USGDPG Innovation
Response of COEG to COEG Innovation
Response of COEG to GOSG Innovation
Response of COEG to GMIG Innovation
Response of COEG to TLSG Innovation
Response of GOSG to ICPT Innovation
Response of GOSG to ICPC Innovation
Response of GOSG to USGDPG Innovation
Response of GOSG to COEG Innovation
Response of GOSG to GOSG Innovation
Response of GOSG to GMIG Innovation
Response of GOSG to TLSG Innovation
Response of GMIG to ICPT Innovation
Response of GMIG to ICPC Innovation
Response of GMIG to USGDPG Innovation
Response of GMIG to COEG Innovation
Response of GMIG to GOSG Innovation
Response of GMIG to GMIG Innovation
Response of GMIG to TLSG Innovation
Response of TLSG to ICPT Innovation
Response of TLSG to ICPC Innovation
Response of TLSG to USGDPG Innovation
Response of TLSG to COEG Innovation
Response of TLSG to GOSG Innovation
Response of TLSG to GMIG Innovation
Response of TLSG to TLSG Innovation

A.4 10 Period Variance Decomposition

Variance Decomposition of GDI growth for SVAR 1:

Variance Decomposition of GDIG:

Period	S.E.	ICP	USGDPG	GDIG
1	0.799888	10.53296	15.82831	73.63872
		(4.66911)	(5.85036)	(6.50579)
2	0.851224	12.25356	20.14550	67.60094
		(5.00212)	(7.19230)	(7.25385)
3	0.881519	12.30739	20.00067	67.69194
		(4.71865)	(7.16347)	(7.22566)
4	0.896422	13.74353	20.53243	65.72404
		(5.10453)	(7.35449)	(7.60108)
5	0.899056	14.11466	20.41230	65.47303
		(5.23421)	(7.27233)	(7.70731)
6	0.899095	14.12134	20.41085	65.46781
		(5.21664)	(7.26462)	(7.73238)
7	0.899343	14.14133	20.42601	65.43266
		(5.23638)	(7.24936)	(7.73980)
8	0.899425	14.15650	20.42265	65.42085
		(5.26250)	(7.25264)	(7.74967)
9	0.899441	14.15857	20.42234	65.41909
		(5.27266)	(7.25316)	(7.75530)
10	0.899443	14.15855	20.42257	65.41888
		(5.27600)	(7.25245)	(7.75787)

Variance Decomposition of GDP growth for SVAR 2:

Variance Decomposition of GDPG:

Period	S.E.	ICP	USGDPG	GDPG
1	0.611262	2.372489	14.41945	83.20807
		(2.68255)	(5.15301)	(5.00001)
2	0.617127	2.329703	16.00133	81.66897
		(2.71969)	(5.40777)	(5.29060)
3	0.622850	2.420086	16.35333	81.22659
		(2.78915)	(5.31854)	(5.06681)
4	0.624566	2.567735	16.64841	80.78385
		(2.88788)	(5.38452)	(5.15056)
5	0.625202	2.670440	16.67564	80.65392
		(2.90696)	(5.38031)	(5.19832)
6	0.625391	2.701442	16.69117	80.60739
		(2.90506)	(5.38800)	(5.21715)
7	0.625416	2.705138	16.69125	80.60361
		(2.90189)	(5.39176)	(5.22127)
8	0.625419	2.705206	16.69171	80.60309
		(2.90102)	(5.39597)	(5.22579)
9	0.625419	2.705216	16.69172	80.60307
		(2.90082)	(5.39795)	(5.22860)
10	0.625419	2.705214	16.69177	80.60302
		(2.90059)	(5.39900)	(5.23027)

Variance Decomposition of the growth of the component elements of GDI for SVAR 3:

Variance Decomposition of COEG:

Period	S.E.	ICP	USGDPG	COEG	GOSG	GMIG	TLSG
1	0.992186	23.91854	6.233680	69.84778	0.000000	0.000000	0.000000
		(6.51406)	(4.06096)	(6.59063)	(0.00000)	(0.00000)	(0.00000)
2	1.038965	28.92597	5.702152	63.71201	0.226469	0.749109	0.684290
		(6.30323)	(3.83509)	(6.48731)	(1.32118)	(1.82675)	(1.49668)
3	1.066418	27.88689	6.761174	61.35392	0.334043	1.698793	1.965180
		(5.99719)	(4.09280)	(6.20555)	(1.34258)	(2.21926)	(2.33623)
4	1.071830	28.25820	6.696805	60.74628	0.606005	1.709512	1.983197
		(5.99569)	(4.09718)	(6.20341)	(1.45502)	(2.24377)	(2.41730)
5	1.076572	28.03588	7.315143	60.21295	0.679065	1.761365	1.995600
		(5.98120)	(4.34139)	(6.29188)	(1.43402)	(2.26531)	(2.38119)
6	1.078852	28.11263	7.364075	59.96116	0.676222	1.813329	2.072580
		(5.96622)	(4.39580)	(6.35432)	(1.43776)	(2.27901)	(2.39798)
7	1.079819	28.19400	7.372046	59.85432	0.675904	1.818147	2.085587
		(5.95543)	(4.46585)	(6.41872)	(1.43413)	(2.28063)	(2.40915)
8	1.080097	28.20856	7.374915	59.82345	0.683191	1.819910	2.089974
		(5.95764)	(4.51370)	(6.45297)	(1.43716)	(2.28807)	(2.41944)
9	1.080122	28.20741	7.376401	59.82083	0.683276	1.821750	2.090327
		(5.95934)	(4.55698)	(6.48487)	(1.43930)	(2.29096)	(2.42646)
10	1.080131	28.20740	7.376648	59.81982	0.684049	1.821785	2.090300
		(5.96146)	(4.58916)	(6.50508)	(1.44182)	(2.29431)	(2.43157)

Variance Decomposition of GOSG:							
Period	S.E.	ICP	USGDPG	COEG	GOSG	GMIG	TLSG
1	1.942207	0.156899	3.225621	1.095551	95.52193	0.000000	0.000000
		(1.52175)	(3.03142)	(1.76368)	(3.73780)	(0.00000)	(0.00000)
2	2.101906	9.665347	4.330433	1.262181	84.09732	0.506065	0.138651
		(5.24585)	(2.94102)	(2.24875)	(5.81467)	(1.40376)	(1.00652)
3	2.107775	9.785318	4.486049	1.372845	83.65840	0.503597	0.193794
		(4.99034)	(3.12823)	(2.64981)	(5.85107)	(1.73714)	(1.41851)
4	2.132637	10.25014	5.832158	1.348117	81.81967	0.528250	0.221665
		(4.92293)	(3.64594)	(2.60236)	(6.15626)	(1.89805)	(1.43003)
5	2.140948	10.63696	5.793750	1.341447	81.23261	0.570127	0.425105
		(4.94284)	(3.67431)	(2.59359)	(6.22265)	(2.00486)	(1.50633)
6	2.143145	10.77768	5.792088	1.338701	81.09209	0.574723	0.424716
		(5.00726)	(3.71290)	(2.58854)	(6.28433)	(2.06403)	(1.50189)
7	2.143263	10.77652	5.794979	1.338948	81.08439	0.575549	0.429613
		(5.00402)	(3.70928)	(2.58954)	(6.30092)	(2.10216)	(1.52116)
8	2.143412	10.78624	5.794623	1.338764	81.07320	0.577403	0.429772
		(5.01185)	(3.71606)	(2.58815)	(6.31596)	(2.12748)	(1.52279)
9	2.143479	10.78791	5.796643	1.338794	81.06923	0.577367	0.430059
		(5.02194)	(3.71875)	(2.58780)	(6.32309)	(2.13941)	(1.52483)
10	2.143488	10.78782	5.797230	1.338790	81.06858	0.577366	0.430218
		(5.02513)	(3.72132)	(2.58732)	(6.32485)	(2.14762)	(1.52462)

Variance Decomposition of GMIG:							
Period	S.E.	ICP	USGDPG	COEG	GOSG	GMIG	TLSG
1	4.067120	0.113742	0.008627	2.083073	0.031875	97.76268	0.000000
		(1.15721)	(1.00907)	(2.68257)	(1.04241)	(3.50923)	(0.00000)
2	4.238113	0.453972	0.331287	3.460141	3.402517	92.01932	0.332759
		(1.45074)	(1.54475)	(3.51294)	(2.91761)	(4.68590)	(1.18836)
3	4.446803	1.456800	1.419241	3.278768	3.355615	90.09879	0.390785
		(2.12526)	(2.48472)	(3.10307)	(3.13001)	(5.17262)	(1.40574)
4	4.478348	1.443920	1.798672	3.278138	3.455612	89.63716	0.386493
		(2.14459)	(2.88882)	(3.09628)	(3.28136)	(5.45273)	(1.41477)
5	4.499689	1.488855	2.023997	3.249332	3.439737	89.35320	0.444875
		(2.11749)	(3.05316)	(3.05735)	(3.25049)	(5.60083)	(1.54918)
6	4.506978	1.510541	2.099848	3.239724	3.428782	89.25589	0.465217
		(2.13396)	(3.10876)	(3.05609)	(3.23989)	(5.64592)	(1.56035)
7	4.509332	1.508973	2.099169	3.236747	3.428356	89.25369	0.473061
		(2.14245)	(3.11900)	(3.04864)	(3.25075)	(5.65568)	(1.58384)
8	4.510173	1.512404	2.107370	3.235580	3.428734	89.24299	0.472918
		(2.14275)	(3.14885)	(3.04618)	(3.25479)	(5.66303)	(1.59343)
9	4.510622	1.517165	2.107031	3.235024	3.429561	89.23653	0.474688
		(2.14481)	(3.15563)	(3.04474)	(3.25707)	(5.67541)	(1.60533)
10	4.510735	1.517631	2.107802	3.234923	3.429578	89.23539	0.474672
		(2.14623)	(3.16117)	(3.04417)	(3.25728)	(5.67971)	(1.60925)

Variance Decomposition of TLSG:							
Period	S.E.	ICP	USGDPG	COEG	GOSG	GMIG	TLSG
1	2.235630	8.468701	0.140873	2.448371	0.019934	0.059523	88.86260
		(4.31418)	(0.85955)	(2.73824)	(1.11392)	(0.85379)	(5.15733)
2	2.378877	13.62375	4.255522	2.407424	0.639854	0.071947	79.00150
		(5.52419)	(3.35222)	(2.56617)	(1.74579)	(1.08087)	(6.10189)
3	2.485489	13.55329	8.953801	2.315791	1.985372	0.784136	72.40761
		(5.36372)	(4.20720)	(2.37479)	(2.39940)	(1.85652)	(6.02643)
4	2.496587	13.52468	9.118933	2.297754	2.026098	0.935038	72.09750
		(5.38641)	(4.30484)	(2.30264)	(2.39718)	(1.90559)	(6.16915)
5	2.503358	13.45382	9.179340	2.288397	2.110603	1.150113	71.81772
		(5.43550)	(4.31299)	(2.29611)	(2.47657)	(2.09037)	(6.21923)
6	2.504920	13.43709	9.221728	2.286087	2.111425	1.197473	71.74619
		(5.44188)	(4.32494)	(2.28213)	(2.47234)	(2.10630)	(6.25073)
7	2.505200	13.43915	9.220013	2.285612	2.114202	1.209341	71.73168
		(5.43575)	(4.33389)	(2.27808)	(2.47785)	(2.12479)	(6.27066)
8	2.505575	13.44886	9.222719	2.285220	2.120182	1.212373	71.71065
		(5.45133)	(4.35374)	(2.27800)	(2.47309)	(2.12810)	(6.28252)
9	2.505639	13.44988	9.223445	2.285185	2.120396	1.213065	71.70802
		(5.45694)	(4.36774)	(2.27742)	(2.47105)	(2.13125)	(6.29248)
10	2.505648	13.44996	9.223420	2.285179	2.120707	1.213236	71.70750
		(5.45763)	(4.37869)	(2.27714)	(2.47173)	(2.13111)	(6.29635)

Variance Decomposition of GDI growth for SVAR 4:

Variance Decomposition of GDIG: Period	S.E.	ICPT	ICPC	USGDPG	GDIG
1	0.752824	0.428657	1.035370	16.14511	82.39086
		(1.33580)	(1.67818)	(4.79742)	(4.59551)
2	0.787835	1.442683	3.595024	18.51221	76.45009
		(1.65347)	(2.47220)	(5.53076)	(5.55105)
3	0.834712	4.296222	8.484860	16.59773	70.62119
		(2.72350)	(3.78911)	(5.09513)	(5.86218)
4	0.852687	6.779977	9.403331	16.11070	67.70599
		(3.67048)	(4.14911)	(5.12041)	(6.16764)
5	0.860118	7.877708	9.533014	15.97453	66.61475
		(4.17481)	(4.11599)	(5.00200)	(6.26152)
6	0.866705	7.950621	10.65747	15.77317	65.61874
		(4.27861)	(4.47507)	(4.92587)	(6.46253)
7	0.868795	7.912499	10.96654	15.75207	65.36888
		(4.29194)	(4.61967)	(4.88449)	(6.54606)
8	0.869425	7.982471	10.98575	15.72967	65.30210
		(4.34475)	(4.62094)	(4.87137)	(6.54384)
9	0.871491	8.206457	11.14181	15.65564	64.99610
		(4.52640)	(4.72785)	(4.84658)	(6.58390)
10	0.874171	8.724498	11.10770	15.56017	64.60764
		(4.91037)	(4.77076)	(4.81773)	(6.63579)

Variance Decomposition of GDP growth for SVAR 5:

Variance Decomposition of GDPG: Period	S.E.	ICPT	ICPC	USGDPG	GDPG
1	0.611896	0.827313	0.757061	15.52580	82.88983
		(1.69591)	(1.52729)	(6.22385)	(6.30332)
2	0.620403	0.824723	0.801229	17.74167	80.63238
		(1.59081)	(1.74395)	(6.25274)	(6.43798)
3	0.626431	0.816098	0.801246	18.38843	79.99423
		(1.54179)	(1.99719)	(6.32225)	(6.55264)
4	0.628615	0.829966	0.799867	18.92932	79.44084
		(1.57034)	(2.28467)	(6.45655)	(6.77471)
5	0.629511	0.830546	0.857649	19.08525	79.22656
		(1.58995)	(2.33406)	(6.56130)	(6.88472)
6	0.630034	0.829864	0.888872	19.18603	79.09524
		(1.59690)	(2.35936)	(6.63118)	(6.94291)
7	0.630156	0.830285	0.888957	19.21536	79.06539
		(1.60205)	(2.40399)	(6.66711)	(7.00056)
8	0.630237	0.831781	0.894277	19.22864	79.04530
		(1.62821)	(2.41009)	(6.68956)	(7.03434)
9	0.630270	0.832763	0.896613	19.23368	79.03694
		(1.67384)	(2.43693)	(6.69680)	(7.06494)
10	0.630287	0.832733	0.897121	19.23745	79.03269
		(1.73241)	(2.46650)	(6.69968)	(7.09536)

Variance Decomposition of the growth of the component elements of GDI for SVAR 6:

Variance Decomposition of COEG: Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	0.934799	3.293355	11.94418	6.484323	78.27814	0.000000	0.000000	0.000000
		(2.89059)	(4.77356)	(4.23426)	(6.22984)	(0.00000)	(0.00000)	(0.00000)
2	0.948643	3.239388	12.20961	6.466604	76.01120	0.292618	1.187915	0.592663
		(2.74908)	(4.53192)	(4.16198)	(6.11265)	(1.38624)	(2.22203)	(1.11851)
3	1.022000	3.728407	17.07546	9.336863	66.17724	0.341954	1.566301	1.773770
		(2.63973)	(4.88445)	(4.24026)	(5.66139)	(1.46957)	(2.09336)	(1.98716)
4	1.038365	4.555157	17.53348	9.379952	64.14136	1.089730	1.518591	1.781739
		(2.82618)	(4.95006)	(4.25412)	(5.60427)	(1.79712)	(2.02790)	(2.04070)
5	1.056217	4.763022	17.65523	10.66384	62.05712	1.476824	1.661594	1.722368
		(2.87624)	(5.00578)	(4.17460)	(5.73752)	(1.98099)	(2.03997)	(2.01338)
6	1.071268	4.675757	19.19968	10.66811	60.38504	1.435641	1.700191	1.935580
		(2.87425)	(5.33178)	(4.13309)	(5.85351)	(1.95313)	(2.01923)	(1.95043)
7	1.075940	4.635381	19.65241	10.65107	59.86216	1.448819	1.707058	2.043104
		(2.83023)	(5.38420)	(4.12118)	(5.84049)	(1.93579)	(1.98981)	(1.93743)
8	1.077121	4.625253	19.66612	10.64390	59.76665	1.449064	1.778202	2.070808
		(2.80391)	(5.44068)	(4.12581)	(5.86072)	(1.95462)	(2.03240)	(1.93689)
9	1.079994	4.605377	20.05044	10.60681	59.46531	1.443324	1.768940	2.059809
		(2.78762)	(5.58241)	(4.15153)	(5.89835)	(1.95687)	(2.02544)	(1.92951)
10	1.081099	4.596048	20.14552	10.61941	59.34521	1.469038	1.768317	2.056455
		(2.78697)	(5.63639)	(4.18546)	(5.93255)	(1.96267)	(2.01871)	(1.92559)

Variance Decomposition of GOSG: Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	1.950231	0.423101	0.046473	3.047003	1.274885	95.20854	0.000000	0.000000
		(1.78068)	(1.11040)	(2.75078)	(1.93282)	(3.76610)	(0.00000)	(0.00000)
2	2.024431	0.577723	1.608913	4.305658	1.575742	91.19783	0.512013	0.222119
		(1.79962)	(2.19912)	(2.62624)	(2.22601)	(4.28352)	(1.05279)	(1.00463)
3	2.061805	0.805893	3.920563	4.905156	1.684761	87.93586	0.527143	0.220625
		(1.87701)	(2.95290)	(2.74269)	(2.30898)	(4.79316)	(1.53730)	(1.23891)
4	2.101225	1.636956	5.821885	5.406823	1.640165	84.71839	0.522394	0.253390
		(2.02215)	(3.74551)	(2.89735)	(2.19556)	(5.50460)	(1.60940)	(1.20874)
5	2.115735	2.249381	5.765951	5.498651	1.696243	83.78026	0.634978	0.374538
		(2.17779)	(3.67255)	(2.92886)	(2.20153)	(5.62044)	(1.58421)	(1.29172)
6	2.124866	2.472415	6.224179	5.458576	1.741885	83.06982	0.631828	0.401300
		(2.26561)	(3.87282)	(2.87594)	(2.14478)	(5.75400)	(1.60302)	(1.28857)
7	2.133039	2.470499	6.874157	5.418503	1.737867	82.45468	0.630656	0.413636
		(2.28737)	(4.15077)	(2.88518)	(2.13062)	(5.99001)	(1.58225)	(1.27535)
8	2.134485	2.469193	6.910826	5.413189	1.743415	82.36677	0.671003	0.425604
		(2.30488)	(4.17409)	(2.91295)	(2.12453)	(6.05861)	(1.56402)	(1.27210)
9	2.136457	2.474303	7.030281	5.411112	1.756952	82.22525	0.677211	0.424891
		(2.32822)	(4.28802)	(2.92493)	(2.11480)	(6.14730)	(1.56546)	(1.26997)
10	2.138727	2.498685	7.188438	5.399634	1.755029	82.05391	0.676017	0.428291
		(2.34972)	(4.41742)	(2.93050)	(2.11030)	(6.23343)	(1.55896)	(1.26650)

Variance Decomposition of GMIG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	4.086127	0.041049	0.000787	0.002753	2.084983	0.013433	97.85699	0.000000
		(1.10397)	(1.15038)	(1.10731)	(2.63242)	(1.21877)	(2.81585)	(0.00000)
2	4.245718	0.122072	0.020247	0.343664	3.405573	3.213724	92.65049	0.244230
		(1.06209)	(1.25859)	(1.60657)	(3.30456)	(3.21318)	(4.87740)	(1.55575)
3	4.432802	0.157321	0.018768	1.352428	3.251703	3.224730	91.72619	0.268859
		(1.06421)	(1.34938)	(3.00685)	(3.12512)	(3.11177)	(5.45218)	(1.68425)
4	4.488829	0.183791	0.837889	1.993598	3.220789	3.229015	90.26940	0.265518
		(1.03733)	(1.74698)	(3.54117)	(3.05822)	(3.17305)	(6.05688)	(1.75966)
5	4.511960	0.281766	1.019854	2.087699	3.194523	3.240071	89.87321	0.302876
		(1.15994)	(1.87600)	(3.97647)	(3.02349)	(3.15793)	(6.30614)	(1.77416)
6	4.525284	0.360198	1.019209	2.272134	3.184057	3.232610	89.61920	0.312592
		(1.21082)	(1.93372)	(4.23922)	(2.98991)	(3.13677)	(6.45806)	(1.76112)
7	4.533238	0.399218	1.185459	2.264295	3.181893	3.224324	89.40509	0.339724
		(1.27200)	(2.13943)	(4.28631)	(2.97241)	(3.12256)	(6.54761)	(1.75261)
8	4.536211	0.419127	1.258823	2.273831	3.177729	3.229104	89.29870	0.342684
		(1.29902)	(2.23091)	(4.32676)	(2.96072)	(3.11824)	(6.61891)	(1.74473)
9	4.537620	0.437089	1.258084	2.273021	3.177162	3.227853	89.27848	0.348309
		(1.33082)	(2.25714)	(4.35303)	(2.95709)	(3.11090)	(6.63837)	(1.74722)
10	4.539061	0.454950	1.297566	2.273247	3.176729	3.226716	89.22269	0.348103
		(1.35072)	(2.33497)	(4.35948)	(2.95386)	(3.11039)	(6.66249)	(1.74550)

Variance Decomposition of TLSG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	2.188933	0.838548	1.940261	0.212542	2.537001	0.015222	0.090910	94.36552
		(1.83040)	(2.53473)	(1.35947)	(2.92518)	(0.91825)	(0.86436)	(4.61166)
2	2.239409	0.801348	1.856220	3.498668	2.701132	0.430998	0.157921	90.55371
		(1.69861)	(2.62489)	(3.30910)	(3.10907)	(1.47519)	(1.26562)	(5.54142)
3	2.386777	1.049985	3.212160	10.93950	2.393598	2.176492	0.501056	79.72721
		(1.51574)	(2.99372)	(4.78057)	(2.69279)	(2.49082)	(1.63617)	(6.76853)
4	2.416079	2.235028	3.928431	10.67733	2.337348	2.128250	0.641072	78.05254
		(1.72749)	(3.14319)	(4.62920)	(2.64890)	(2.43450)	(1.67783)	(6.87910)
5	2.447228	3.006407	4.039224	11.23222	2.390750	2.366159	0.879410	76.08582
		(2.03689)	(3.27308)	(4.81641)	(2.63053)	(2.39520)	(1.87879)	(7.15210)
6	2.469984	3.406821	4.750022	11.29344	2.388928	2.325264	0.964867	74.87066
		(2.31432)	(3.61062)	(4.81817)	(2.55503)	(2.35351)	(1.87081)	(7.33167)
7	2.478439	3.583922	5.054690	11.25868	2.373022	2.335053	0.964620	74.43001
		(2.44207)	(3.69218)	(4.80720)	(2.53221)	(2.32014)	(1.84781)	(7.36950)
8	2.481160	3.668516	5.044424	11.26036	2.374033	2.331162	1.028038	74.29347
		(2.49208)	(3.71541)	(4.83990)	(2.52800)	(2.30245)	(1.85918)	(7.40418)
9	2.483787	3.692026	5.181215	11.25593	2.374025	2.326904	1.029192	74.14071
		(2.50660)	(3.81395)	(4.86087)	(2.51801)	(2.29021)	(1.85273)	(7.42784)
10	2.484790	3.691348	5.224245	11.26806	2.372635	2.333845	1.028664	74.08120
		(2.53065)	(3.84999)	(4.88116)	(2.51228)	(2.28349)	(1.84860)	(7.42724)

Variance Decomposition of GDI growth for SVAR 7:

Variance Decomposition of GDIG:

Period	S.E.	ICPT	ICPC	USGDPG	GDIG
1	0.813696	3.322730	0.659773	26.52108	69.49641
		(4.62378)	(3.18966)	(8.81238)	(9.29879)
2	0.850056	3.082836	0.678715	31.68728	64.55117
		(4.44077)	(3.49894)	(9.82184)	(9.37378)
3	0.877126	3.778168	2.228814	30.02333	63.96969
		(4.68029)	(4.41171)	(9.25475)	(9.42587)
4	0.887782	4.040512	2.391722	30.88870	62.67907
		(4.80379)	(4.57203)	(9.50126)	(9.62932)
5	0.890899	4.357198	2.398664	30.67478	62.56935
		(5.03595)	(4.57383)	(9.45439)	(9.68070)
6	0.892010	4.453020	2.438740	30.69294	62.41530
		(5.20308)	(4.63497)	(9.56087)	(9.82847)
7	0.892442	4.528637	2.437564	30.67274	62.36106
		(5.43523)	(4.64044)	(9.55860)	(9.90301)
8	0.892590	4.544757	2.437129	30.67645	62.34167
		(5.63838)	(4.62261)	(9.62837)	(10.0242)
9	0.892596	4.544735	2.437116	30.67693	62.34122
		(5.78925)	(4.61025)	(9.66395)	(10.0914)
10	0.892741	4.570533	2.440117	30.66793	62.32142
		(5.89504)	(4.59340)	(9.71424)	(10.1560)

Variance Decomposition of GDP growth for SVAR 8:

Variance Decomposition of GDPG:

Period	S.E.	ICPT	ICPC	USGDPG	GDPG
1	0.750400	1.385441	1.130734	29.83685	67.64697
		(3.06699)	(2.88252)	(7.45779)	(7.64663)
2	0.764062	1.461846	1.091502	31.93283	65.51383
		(2.99406)	(3.32336)	(7.96635)	(8.18053)
3	0.789687	1.765450	4.717971	31.31768	62.19890
		(2.94944)	(4.97571)	(8.14546)	(8.04646)
4	0.796068	1.898296	4.959750	31.79985	61.34210
		(2.96008)	(5.31191)	(8.41213)	(8.27843)
5	0.796814	1.943080	5.043361	31.77618	61.23738
		(3.01655)	(5.45714)	(8.55040)	(8.39007)
6	0.797547	1.969619	5.156868	31.74799	61.12553
		(3.08971)	(5.66878)	(8.65198)	(8.47918)
7	0.797773	2.017324	5.155005	31.73671	61.09096
		(3.23851)	(5.70077)	(8.72649)	(8.55225)
8	0.798008	2.053587	5.157807	31.73271	61.05590
		(3.40025)	(5.75457)	(8.78229)	(8.63559)
9	0.798056	2.062204	5.157305	31.73167	61.04882
		(3.54807)	(5.76669)	(8.82055)	(8.69827)
10	0.798077	2.062917	5.160838	31.73066	61.04558
		(3.66256)	(5.77054)	(8.84956)	(8.73672)

Variance Decomposition of the growth of the component elements of GDI for SVAR 9:

Variance Decomposition of COEG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	1.034327	0.264554	4.016578	21.01204	74.70683	0.000000	0.000000	0.000000
		(3.72375)	(5.49568)	(7.69476)	(8.32481)	(0.00000)	(0.00000)	(0.00000)
2	1.056266	0.332701	3.882287	20.35388	72.59135	0.411130	1.895363	0.533287
		(3.42062)	(5.42727)	(7.02496)	(8.41732)	(2.78822)	(3.55272)	(1.95612)
3	1.131433	0.321711	3.639720	22.87879	67.13666	0.382119	2.090642	3.550354
		(2.84641)	(4.99627)	(6.99970)	(7.21426)	(3.15693)	(3.57669)	(3.97330)
4	1.154624	0.327636	3.508463	22.04521	65.05349	1.421429	3.305648	4.338119
		(2.77160)	(4.79235)	(6.69128)	(7.28039)	(3.45714)	(3.64268)	(4.00564)
5	1.173233	0.485134	3.612519	22.59763	63.51387	1.907059	3.238299	4.645494
		(2.77320)	(4.63082)	(6.63644)	(7.25508)	(3.27337)	(3.59608)	(3.87449)
6	1.177201	0.492572	3.648736	22.62049	63.09907	1.915186	3.343060	4.880884
		(2.77479)	(4.68877)	(6.63768)	(7.27763)	(3.30048)	(3.66059)	(4.01923)
7	1.178950	0.493032	3.734142	22.60215	62.91399	1.920339	3.400771	4.935578
		(2.79876)	(4.67705)	(6.67226)	(7.43875)	(3.31154)	(3.67734)	(4.04250)
8	1.180880	0.500067	3.723245	22.55738	62.71348	2.063150	3.519254	4.923430
		(2.83064)	(4.71956)	(6.70865)	(7.55673)	(3.34846)	(3.72475)	(4.10225)
9	1.181557	0.503569	3.737066	22.59967	62.64316	2.067365	3.528804	4.920361
		(2.82724)	(4.70527)	(6.75679)	(7.64046)	(3.42472)	(3.73264)	(4.10049)
10	1.181888	0.520428	3.736662	22.58746	62.60972	2.068033	3.541448	4.936251
		(2.83421)	(4.74012)	(6.78605)	(7.69802)	(3.45951)	(3.74422)	(4.11027)

Variance Decomposition of GOSG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	2.177883	0.036371	0.200830	1.112694	0.215414	98.43469	0.000000	0.000000
		(3.08115)	(2.21630)	(3.26277)	(2.08684)	(5.61750)	(0.00000)	(0.00000)
2	2.296583	0.148676	0.224447	6.806955	0.204564	90.33878	2.108265	0.168313
		(2.79783)	(2.33367)	(5.49100)	(2.24096)	(6.74419)	(2.39924)	(2.54301)
3	2.361355	1.172385	2.772201	7.244042	0.193928	85.98468	2.188880	0.443880
		(2.79276)	(3.60437)	(5.90478)	(2.72659)	(7.51155)	(2.29114)	(2.85709)
4	2.383667	1.228523	2.782725	7.502335	0.381424	84.88611	2.736548	0.482336
		(2.72055)	(3.61165)	(5.89208)	(2.73339)	(7.77522)	(2.38703)	(2.90495)
5	2.401701	1.212021	3.488763	7.395797	0.395431	83.84960	3.104353	0.554040
		(2.70562)	(3.77787)	(5.82130)	(2.82138)	(8.01705)	(2.61804)	(3.06008)
6	2.406208	1.265781	3.492757	7.386282	0.442052	83.53580	3.317097	0.560230
		(2.73772)	(3.68272)	(5.82784)	(2.84500)	(8.11875)	(2.72595)	(3.16635)
7	2.411056	1.396199	3.478756	7.358360	0.500792	83.38215	3.320924	0.562822
		(2.79249)	(3.70394)	(5.85214)	(2.93392)	(8.24207)	(2.70797)	(3.17172)
8	2.414277	1.559946	3.476007	7.382106	0.523402	83.16414	3.331867	0.562528
		(2.88020)	(3.69801)	(5.85149)	(2.93819)	(8.27287)	(2.70174)	(3.15768)
9	2.416268	1.674015	3.494891	7.370177	0.536772	83.02738	3.328946	0.567814
		(2.93852)	(3.73874)	(5.84571)	(2.98577)	(8.33045)	(2.70682)	(3.18484)
10	2.418173	1.804692	3.491107	7.361442	0.536903	82.89944	3.334009	0.572402
		(3.02438)	(3.73285)	(5.83987)	(2.98374)	(8.34627)	(2.71963)	(3.18788)

Variance Decomposition of GMIG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	4.418797	0.805419	0.000937	1.848668	1.604132	2.770447	92.97040	0.000000
		(2.90730)	(2.04382)	(2.91863)	(3.33779)	(3.60505)	(6.73009)	(0.00000)
2	4.821966	0.693161	0.563012	1.645806	6.773037	8.693670	81.53649	0.094824
		(2.64989)	(2.66956)	(2.84563)	(5.92188)	(7.63902)	(8.73865)	(1.52511)
3	5.223202	0.618969	1.622695	3.493320	6.085330	9.550254	78.53852	0.090913
		(2.65033)	(3.77748)	(3.83000)	(5.08882)	(7.96640)	(8.84986)	(1.91193)
4	5.411589	0.640618	1.796295	4.329687	5.700080	10.19239	77.16391	0.177021
		(2.75382)	(3.51001)	(4.74851)	(4.87103)	(8.22140)	(9.55635)	(1.83923)
5	5.489347	1.054913	1.815451	5.167748	5.539739	10.43683	75.31481	0.670502
		(2.97799)	(3.53275)	(5.12471)	(4.64562)	(8.44559)	(10.0044)	(2.08591)
6	5.539954	1.270898	1.883889	5.486461	5.447999	10.30769	74.71444	0.888621
		(2.76875)	(3.59753)	(5.21173)	(4.59919)	(8.54934)	(10.0858)	(2.20774)
7	5.583125	1.950619	1.856687	5.459799	5.435815	10.18865	74.10745	1.000978
		(3.17497)	(3.61420)	(5.19063)	(4.56034)	(8.56359)	(10.1163)	(2.23434)
8	5.603668	2.348416	1.843201	5.449944	5.396201	10.28853	73.67994	0.993772
		(3.17059)	(3.64224)	(5.25882)	(4.52229)	(8.66206)	(10.1872)	(2.20314)
9	5.620779	2.654655	1.862230	5.473949	5.373241	10.27883	73.34510	1.011992
		(3.43462)	(3.66004)	(5.30562)	(4.48888)	(8.69809)	(10.2611)	(2.23639)
10	5.626837	2.709130	1.883551	5.483470	5.365395	10.28118	73.26611	1.011167
		(3.43498)	(3.67178)	(5.32976)	(4.47572)	(8.72639)	(10.3054)	(2.23318)

Variance Decomposition of TLSG: Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	2.393878	0.546714	0.363798	0.143891	4.597714	0.130551	8.759163	85.45817
		(2.63974)	(2.79296)	(2.29775)	(5.08895)	(2.09975)	(6.40985)	(7.32272)
2	2.484911	0.602619	1.110838	5.026623	4.837507	0.391273	8.606135	79.42501
		(2.56259)	(3.39615)	(5.59751)	(4.87844)	(2.34924)	(6.07644)	(8.05382)
3	2.675412	0.586627	1.843030	11.44587	4.796774	5.042616	7.478707	68.80637
		(2.30275)	(3.17798)	(7.00939)	(4.67606)	(4.59842)	(5.28856)	(8.03759)
4	2.714278	0.748673	1.912260	11.19853	4.708863	5.089350	8.329707	68.01262
		(2.25948)	(3.37959)	(6.93805)	(4.60090)	(4.55678)	(5.05789)	(7.99891)
5	2.726600	0.810885	2.062639	11.15153	4.906589	5.054794	8.465859	67.54770
		(2.21092)	(3.45272)	(6.93292)	(4.55828)	(4.38573)	(4.96068)	(8.06083)
6	2.736956	0.891446	2.092191	11.15985	4.869860	5.268455	8.642344	67.07585
		(2.25784)	(3.46577)	(6.89666)	(4.59863)	(4.26736)	(4.83809)	(8.03071)
7	2.742294	0.956993	2.086436	11.14031	4.878252	5.451785	8.626426	66.85980
		(2.25610)	(3.47838)	(6.94519)	(4.52914)	(4.22222)	(4.81781)	(8.01427)
8	2.744554	1.009545	2.083274	11.12941	4.879133	5.502574	8.628902	66.76717
		(2.30948)	(3.48866)	(6.95288)	(4.52999)	(4.18210)	(4.83999)	(8.03809)
9	2.745427	1.009534	2.099940	11.15400	4.884748	5.501141	8.623729	66.72690
		(2.34939)	(3.50285)	(6.95434)	(4.53932)	(4.16793)	(4.83794)	(8.08321)
10	2.745682	1.011029	2.104593	11.15193	4.884887	5.500118	8.623957	66.72348
		(2.39413)	(3.49587)	(6.95132)	(4.51467)	(4.17713)	(4.83513)	(8.07657)

Variance Decomposition of GDI growth for SVAR 10:

Variance Decomposition of GDIG: Period	S.E.	ICPT	ICPC	USGDPG	GDIG
1	0.685468	1.482289	5.555744	8.533375	84.42859
		(3.86085)	(5.69644)	(7.07114)	(9.66892)
2	0.718311	4.487561	10.35478	7.788551	77.36911
		(4.88407)	(6.53658)	(6.27368)	(10.5136)
3	0.798858	11.63659	18.37017	6.455999	63.53724
		(6.35208)	(7.38240)	(5.09710)	(9.93368)
4	0.836512	17.15860	18.64761	6.145014	58.04878
		(7.36569)	(7.50409)	(4.84182)	(9.72936)
5	0.855056	19.10240	18.89373	6.445694	55.55817
		(7.64084)	(7.27393)	(5.06343)	(9.71928)
6	0.872523	18.74246	21.30219	6.438772	53.51658
		(7.58391)	(7.85662)	(5.10948)	(9.73763)
7	0.878386	18.49348	21.82714	6.413439	53.26594
		(7.51736)	(8.21406)	(5.16984)	(9.78588)
8	0.880577	18.55989	21.83131	6.386629	53.22217
		(7.50602)	(8.33869)	(5.24702)	(9.76139)
9	0.885564	18.89164	22.16100	6.322460	52.62490
		(7.64028)	(8.56414)	(5.30080)	(9.72749)
10	0.892149	19.85843	21.92490	6.251026	51.96564
		(7.98940)	(8.65897)	(5.28804)	(9.77668)

Variance Decomposition of GDP growth for SVAR 11:

Variance Decomposition of GDPG: Period	S.E.	ICPT	ICPC	USGDPG	GDPG
1	0.398839	5.748733	1.903415	5.096483	87.25137
		(5.12262)	(2.91299)	(5.11491)	(7.59175)
2	0.401909	5.722888	2.673685	5.218455	86.38497
		(5.02075)	(3.33501)	(5.49461)	(7.90167)
3	0.404890	5.652198	3.409465	5.145532	85.79280
		(4.74427)	(4.04056)	(5.94179)	(7.98223)
4	0.405376	5.712695	3.448722	5.187981	85.65060
		(4.81907)	(4.63459)	(5.99658)	(8.17574)
5	0.405928	5.697248	3.678740	5.206064	85.41795
		(4.74380)	(4.76061)	(6.20361)	(8.45959)
6	0.406578	5.697619	3.943739	5.211398	85.14724
		(4.76155)	(5.12063)	(6.20016)	(8.65344)
7	0.406665	5.722036	3.954967	5.209398	85.11360
		(4.84655)	(5.44698)	(6.25707)	(8.85979)
8	0.406810	5.727274	4.009623	5.207441	85.05566
		(4.93111)	(5.55079)	(6.24945)	(8.97381)
9	0.406948	5.725501	4.070561	5.205099	84.99884
		(5.02938)	(5.69109)	(6.25637)	(9.07200)
10	0.406957	5.727528	4.072252	5.204924	84.99530
		(5.09064)	(5.81855)	(6.25221)	(9.14315)

Variance Decomposition of the growth of the component elements of GDI for SVAR 12

Variance Decomposition of COEG: Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	0.838673	5.849972	24.22350	1.093156	68.83337	0.000000	0.000000	0.000000
		(6.59085)	(9.52594)	(2.27578)	(10.9043)	(0.00000)	(0.00000)	(0.00000)
2	0.883218	5.359282	23.24801	2.851497	62.82632	0.144563	0.134178	5.436153
		(6.01181)	(8.76839)	(4.40635)	(10.2621)	(2.08881)	(2.16216)	(5.93209)
3	0.977768	4.990643	29.32636	4.624708	51.27404	2.257473	3.044808	4.481967
		(5.08080)	(8.38753)	(4.93018)	(8.67606)	(3.15186)	(3.81891)	(5.22412)
4	1.017128	6.475004	29.11437	5.926441	47.60114	2.839498	3.719494	4.324053
		(5.07589)	(7.88797)	(5.59346)	(8.41697)	(3.17067)	(3.52981)	(5.16071)
5	1.038607	7.448280	29.16085	6.421224	46.30386	2.890098	3.619115	4.156571
		(5.16326)	(7.58659)	(5.91486)	(8.11993)	(3.12021)	(3.43089)	(5.00356)
6	1.070097	7.242018	31.69985	6.180812	44.23495	2.984354	3.521959	4.136054
		(4.98571)	(7.86147)	(5.93920)	(8.15613)	(3.04203)	(3.22826)	(4.80120)
7	1.087672	7.010998	32.24721	6.161798	42.84651	3.731776	3.755300	4.246405
		(4.82767)	(7.83463)	(5.76074)	(8.15197)	(3.40444)	(3.16577)	(4.83391)
8	1.091830	7.041855	32.08700	6.270391	42.62361	3.920061	3.822148	4.234929
		(4.85423)	(7.84559)	(5.72558)	(8.10914)	(3.52254)	(3.15320)	(4.75409)
9	1.102596	6.989991	33.02278	6.150647	42.03164	3.861824	3.762870	4.180247
		(4.92398)	(8.13712)	(5.77238)	(8.14433)	(3.49036)	(3.12805)	(4.70047)
10	1.111249	6.962992	33.41091	6.137861	41.41932	4.072482	3.808149	4.188284
		(4.94303)	(8.21205)	(5.84140)	(8.20205)	(3.59061)	(3.10146)	(4.71349)

Variance Decomposition of GOSG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	1.615869	3.484544	0.164748	2.650292	4.963913	88.73650	0.000000	0.000000
		(5.20661)	(1.88127)	(4.02798)	(5.51474)	(7.66512)	(0.00000)	(0.00000)
2	1.821844	3.736628	4.524600	3.696725	6.084589	80.34581	1.590958	0.020694
		(4.92330)	(6.03827)	(4.52064)	(5.95994)	(8.60284)	(2.65164)	(1.83106)
3	1.941685	4.024738	9.473694	5.014503	7.157217	71.62651	1.631220	1.072121
		(4.38404)	(6.62602)	(4.97650)	(6.13464)	(8.44346)	(2.95045)	(2.40043)
4	1.995017	5.866815	11.17768	5.151809	6.834788	68.04308	1.568761	1.357068
		(4.19050)	(6.20764)	(5.12473)	(5.73544)	(8.49822)	(2.93050)	(2.72594)
5	2.043200	7.326038	10.67856	6.694932	6.726184	65.46085	1.645841	1.467599
		(4.13450)	(5.91470)	(5.44520)	(5.47376)	(8.31285)	(2.84251)	(2.74030)
6	2.068818	8.478552	11.12490	6.557328	6.678930	64.06426	1.621085	1.474942
		(4.20892)	(5.75078)	(5.38442)	(5.31293)	(8.03942)	(2.76052)	(2.73188)
7	2.095000	8.555561	12.29941	6.406351	6.805519	62.63522	1.829787	1.468153
		(4.08801)	(5.94236)	(5.33111)	(5.17562)	(8.06690)	(2.77948)	(2.84147)
8	2.102260	8.506386	12.34018	6.392034	6.758723	62.57130	1.931171	1.500207
		(4.09382)	(5.94729)	(5.29544)	(5.12306)	(8.09554)	(2.79184)	(2.94140)
9	2.107131	8.508851	12.48975	6.423944	6.794940	62.33308	1.956154	1.493291
		(4.10687)	(5.99057)	(5.24472)	(5.09767)	(8.04922)	(2.79513)	(2.93830)
10	2.115975	8.606811	12.91349	6.381190	6.782452	61.86191	1.950624	1.503527
		(4.09813)	(6.14486)	(5.19512)	(5.03643)	(8.06468)	(2.76189)	(2.94868)

Variance Decomposition of GMIG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	2.952007	0.136331	1.908474	1.755946	1.907270	2.671887	91.62009	0.000000
		(1.54661)	(3.76894)	(3.89723)	(4.11661)	(3.68021)	(6.65215)	(0.00000)
2	3.042813	0.130710	2.334594	1.721514	3.558772	3.282768	86.62407	2.347568
		(1.67305)	(4.80232)	(4.32626)	(4.54740)	(3.63990)	(7.63415)	(3.92146)
3	3.108243	0.216887	2.254844	1.888149	5.645282	3.380464	84.30464	2.309734
		(2.26229)	(4.46588)	(4.59136)	(5.01502)	(4.19782)	(8.07536)	(4.05741)
4	3.126772	0.325480	3.065661	1.951648	5.581850	3.442472	83.34603	2.286858
		(2.19625)	(4.84188)	(4.72456)	(4.87090)	(4.20925)	(8.55877)	(4.25549)
5	3.155589	0.802927	3.522349	2.390903	5.481580	3.556594	81.95289	2.292759
		(2.27327)	(4.89752)	(4.67806)	(4.71569)	(4.14964)	(8.82539)	(4.31659)
6	3.169889	1.656819	3.494376	2.392397	5.436964	3.524593	81.21789	2.276962
		(2.58066)	(4.91202)	(4.64696)	(4.78841)	(4.10996)	(8.94072)	(4.37579)
7	3.189943	2.297032	3.834548	2.383408	5.523583	3.486921	80.22574	2.248771
		(2.88879)	(5.08176)	(4.60926)	(4.75710)	(4.07904)	(9.07713)	(4.30674)
8	3.204589	2.693714	4.021810	2.365296	5.499950	3.625448	79.54884	2.244942
		(3.13599)	(5.18278)	(4.57963)	(4.70801)	(4.11775)	(9.25583)	(4.27047)
9	3.210988	2.870949	4.008618	2.393789	5.478071	3.716628	79.29461	2.237334
		(3.25717)	(5.17557)	(4.56816)	(4.72263)	(4.16468)	(9.38338)	(4.26000)
10	3.214178	2.917855	4.112275	2.391189	5.473806	3.720917	79.14641	2.237551
		(3.29799)	(5.30052)	(4.56728)	(4.74058)	(4.14842)	(9.50748)	(4.22970)

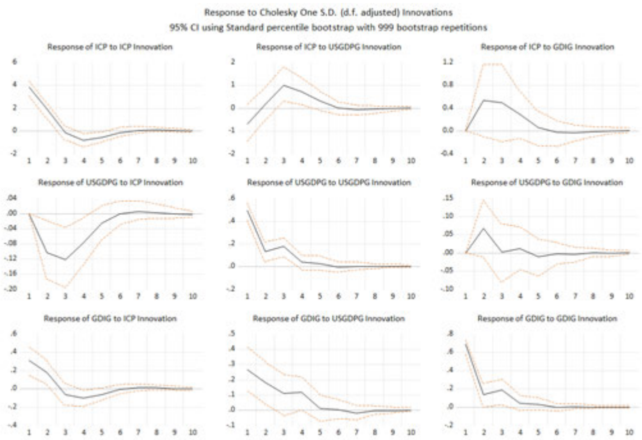
Variance Decomposition of TLSG:

Period	S.E.	ICPT	ICPC	USGDPG	COEG	GOSG	GMIG	TLSG
1	1.797934	5.615929	4.410729	0.164685	3.073912	0.000529	1.576778	85.15744
		(5.36062)	(6.06377)	(2.76116)	(4.25700)	(1.47682)	(3.22843)	(9.06983)
2	1.888305	5.217076	4.259856	7.306602	2.787137	1.526418	1.611251	77.29166
		(4.59355)	(5.50276)	(5.64570)	(4.39064)	(4.11146)	(3.50759)	(8.85568)
3	2.041096	5.211758	8.471339	8.816321	4.358817	1.313945	4.888854	66.93897
		(4.21139)	(5.98832)	(6.55206)	(5.31108)	(3.71835)	(5.10959)	(8.79632)
4	2.076939	7.115540	9.058379	8.533192	4.324380	1.520893	4.797860	64.64976
		(4.28599)	(6.06138)	(6.19112)	(4.77342)	(3.60693)	(4.86684)	(9.01934)
5	2.121073	9.027914	8.803797	8.712398	4.955881	1.862263	4.629513	62.00823
		(4.64922)	(5.88349)	(6.15561)	(4.72200)	(3.62005)	(4.63437)	(8.99559)
6	2.156750	10.32856	9.620843	8.438243	4.959111	2.159011	4.500520	59.99371
		(4.98006)	(6.32205)	(5.94963)	(4.68797)	(3.75751)	(4.49801)	(9.09859)
7	2.184387	10.58364	10.39851	8.340004	4.940576	2.516269	4.707497	58.51351
		(5.16656)	(6.69789)	(5.80547)	(4.61164)	(3.85881)	(4.37191)	(9.32686)
8	2.190216	10.61236	10.34385	8.346783	4.915677	2.761897	4.806603	58.21283
		(5.24172)	(6.72837)	(5.79268)	(4.60173)	(3.95592)	(4.36556)	(9.41303)
9	2.197075	10.54631	10.76469	8.320148	4.956381	2.765621	4.788922	57.85793
		(5.23489)	(6.92425)	(5.66555)	(4.60928)	(3.90315)	(4.28125)	(9.49589)
10	2.204605	10.56748	11.12876	8.284361	4.940850	2.810864	4.766406	57.50128
		(5.24087)	(7.04556)	(5.59035)	(4.56454)	(3.95860)	(4.24375)	(9.58749)

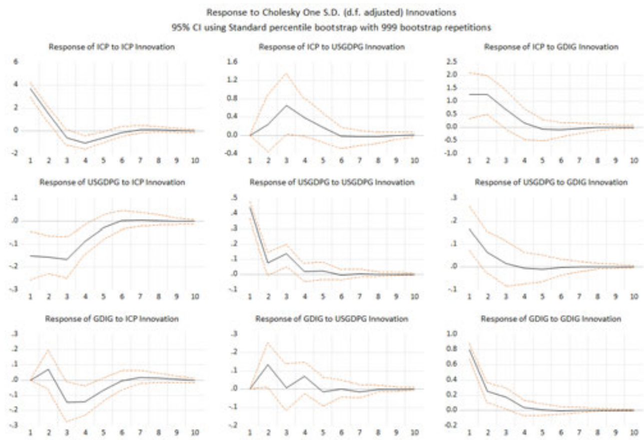
A.5 Robustness Checks

SVAR 1

US ordered first:



GDI ordered first:



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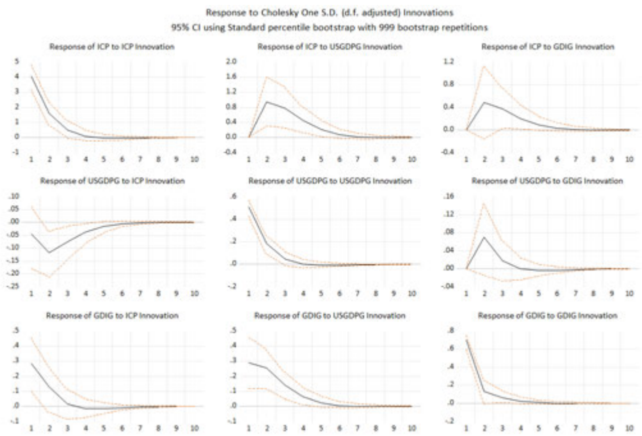
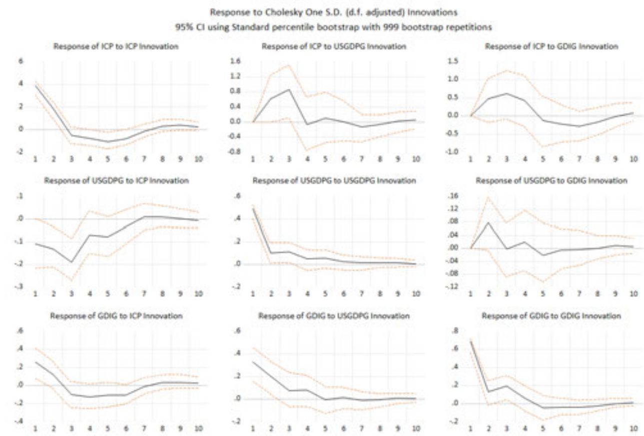
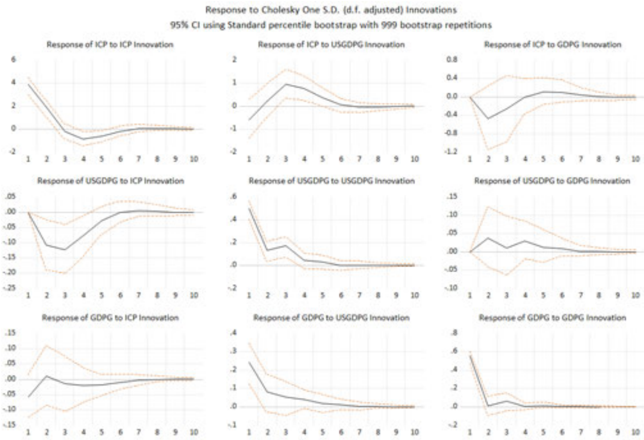


4 lags:

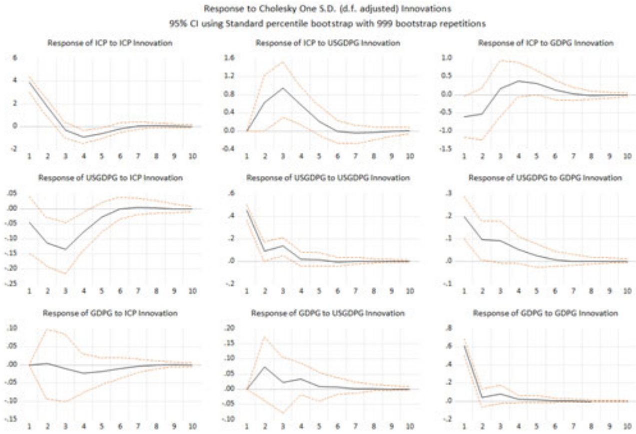


SVAR 2

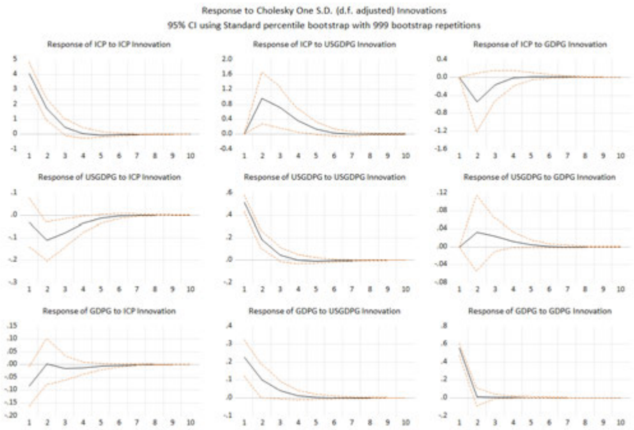
US ordered first:



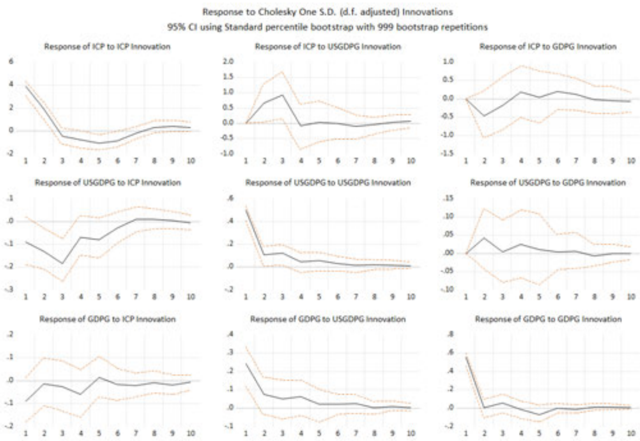
GDP ordered first:



1 lag:



4 lags:



SVAR 3

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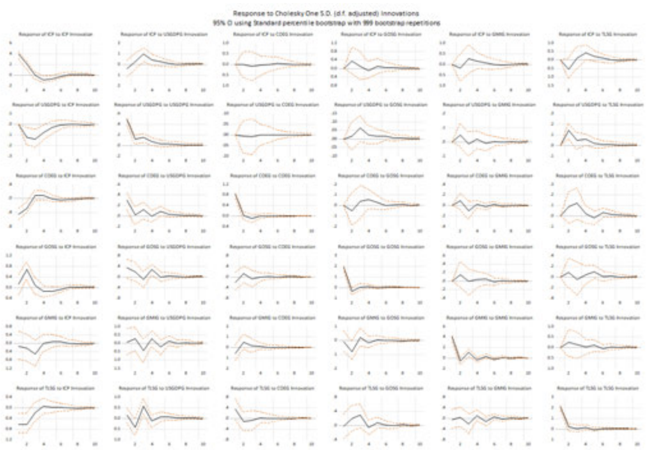
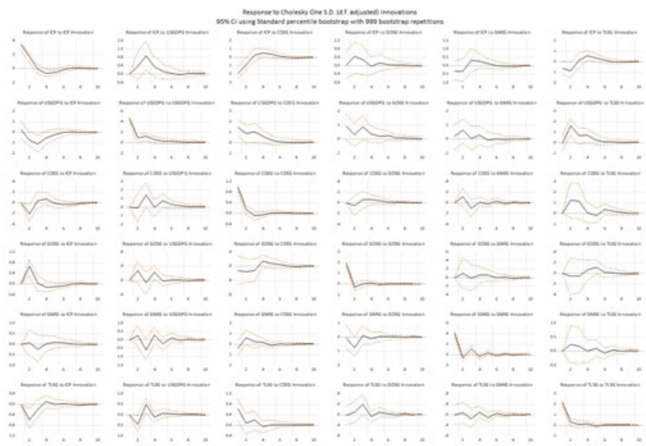


Components ordered first:



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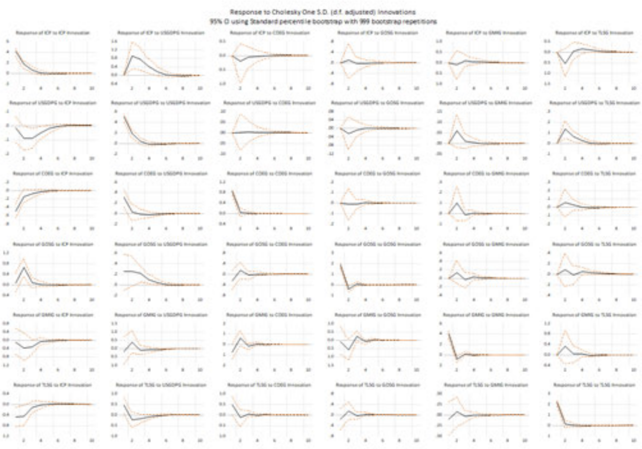
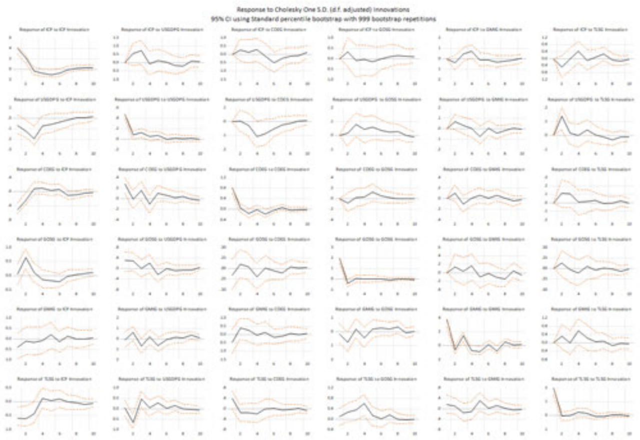


4 lags:

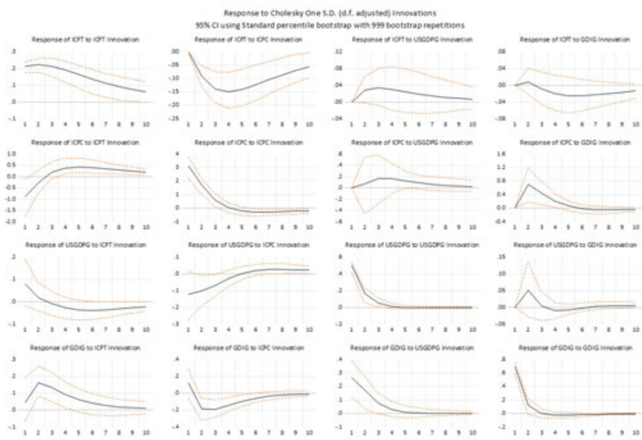


SVAR 4

Cycle component ordered first:

GDI ordered first:

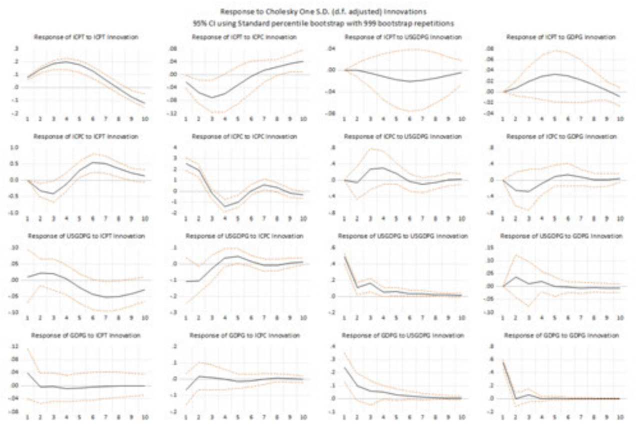
1 lag:



4 lags:

SVAR 5

Cycle component ordered first:



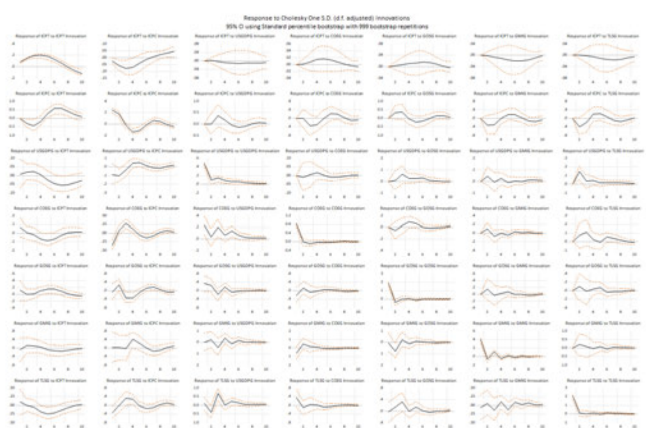
GDP ordered first:

1 lag:

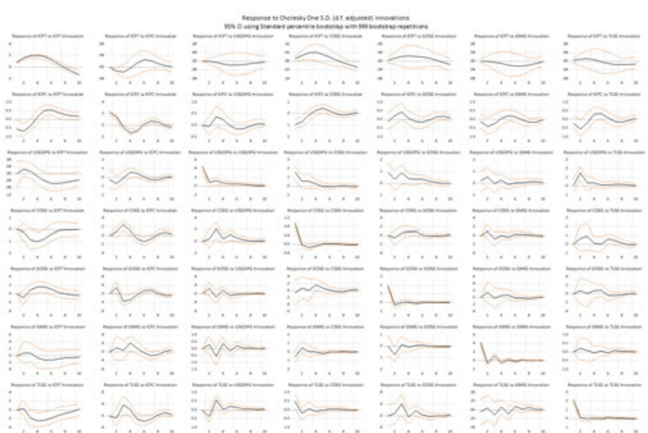
4 lags:

SVAR 6

Cycle component ordered first:

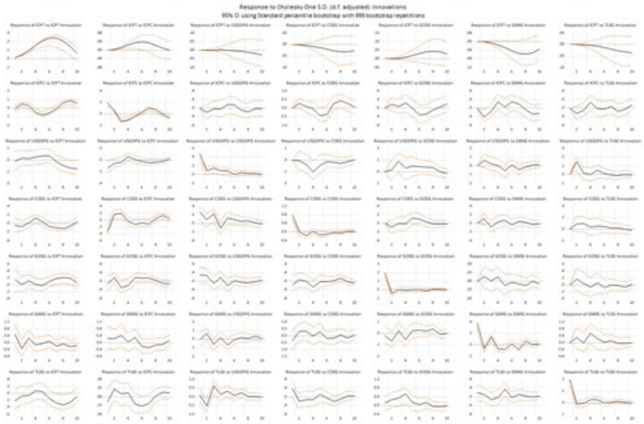


Components ordered first:



1 lag:

4 lags:



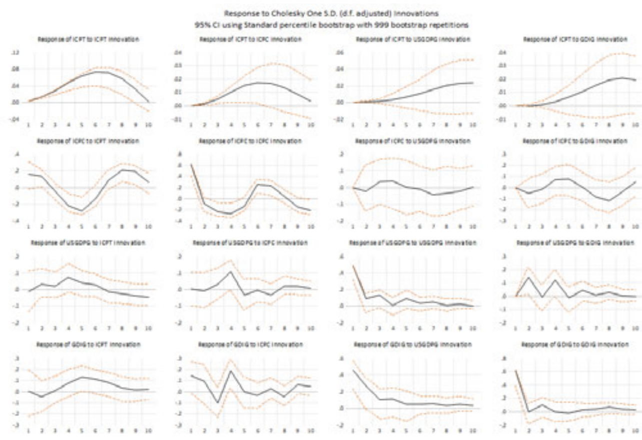
SVAR 7

Cycle component ordered first:

GDI ordered first:

1 lag:

4 lags:

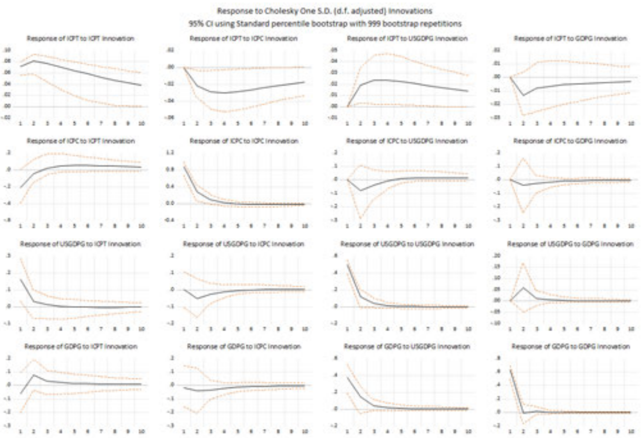


SVAR 8

Cycle component ordered first:

GDP ordered first:

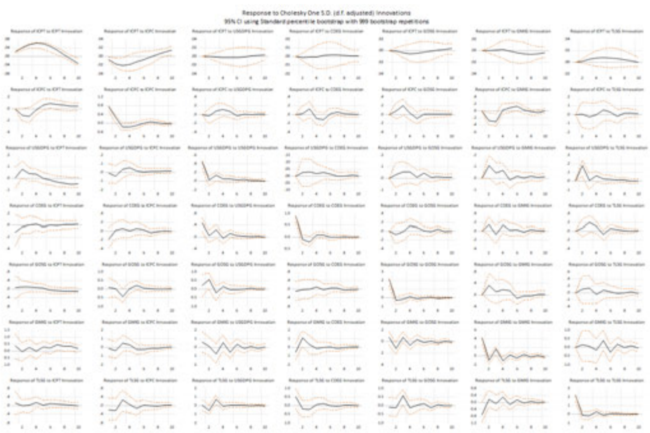
1 lag:



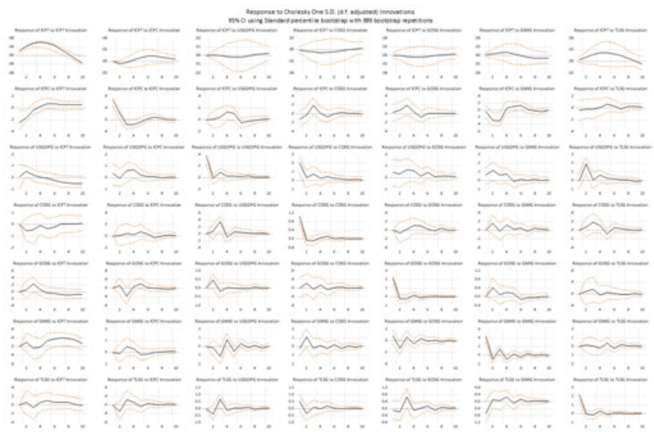
4 lags:

SVAR 9

Cycle component ordered first:

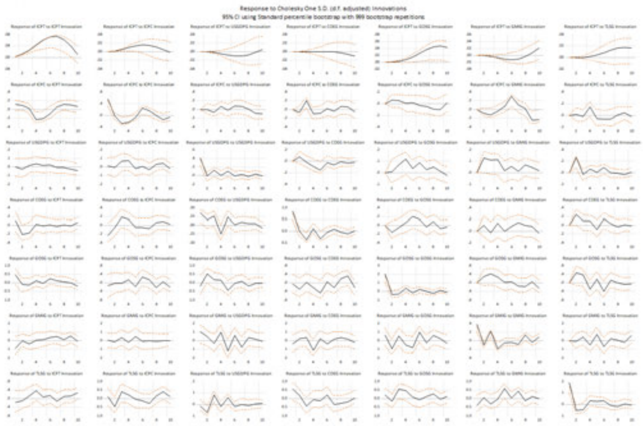


Components ordered first:



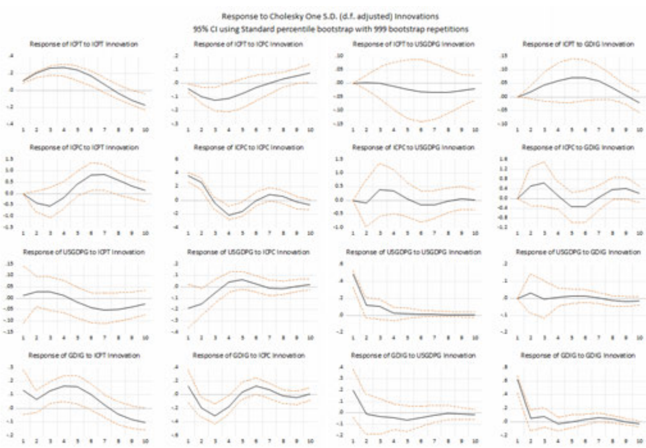
1 lag:

4 lags:

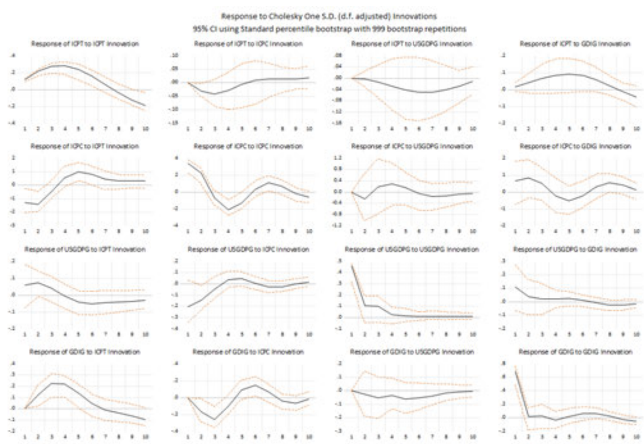


SVAR 10

Cycle component ordered first:



GDI ordered first:



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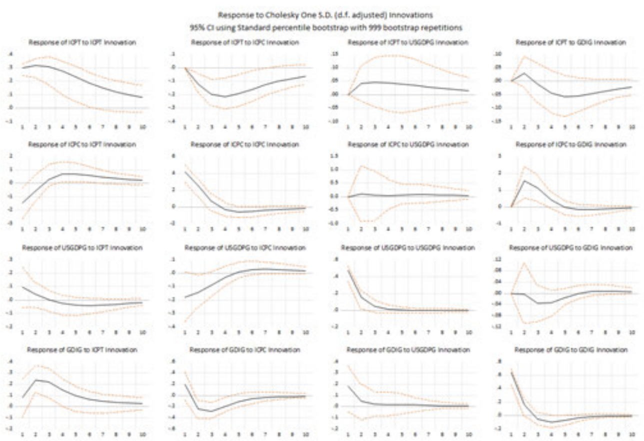
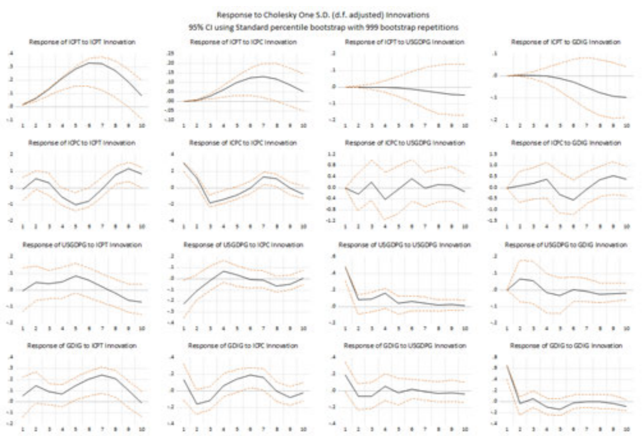


4 lags:



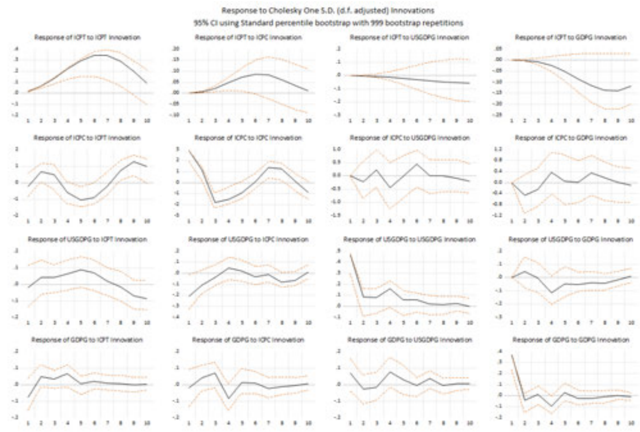
SVAR 11

Cycle component ordered first:

GDP ordered first:

1 lag:

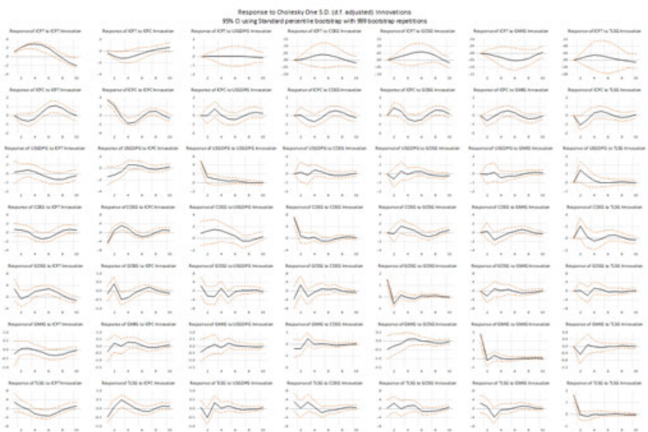
4 lags:

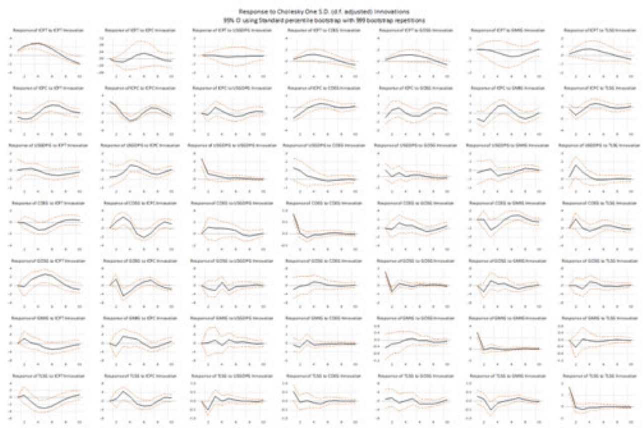


SVAR 12

Cycle component ordered first:

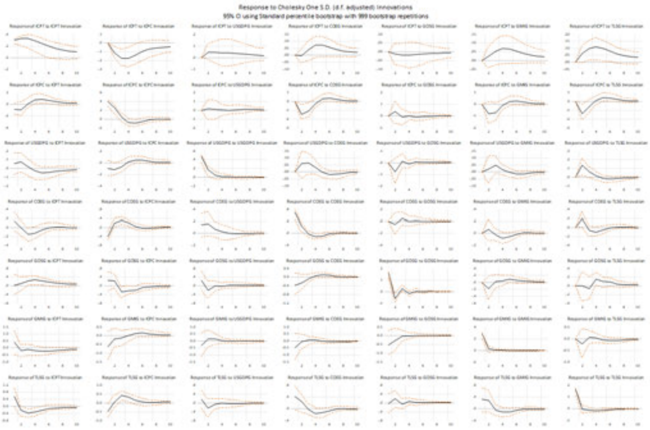
Components ordered first:

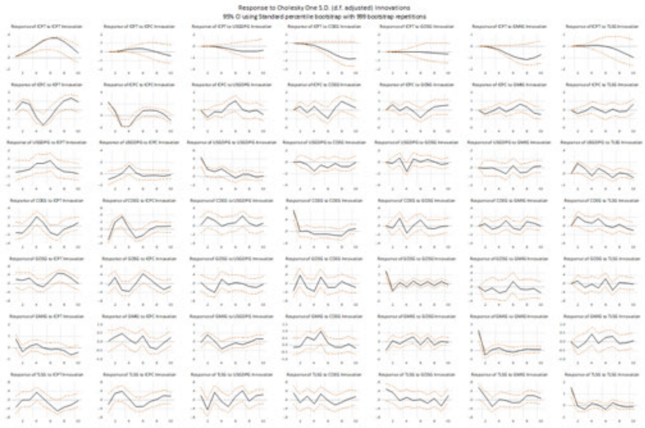




1 lag:

4 lags:

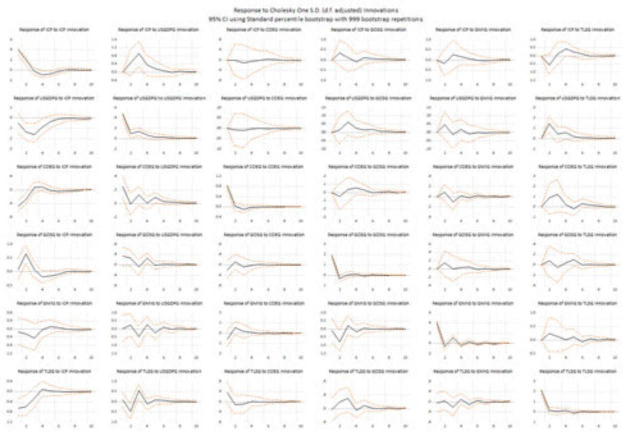


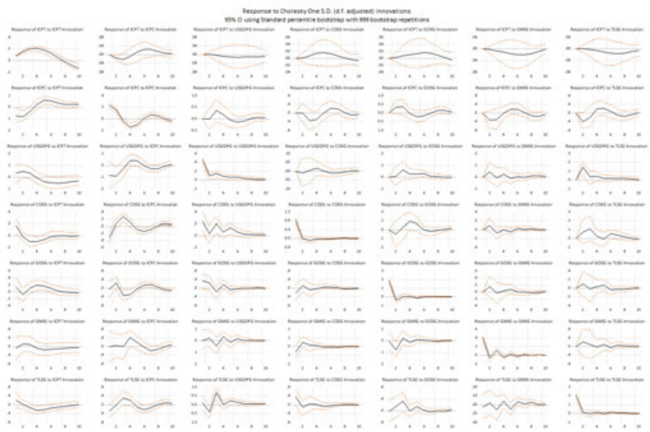


Over-Identification

SVAR 3

SVAR 6





SVAR 9

SVAR 12