Relative Price of Equipment, Investment Shocks and Oil-Food Prices

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Abstract

This study explores how fluctuations in oil and food prices may significantly influence the estimation of investment-specific technology (IST) shocks, which are typically derived using the relative price of equipment. The findings reveal a strong correlation between standard IST shock estimates and oil price shocks. Furthermore, impulse response analysis shows that estimated IST shocks are associated with a decrease in real wages and an increase in consumption price variables. However, once the influence of oil and food price movements is accounted for, the increase in price variables disappears, and the correlation with oil shocks weakens substantially. Additionally, the role of IST shocks in explaining variations in GDP, consumption, investment, and hours worked is considerably diminished. These results underscore the importance of accounting for oil and food price dynamics in IST shock estimation and are consistent with predictions from a medium-scale DSGE model that incorporates a commodity sector critical to both investment and consumption goods production.

Keywords— Relative Price of Equipment, Investment shocks, Oil prices.

1 Introduction

The relative price of equipment (RPE) has been a significant focus of economic research since the seminal contributions of Greenwood et al. (2000). The RPE is defined as the price of equipment and durable consumption goods relative to the price of non-durable consumption goods (Ben Zeev & Khan, 2015). Since the mid-1950s, the RPE has exhibited a consistent

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downward trend (Figure 1). A plausible interpretation of this trend involves IST, a technology factor that enhances productivity specifically within the investment goods sector. An IST shock is an exogenous innovation affecting this technology factor. While empirical studies have provided evidence of the significance of IST in explaining macroeconomic fluctuations at business cycle frequencies, I show that a portion of its impact is attributable to fluctuations in oil and food prices that are not accounted for in the estimation of IST shocks. Once these factors are controlled for, the estimated importance of IST shocks, as identified through the RPE, is reduced.

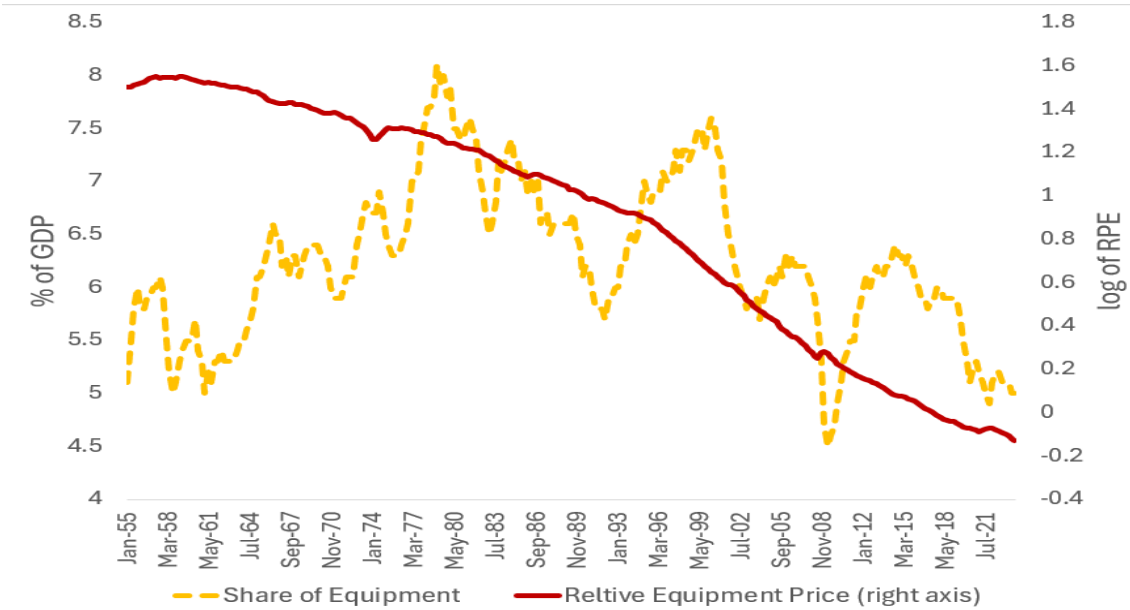


Figure 1: log of the relative price of equipment and share of equipment on GDP.

The role of IST in explaining business cycle fluctuations has been examined through both empirical analyses and structural models. Empirical studies have provided evidence supporting the importance of IST shocks. This line of research typically employs a VAR framework to extract IST shocks and uses forecast error variance decomposition (FEVD) to analyze their impact on macroeconomic variables (Ramey, 2016). For instance, studies by Fisher (2006), Galí and Gambetti (2009), and Chen and Wemy (2015) use long-run and medium-run restrictions to identify IST shocks, presenting evidence of their considerable influence on macroeconomic performance. Additionally, Ben Zeev and Khan (2015) focuses on identifying news shocks to IST, demonstrating that these shocks account for a significant portion of the forecast error variance in consumption, hours worked, investment, and GDP.

On the other hand, structural models calibrated to the U.S. economy, as explored in studies by Greenwood et al. (2000), Christensen and Dib (2008), Jaimovich and Rebelo (2009), and Justiniano et al. (2010), also indicate that IST accounts for a substantial portion of the variance in consumption, investment, and GDP at business cycle frequencies. Additionally, research by Jaimovich and Rebelo (2009), Choi (2020), and Liao and Chen (2023) investigates the impact of news shocks to IST (defined as anticipated exogenous changes in the technology variable) and find that these news shocks significantly explain the variance in macroeconomic variables.

Despite this evidence, another segment of the literature argues that IST shocks have limited significance in explaining macroeconomic behavior. This research utilizes a rich stochastic structure within a dynamic stochastic general equilibrium (DSGE) model, following the approach of Smets and Wouters (2007). These studies estimate the model using Bayesian techniques and incorporate the RPE to discipline it. Notable examples include Justiniano et al. (2011), which focuses on non-news shocks, and Schmitt-Grohé and Uribe (2012) as well as Ben Zeev and Khan (2015) which addresses news shocks. Understanding the reasons behind these differing perspectives is crucial for disentangling the impact of IST on the economy.

This paper aims to address part of this discrepancy by investigating how oil and food prices affect the estimation of IST shocks through the RPE. I show that standard empirical estimates of IST shocks are significantly correlated with oil shocks that have been estimated in previous literature. The intuition is simple: A rise in oil prices raises non-durable consumption prices, the denominator of the relative price of investment, leading to a fall in the relative price of investment. I show that, after cleaning IST shocks for movements in oil prices, the proportion of forecast error variance attributed to IST shocks declines, especially for GDP, investment, and consumption at business cycle frequencies. This suggests that the empirical significance often assigned to IST shocks may partialy capture the influence of fluctuations in oil and food prices.

Furthermore, IST shocks that are free of oil price movements lead to impulse response functions (IRFs) that are more consistent with standard macroeconomic theory. IRFs from IST shocks that ignore such oil price movements display a puzzling decline in real wages and increases in consumer price indexes. In contrast, after controlling for oil price movements, I find that real wages increase after the shock, while consumer prices decrease.

Next, I provide additional evidence for oil and food price shocks affecting the estimation of IST shocks from an estimated DSGE model, inspired by Justiniano et al. (2011). In this model, there is a commodity production sector that supplies inputs to the intermediate production sector, which in turn provides inputs to both consumption and investment goods producers, as well as directly to the final consumption goods producer. Consequently, the price of the commodity directly affects the production cost of final goods and, in turn, influences the conventional measure of the relative price of investment. The model is estimated using Bayesian techniques, incorporating the RPE as an observable variable to discipline the model.

The estimated model yields three main conclusions: (i) IST has a small role in explaining the variance of GDP and consumption; (ii) the theoretical IRFs of macroeconomic variables to IST shocks closely match those observed in the empirical analysis; and (iii) applying the empirical strategy from Section 2 to the simulated data produces a similar outcome: using an inaccurate measure of the relative price of investment can result in differing conclusions in the IRFs.

The structure of the paper is as follows: Section 2 outlines the empirical methodology, examines the relationship between IST shocks and oil price shocks, and discusses the responses of real and price variables once corrected for oil and food prices. Section 3 offers robustness checks to validate the main findings presented in Section 2. Section 4 introduces a medium-scale DSGE model to rationalize the empirical results, and Section 5 concludes the paper.

2 RPE, IST shocks and oil-food prices

In this section, I follow the empirical literature and employ the RPE to identify IST shocks. I then use local projections, as in Jordà (2005), to analyze the impulse responses of various macroeconomic variables to these shocks. My findings indicate that consumer price variables experience increases in response to the IST shock, which can explain the decrease in real wages. Additionally, I demonstrate that the estimated IST shocks are significantly correlated with oil price shocks identified in the literature. However, once oil and food prices are incorporated into the system, the correlation with oil shocks and the observed increases in consumer prices after the shock, diminish. Furthermore, the forecast error variance (FEV) attributed to the identified IST shocks for GDP, consumption, and investment decreases following this adjustment.

2.1 Identification of IST shocks

IST shocks are usually estimated by identifying the structural innovations that account for the medium-term or long-term variance of the RPE (Ramey, 2016). This procedure entails estimating a VAR model and using its reduced-form residuals to compute orthogonal shocks that maximize the forecast error variance (FEV) of the RPE over h periods ahead.(Barsky & Sims, 2011).

Following the estimation in Chen and Wemy (2015), consider the following VAR process and assume that it can approximate the true data-generating process sufficiently well:

$$Y_t = \beta(L)Y_t + u_t \tag{1}$$

Where Y_t is an $(n \times 1)$ vector of macroeconomic variables at time t that includes the total factor productivity and RPE.[1] Notice that in the empirical literature, macroeconomic

[1] I include the variables used in the baseline estimation of Chen and Wemy (2015): TFP, log of RPE, log of GDP per capita, log of investment per capita, log of consumption per capita and log of total hours worked.

variables typically exclude both oil prices and food prices from the system of equations. All variables are in levels, following Sims et al. (1990). $\beta(L) = B_1(L) + B_2(L^2) + ... + B_P(L^P)$ is a lag polynomial and u_t is a $(n \times 1)$ vector of reduced form innovations. The latter is assumed to be a linear combination of structural shocks (ε_t):

$$u_t = A\varepsilon_t \tag{2}$$

Where the variance-covariance matrix of the reduced-form innovations is:

$$\Sigma_u = E[u_t u_t'] = E[A\varepsilon_t\varepsilon_t' A'] = AA' \tag{3}$$

However, it is well known that A cannot be uniquely identified. To see why, consider $A = \tilde{A}Q$ where Q is an orthonormal matrix. Note that $\tilde{A}$ satisfies (3) and therefore is also a matrix that can be used to obtain the structural shocks:

$$\Sigma_u = E[AA'] = E[\tilde{A}QQ'\tilde{A}'] = E[\tilde{A}\tilde{A}'] \tag{4}$$

Hence, identifying the IST shocks is equivalent to finding a column $\tilde{q}_1$ in Q that maximizes the FEV of the RPE at the horizon h:

$$\tilde{q}_1 = \arg\max q_1' S^h q_1 \tag{5}$$

subject to

$$q_1' q_1 = 1, \tag{6}$$

where S^h is the variance of the forecast error of the variable of interest h steps ahead, using the Cholesky decomposition on Σ to obtain $\tilde{A}$. Equation (6) guarantees that q_1 is a unit-length column vector that belongs to an orthonormal matrix. Then, the IST shock is obtained as the first value of the vector:

$$\epsilon_t = A^{-1}u_t = (Q\tilde{A})^{-1}u_t \tag{7}$$

Uhlig (2004) shows that the problem can also be written in a quadratic form where the q_1 is the eigenvector associated with the largest eigenvalue of the matrix S^h (Chen & Wemy, 2015). I estimate the VAR with standard OLS using quarterly data from 1964:I to 2019:IV.[2]

2.2 Local projections

Although computing the IRF within the VAR framework is relatively simple, I employ local projections as proposed by Jordà (2005) for two primary reasons. First, as noted by Ramey (2016), local projections are robust to non-linearities and to misspecification within the

[2]Results are robust to the estimation technique in the VAR.

VAR.[3] Second, my approach entails estimating IST shocks using standard methods in the literature that do not consider food and oil prices during the estimation process. I then utilize these estimated shocks to analyze the responses of various consumer price variables, which were excluded from the original estimation. By examining how these variables respond to the shocks, I can assess whether the shocks contain additional information.

Let y_t be the variable of interest, $\hat{\epsilon}_t^{IST}$ be the estimated measure of IST shock, X_t a vector of macroeconomic controls at time t and u_t residuals. I obtain the IRFs from the following OLS regression:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h \hat{\epsilon}_t^{IST} + \sum_{j=1}^{4} \gamma_{h,j} X_{t-j} + u_t, \tag{8}$$

Where β_h is the value of the IRF at horizon h. The confidence interval is computed by using HAC standard errors (Jordà, 2023).

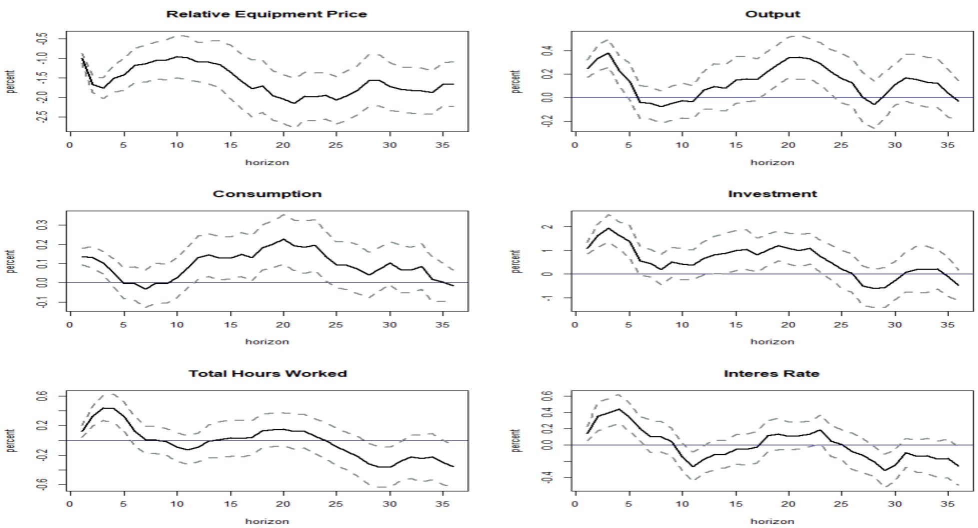
Figure 2 presents the IRFs for various macroeconomic variables in response to the estimated IST shocks. The reactions of real economic activity indicators align with traditional findings: investment, GDP, and hours worked increase immediately after the positive shock, while consumption shows a delayed increase, occurring several quarters later. However, there is a puzzling response in real wages, which declines following the shock.[4] This pattern is also connected to the behavior of nominal variables, including the consumer price index (CPI), core CPI, and food CPI, which exhibit non-monotonic responses. In particular, CPI measures show an initial increase shortly after the shock, followed by a subsequent decline.

Changes in oil and food prices provide a possible explanation for those puzzling responses.: a portion of the decline in the relative price of equipment (RPE) associated with IST shocks is driven by shocks that increase the prices of non-durable consumption goods (i.e., the denominator in the RPE ratio), primarily due to energy and food price increases. These shocks are distinct from IST shocks and represent a different economic phenomenon. In the analysis that follows in the next section, I focus on the relationship with oil price shocks, as there is a well-established body of research on identifying exogenous oil price movements. In contrast, the identification of food price shocks has received relatively little attention in the economic literature, and credible estimates isolating food-specific shocks remain unavailable. Nevertheless, rising food prices likely influence IST shock estimations through mechanisms similar to those associated with oil price fluctuations.[5]

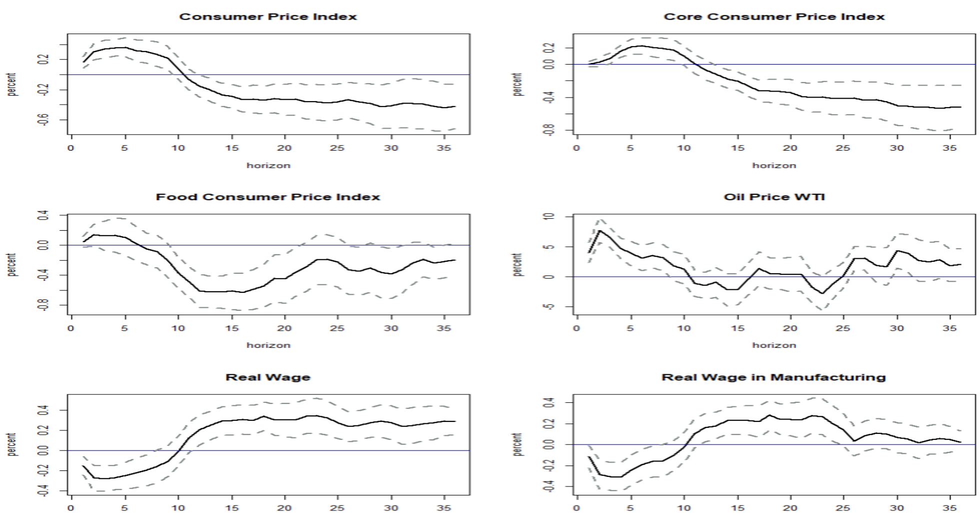
[3]See, for example, Auerbach and Gorodnichenko (2013). For a survey in Local Projections literature, see Jordà (2023).

[4]Real wages are generally expected to increase in response to IST shocks, as noted in DSGE models by Justiniano et al. (2010) and Justiniano et al. (2011).

[5]Food prices are also important in understanding the US and Euro-area economies. For recent works see for example De Winne and Peersman (2016), Peersman (2022), and Jo and Adjemian (2023).



(a) Real Variables.



(b) Price Variables

Figure 2: Impulse response of macroeconomic variables to baseline estimation of IST shocks. The dotted lines represent the 90,0% interval.

2.3 IST shocks and oil price shocks

For the accurate identification of IST shocks, they must be uncorrelated with other exogenous disturbances, as structural shocks should exhibit no correlation with any other shocks (Ramey, 2016). This subsection investigates the relationship between the identified IST shocks and oil price shocks. The analysis indicates a significant correlation suggesting that the current methods for identifying IST shocks still capture information beyond investment technology changes.

I focus on five series of oil price shocks found in the literature:

1. O(1). Oil price surprises from Känzig (2021): This paper uses the change in oil futures prices around OPEC announcements. Oil futures serve as a market-based proxy for oil price expectations, making them suitable for measuring the impact of these announcements. Although OPEC's decisions may be influenced by political and global economic conditions, using a tight window around the announcements helps isolate their impact and mitigate endogeneity concerns. This approach assumes that global economic conditions are already priced in by the market and remain stable within the window, ensuring that the series captures changes in oil price expectations due to OPEC's decisions.

2. O(2). Oil Price news from Känzig (2021): To interpret OPEC announcements as news about future oil supply, the announcements mustn't introduce new information about other factors like oil demand, global economic activity, or geopolitical developments. To address this, one alternative is to see how OPEC announcements are covered in the financial press, typically focusing on production quotas. Given the political nature of OPEC and its less systematic response to economic developments, the information channel problem may be less significant compared to monetary policy shocks. To further mitigate this concern, this measure constructs an informationally robust surprise series by removing the effects of revisions in OPEC's global demand forecasts, similar to the refinement used by Romer and Romer (2004) in the monetary policy context, ensuring the robustness of the results.

3. O(3). "Pure" oil price expectation shocks from Baumeister and Hamilton (2019): The shocks are obtained by first identifying market-based oil price surprises, which are the deviations between the realized price of oil (such as WTI) and what market participants had expected the price to be a month before. To isolate the "pure" expectation component, the authors regress these market-based surprises on a set of fundamental oil supply and demand shocks. By filtering out the influence of these fundamental shocks, the residuals from this regression are interpreted as the orthogonalized, or "pure" oil price expectation shocks. These shocks represent changes in oil prices driven solely by shifts in market expectations, independent of new information about underlying oil market fundamentals.

4. Oil supply O(4), and oil demand O(5) shocks from Baumeister (2023): The authors propose a Bayesian approach to estimate oil supply and demand shocks using structural vector autoregressions (SVARs). Their method incorporates prior information about the parameters in the model, including the short-run price elasticities of oil supply and demand. They account for measurement errors, particularly in global oil inventories, and utilize historical data to refine their estimates. By generating impulse-response functions, they analyze the dynamic effects of these shocks on oil prices and economic activity. Their approach also includes a historical decomposition to assess the contributions of supply and demand shocks to significant oil price movements, ensuring a robust and nuanced understanding of the underlying factors driving these fluctuations.

Table 1 presents the correlations between oil price shocks and IST shocks, including comparisons with IST shocks estimated in previous studies. IST(1) refers to the shock estimated in Section 2.1, while IST(2) corresponds to the estimation by Drechsel (2023) , who closely follows the identification method proposed by Fisher (2006). Ben Zeev and Khan (2015), hereafter referred to as BZK, estimates two series of IST shocks: IST(3), which represents unanticipated IST shocks that immediately affect the RPE and maximize its FEV, and IST(4), which represents news shocks that maximize the FEV of the RPE while being orthogonal to the unanticipated IST shocks. The latter is considered the most significant component of IST, as it explains most of the variance in economic activity.

	O(1)	O(2)	O(3)	O(4)	O(5)
IST(1)	0.04	0.10	0.25***	0.13*	0.16**
IST(2)	0.15*	0.13*	0.18**	0.14*	0.16**
IST(3)	0.00	0.08	0.34***	0.18**	0.07
IST(4)	-0.11	-0.28***	-0.28***	-0.05	-0.28***

Table 1: Correlation between IST shocks and Oil shocks. Correlations with O(4) are multiplied by -1 because the nature of the shock implies a decrease in the oil price. *p-value $<$ 0.1, ** p-value $<$ 0.05, *** p-value $<$ 0.01

The results indicate a significant correlation between IST shocks identified using long-run restrictions (Drechsel, 2023) and medium-run restrictions (as in Chen and Wemy, 2015; and BZK)with oil price shocks. Specifically, the correlation between the first two IST shock estimates and oil price innovations (O(3) and O(5)) is positive, suggesting that an exogenous increase in oil prices is significantly associated with higher IST shocks. In contrast, the correlation with O(4), which represents oil supply shocks (i.e., reductions in oil prices), is negative. When examining the correlations with the estimates from BZK, the correlation between unanticipated IST shocks and oil supply shocks remains strong, while the correlation with news shocks exhibits a different but still significant pattern.

For IST(4), there is no clear theoretical basis for expecting a specific correlation with contemporaneous oil price shocks, given that IST news shocks are anticipatory and pertain to future shifts in the relative price of investment. However, as indicated in Table 1, the results reveal a statistically significant negative correlation between the estimated news shocks and current oil price shocks.

Fisher (2006) also notes the significant correlation between IST shocks and oil price movements, but he interprets it differently, suggesting that oil shocks could be viewed as IST shocks. Specifically, Fisher (2006, p.446) argues:

The oil shock result might not be surprising. Suppose that an exogenous increase in the price of oil induces substitution toward equipment that the United States is not good at producing, such as high-mileage cars. If this is the case, then the real price of equipment *rises. From this perspective, a permanent oil shock is very much like an I-shock.*

The results in this paper suggest a different interpretation. My analysis demonstrates that oil shocks influence movements in the relative price of equipment (RPE) primarily through direct changes in the price of consumption, constituting the RPE ratio denominator. These movements introduce distortions into the estimated measures of IST shocks.

2.4 Re-estimating the IST shocks: oil and food prices.

The relationship between oil prices and IST shocks indicates the need to adjust the identification strategy. In this paper, I incorporate two additional variables into the VAR framework to account for the influence of oil and food prices. The adjustment involves including the logarithms of the West Texas Intermediate (WTI) oil price and the food consumer price index (CPIF) in the VAR model used to compute the IST shock, as outlined in Section 2.1. This modification is applied to the estimation strategies of Drechsel (2023) and BZK.[6] After Incorporating these variables, the identified IST shocks significantly reduce their correlation with oil price shocks (Table 2).[7]

	O(1)	O(2)	O(3)	O(4)	O(5)
IST(1)	-0.05	0.09	0.01	0.05	-0.03
IST(2)	-0.01	0.07	-0.10	0.04	-0.08
IST(3)	0.01	0.07	0.27***	0.17**	0.04
IST(4)	-0.14	-0.04	-0.08	0.12	-0.13

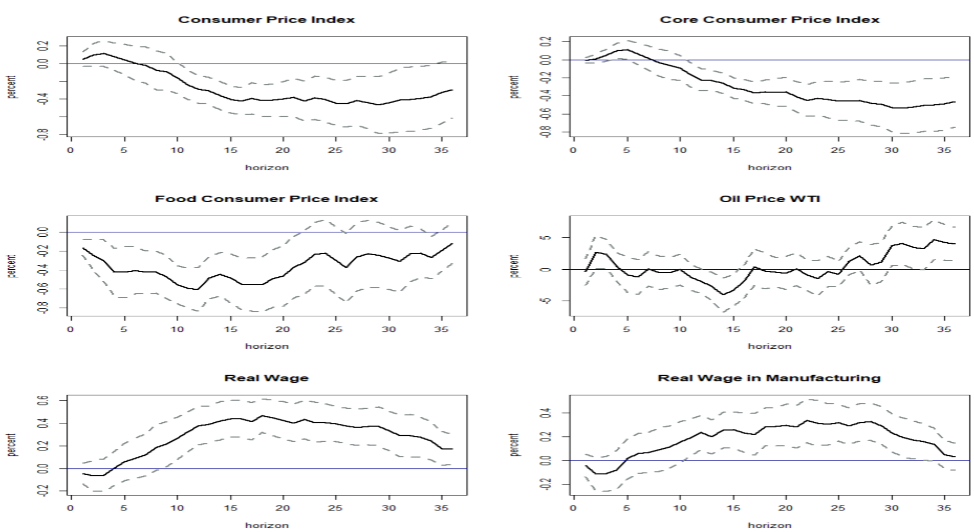
Table 2: Correlation between IST shocks including food and oil prices in the estimation and Oil shocks. Correlations with O(4) are multiplied by -1.0 because the nature of the shock implies a decrease in the oil price. *p-value < 0.1, ** p-value < 0.05

The estimation of the IST shocks controlling for oil and food prices enables the analysis of impulse responses using the LP strategy described in Section 2.2. It is noteworthy that incorporating both price variables into the VAR system results in the estimation of IST shocks that do not produce increases in consumer price variables nor decreases in real wages (Figure 3). The response of other real economic variables does not present any qualitative change.

[6]In appendix B, I explain how I modify the procedure of BZK to incorporate the information on oil prices and food prices.

[7]The correlation between IST(3) and both O(3) and O(4) is still significant. Nevertheless, the impact of IST(3) on macroeconomic variables is minimal, as the variance it explains is relatively small (Ben Zeev & Khan, 2015).

(a) Real Variables.



(b) Price Variables

Figure 3: Impulse response of macroeconomic variables to oil and food price adjusted estimation of IST shocks. The dotted lines represent the 90,0% interval.

The adjustment described above reduces the relative contribution of identified IST shocks to the dynamics of key macroeconomic variables. To illustrate this, I analyze the fraction of FEV attributable to the identified IST shock within a VAR framework, comparing results with and without the inclusion of oil and food prices. As shown in Table 3, incorporating these variables ("Clean") diminishes the estimated share of FEV explained by IST shocks, particularly over business-cycle frequencies (one to ten quarters). For example, at the five-quarter horizon, the adjustment decreases the FEV of GDP attributed to IST shocks by 16.2

percentage points (p.p.), investment by 10.6 p.p., and consumption by 14.9 p.p. Additionally, Appendix B corroborates this pattern for IST news shocks, as identified by BZK.

	GDP	GDP	Inv.	Inv.	Cons.	Cons.	Hours	Hours
h	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**
1	0.192	0.053	0.181	0.073	0.237	0.063	0.061	0.058
5	0.373	0.212	0.452	0.346	0.255	0.116	0.268	0.219
10	0.318	0.214	0.368	0.280	0.224	0.140	0.176	0.167
15	0.298	0.230	0.342	0.258	0.209	0.163	0.138	0.131
20	0.277	0.246	0.332	0.261	0.191	0.182	0.110	0.117

Table 3: FEVD of the IST shocks

3 Robustness analysis

3.1 Modifying the RPE

An alternative way to control for exogenous fluctuations in oil and food prices is to calculate the RPE as the ratio between the price of equipment and durable consumption over the price of non-durable consumption excluding energy and food (RPENE). These are the components of the private consumption expenditure directly associated with oil and food. This measure was first analyzed by Beaudry et al. (2015) when studying the cyclical behavior of the RPE. With this adjustment, it is no longer necessary to include the two variables in the VAR system as done in the previous section.

Figure A1 in Appendix A shows the IRF to the IST shocks estimated using the RPENE. Results are similar to those in Figure 3: the price variables show no increases after the shock. Meanwhile, Table 4 shows the FEVD with this change. The share of the forecast error variance in business cycle frequencies explained by identified IST shocks is smaller than the baseline scenario. The reduction is more noticeable in GDP, consumption, and investment per càpita variables.

3.2 Joint price index of food and energy

The empirical findings remain robust to the choice of variables used to account for fluctuations in food and oil prices. To verify this, I incorporate an alternative measure into the VAR framework. Instead of using the CPIF and WTI price indices, I substitute a combined index of food and oil prices derived from the Personal Consumption Expenditures (PCEFE) data. This alternative variable is constructed as a weighted average of energy and food prices within non-durable consumption, with weights based on national accounts data.

	GDP	GDP	Inv.	Inv.	Cons.	Cons.	Hours	Hours
h	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**
1	0.192	0.063	0.181	0.088	0.237	0.113	0.061	0.032
5	0.373	0.265	0.452	0.387	0.255	0.183	0.268	0.243
10	0.318	0.267	0.368	0.356	0.224	0.204	0.176	0.182
15	0.298	0.280	0.342	0.354	0.209	0.212	0.138	0.148
20	0.277	0.277	0.332	0.352	0.191	0.207	0.110	0.126

Table 4: FEVD of the IST shocks (RPENE)

Figure A2 in Appendix A presents the IRFs to IST shocks identified using the PCEFE index in the VAR system. The shape of these responses closely resembles those shown in Figure 3. Additionally, the share of the FEV explained by IST shocks is smaller compared to the baseline scenario for GDP, consumption, and investment càpita at business cycle frequencies (Table 5).

	GDP	GDP	Inv.	Inv.	Cons.	Cons.	Hours	Hours
h	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**
1	0.192	0.064	0.181	0.084	0.237	0.121	0.061	0.060
5	0.373	0.261	0.452	0.367	0.255	0.173	0.268	0.247
10	0.318	0.247	0.368	0.312	0.224	0.186	0.176	0.185
15	0.298	0.256	0.342	0.298	0.209	0.200	0.138	0.152
20	0.277	0.266	0.332	0.303	0.191	0.209	0.110	0.136

Table 5: FEVD of the IST shocks (PCEFE)

4 Evidence in a DSGE model

Next, I provide evidence for oil and food price shocks affecting the estimation of IST shocks from a DSGE model. DSGE models have been employed in the economic literature to assess the relative significance of IST shocks in explaining the variance of macroeconomic aggregates at business cycle frequencies. Within this body of research, two key studies emphasize that, when using the RPE to calibrate the model, IST shocks seem to play a limited role in accounting for the variance of major macroeconomic variables. Justiniano et al. (2011) uses a medium-scale DSGE model featuring both neutral and IST technology shocks, alongside price and wage-setting frictions, while Schmitt-Grohé and Uribe (2012) incorporates news shocks into both neutral and IST technologies.[8] This section focuses on developing a model

[8]Both studies employ a rich stochastic framework and estimate their models using Bayesian techniques, following the approach of Smets and Wouters (2007).

inspired by Justiniano et al. (2011), incorporating a production sector (referred to as the commodity sector) whose price influences the standard measure of the RPE. Consequently, shocks to the price of the commodity sector impact the RPE as well.

4.1 The model

The model builds on the framework of Justiniano et al. (2011), but incorporates an additional commodity goods sector into the economy that is not produced through capital and labor but is produced without cost and whose price is exogenously given. The idea behind this shortcut is that commodities are traded on the world market, and price fluctuations represent a substantial degree of changes in demand and supply of the commodity in the rest of the world. This sector serves as both a production input and a consumption good. Hence, the price of this commodity influences both the price of investment goods (through its impact on production costs) and the price of the consumption bundle (directly). Consequently, the relative price of investment, defined as the price of investment goods relative to the consumption bundle, is not solely driven by IST shocks but also reflects fluctuations in the commodity sector.

The economy consists of two primary components. The first block captures the interactions among the government, firms, households, and labor unions (or labor assemblers). In this block, households finance the government through taxes and short-term bonds, while also supplying firms with utilization-adjusted capital and providing labor to the labor assemblers. Firms, in turn, acquire a labor bundle from the labor assemblers and combine them with utilization-adjusted capital and part of the commodity good to produce both investment goods and final consumption goods, which they sell to households. Additionally, firms supply consumption goods to the government. Households receive interest payments from the government and use the final investment goods to generate and supply utilization-adjusted capital. Figure A3, Panel A, in Appendix A illustrates the flow of resources within this first block of the model economy.

The second block represents the production structure of the economy, which is organized into seven tiers: wholesalers, commodity goods producers, intermediaries, non-commodity assemblers, investment goods producers, capital producers, and final consumption goods producers. Key to the model is the introduction of a commodity goods producer. This sector takes as given the exogenously determined price and produces the required quantity of the commodity good, to satisfy its demand. The firm sells the commodity good to both wholesalers and the final consumption goods producer as input. This approach is similar to the oil sector specification in Guerrieri and Bodenstein (2012), but inspired by the results in Section 3, the commodity sector includes not only oil but also the food sector. Figure A3, Panel B, in Appendix A presents a diagram illustrating this block within the economy. The following subsections provide a detailed specification of each component of the production structure.

4.1.1 Wholesale sector

The wholesaler is a competitive producer that uses utilization-adjusted capital, labor from the labor assemblers, and the commodity good as inputs. These inputs are combined using a Cobb-Douglas production function that exhibits constant returns to scale, resulting in the production of a single aggregate good. The optimization problem faced by the wholesaler is as follows:

$$\max_{L_t, K_t, O_t} P_t^{\omega} Y_{\omega,t} - R_t^k K_t - W_t L_t - P_t^o O_{p,t}$$

subject to

$$Y_{\omega,t} = K_t^{\alpha} O_{p,t}^{\beta_o} (A_t L_t)^{1-\alpha-\beta_o},$$

where $Y_{\omega,t}$ is the quantity of wholesale sector, L_t is the labor, K_t is the utilization-adjusted capital, $O_{p.t}$ is the quantity of commodity that is demanded for production of the wholesale product, and P_t^{ω}, R_t^k, W_t, and P_t^o are the prices of each good. The final product of this sector is sold to each intermediary in a competitive market that uses it as input to produce an intermediary-specific good. The neutral technology variable (A_t) follows an $AR(1)$ in logs:

$$logA_t = (1 - \rho_a) log\bar{A} + \rho_a log A_{t-1} + \epsilon_{a,t},$$

with $\epsilon_{a,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_a)$.

4.1.2 Non-commodity assembler

The non-commodity assembler (NCA) uses the output of all intermediary producers as inputs. Since each intermediary producer holds monopoly power over its respective good, I introduce the non-commodity sector first to determine the total demand for each intermediary good. The NCA operates in a perfectly competitive market and faces the following optimization problem:

$$\max_{Y_t(i)} P_t Y_t - \int_0^1 P_t(i) Y_t(i) \delta_i$$

subject to

$$Y_t = \Big[\int_0^1 Y_t(i)^{\frac{1}{1+\lambda_t}} \Big]^{1+\lambda_t}$$

where Y_t is the total quantity of the non-commodity assembler. Its price, P_t, is the model equivalence of the core consumer price index. $Y_t(i)$ and $P_t(i)$ are the output and price of each intermediary producer. Finally, the variable that governs the substitutability degree among the intermediary goods, λ_t, follows an $AR(1)$ process:

$$log\lambda_t = (1-\rho_p)log\bar{\lambda} + \rho_p log\lambda_{t-1} + \epsilon_{p,t}$$

where $\epsilon_{p,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_p)$.

Solving the non-commodity assembler problem allows me to know the demand for each intermediary good i:

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\frac{1+\lambda_t}{\lambda_t}} Y_t \tag{9}$$

4.1.3 Intermediaries

There is a mass-one continuum of intermediaries indexed by $i \in [0,1]$. Each intermediary good $Y_t(i)$ is produced by a monopolist and uses the output from the wholesaler as input. They take the quantity of the wholesaler and sell it in a market with monopolistic power. They choose their optimal price given the downward sloping demand curve Equation 9 for their good. In doing so, they take into account that, as in Calvo (1983), they can only reset their price with probability $1-\phi_p$. This sticky price structure introduces a dynamic problem for the intermediary, as any present change in price has implications for the future profit of the firm:

$$\max_{P_t(i)} E_t \sum_{s=0}^{\infty} \phi_p^s \Lambda_{t,t+s} \left[P_t(i) - P_t^{\omega}\right] Y_t(i)$$

subject to

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\frac{1+\lambda_t}{\lambda_t}} Y_t$$

where $\Lambda_{t,t+s}$ is the stochastic discount factor of the household derived below.

4.1.4 Final consumption producing sector

The final consumption good in this economy is produced by a competitive firm that combines a non-commodity good and a commodity good as inputs, using a constant elasticity of substitution (CES) production function. The optimization problem faced by this producer is as follows:

$$\max_{Y_t^c, O_{c,t}} P_t^f Y_t^f - P_t Y_{c,t} - P_t^o O_{c,t}$$

subject to

$$Y_{f,t} = \left[\omega_f Y_{c,t}^{\frac{1}{1+\lambda_f}} + (1-\omega_f) O_{c,t}^{\frac{1}{1+\lambda_f}} \right]^{1+\lambda_f}$$

where Y_t^f is the quantity of the final consumption good, P_t^f its price, which is the model counterpart of the consumer price index, $o_{c,t}$ the quantity of commodity good that is used in the creation of the final consumption good (e.g. the gasoline that uses directly the oil), P_t^o its price, and $y_{c,t}$ is the quantity of the non-commodity good that is used to produce consumption goods.

4.1.5 Commodity good

The commodity is produced without any cost and the firm sells it to the final consumption-producing sector and to the wholesale sector at a price P_t^o. The price follows an $AR(1)$ process:

$$logP_t^o = (1-\rho_o) log\bar{P^o} + \rho_o logP_{t-1}^o + \epsilon_{o,t},$$

with $\epsilon_{o,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_o)$. In equilibrium, the supply of this good must be equal to the total amount of commodity good demanded by the wholesale sector ($O_{p,t}$) and the final good producer ($O_{c,t}$) at the given price.

4.1.6 Investment good producer

This sector uses the non-commodity good as an input and transforms it into an investment good, which is then sold in a competitive market to the capital good producer. The efficiency of this transformation process is governed by an investment-specific technology process (γ_t), which influences the productivity of converting the non-commodity good into the investment good. The firm's optimization problem is as follows:

$$\max_{Y_{i,t}} P_t^i I_t - P_t Y_{i,t}$$

subject to

$$I_t = \gamma_t Y_{i,t}$$

where I_t is the quantity of the investment good, P_t^i its price, $Y_{i,t}$ is the quantity of the non-commodity good that is used in the production of investment goods, and γ_t is the IST. The latter follows an $AR(1)$ process:

$$log\gamma_t = (1-\rho_i)log\bar{\gamma} + \rho_i log\gamma_{t-1} + \epsilon_{i,t}$$

with $\epsilon_{i,t}$ is $i.i.d \sim \mathcal{N}(0,\sigma_i)$. In this economy, this sector is best thought of as the equipment and machinery in real data. Notice that, solving the problem of the investment good producer yields to:

$$P_t^i \gamma_t = P_t$$

hence,

$$\gamma_t = \frac{P_t}{P_t^i}. \tag{10}$$

Equation 10 highlights that the IST process is inversely related to the relative price of investment with respect to the non-commodity good. This adjustment reflects the empirical findings presented in Section 2, where fluctuations in the prices of oil and food may distort the estimation of IST shocks by influencing the consumption price.

The usual measure of the relative price of equipment (i.e. price of equipment relative to the price of consumption expenditure) is:

$$rpi_t = \frac{P_t^i}{P_t^f}$$

4.1.7 Capital good producer

The capital good producer uses the investment good as its input and determines the level of capital production, but is subject to investment adjustment costs.[9] As a result, the firm faces a dynamic optimization problem: changing the level of investment today affects future adjustment costs. Therefore, the firm must decide on a sequence of investment good demands that maximizes the present value of its future profits. The firm's optimization problem is as follows:

$$\max_{\{I_{t+j}\}_0^\infty} E_t \sum_{j=0}^{\infty} \Lambda_{t,t+j} \left[P_{t+j}^k I_{k,t+j} - P_{t+j}^i I_{t+j} \right]$$

[9]This firm's problem is analogous to that of a household, which uses the investment good to produce capital for the next period, subject to adjustment costs.

subject to

$$I_{k,t} = \mu_t \Big[1 - S\big(\frac{I_t}{I_{t-1}}\big)\Big] I_t,$$

where $I_{k,t}$ is the quantity of capital good produced, P_t^k is its price, $S\big(\frac{I_t}{I_{t-1}}\big)$ is a function that governs the investment adjustment cost of the firm, and μ_t is the marginal efficiency of investment (MEI), which indicates the efficiency by which the investment goods are converted into capital goods.[10] The latter, follows an $AR(1)$ process:

$$log\mu_t = (1 - \rho_m)log\bar{\mu} + \rho_m log\mu_{t-1} + \epsilon_{m,t},$$

where $\epsilon_{m,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_m)$. For simplicity, I assume that the cost of adjustment is:

$$S\Big(\frac{I_t}{I_{t-1}}\Big) = \frac{\psi_s}{2}\Bigg[\Big[\frac{I_t}{I_{t-1}}\Big] - 1\Bigg]^2$$

4.1.8 Household

The household decides on the quantity of final consumption goods to demand from the final consumption good producer, the amount of labor to supply to labor unions, and the capital goods to demand from the capital goods producer, which it uses to build its capital stock. The household also chooses the level of capital utilization, which is rented to the wholesaler, and the amount of debt to borrow from the monetary authority. Since the household controls the level of capital utilization, higher utilization levels result in higher costs, which are incurred in units of final consumption goods. The household's optimization problem is as follows:

$$\max_{C_t, L_{s,t}, I_t, B_t, u_t, \hat{K}_t} \sum_{t=0}^{\infty} \beta^t b_t \Bigg[\frac{(C_t - hC_{t-1})^{1-\sigma}}{1-\sigma} - \psi \frac{L_{s,t}^{1+\chi_L}}{1+\chi_L}\Bigg]$$

subject to

$$P_t^f C_t + P_t^k I_{k,t} + B_t + T_t = R_{t-1}B_{t-1} + \tilde{W}_t L_{s,t} + R_t^k u_t \tilde{K}_{t-1} - P_t^f a(u_t)\tilde{K}_{t-1} + \Pi_t$$
$$\tilde{K}_t = (1-\delta)\tilde{K}_{t-1} + I_{k,t}$$
$$log b_t = (1 - \rho_b)log\bar{b} + \rho_b log b_{t-1} + \epsilon_{b,t},$$

where C_t is the consumption of the final good, $L_{s,t}$ is the labor supplied to the labor unions which pays $\tilde{W}_t$, $I_{k,t}$ is the quantity of investment goods, T_t are taxes paid to the fiscal

[10]Ramey (2016) and Justiniano et al. (2011) provide a comprehensive discussion regarding the importance of the difference between MEI and IST.

authority, u_t is the level of utilization of capital, and $a(u_t)$ is a function that indicates the cost in final consumption goods units that must be paid for each level of utilization. Π_t is the total quantity of profits. B_t is the amount of one-period risk-free bond held by the household, while R_t is the interest rate that it pays. Finally, $\tilde{K}_t$ is the stock of physical capital held by the household. Notice that according to this specification, $K_t = u_t \tilde{K}_{t-1}$.

The cost of the utilization of capital follows:

$$a(u_t) = \frac{R^K_{ss}}{\chi_u}\Big[1 - e^{-\chi_u(u_t-1)}\Big]$$

Finally, the measure of GDP in this economy is as follows:

$$gdp_t = Y^f_t + I_{k,t} - a(u_t)\hat{K}_{t-1}$$

Y^f_t contains both the consumption from households and fiscal authority and $I_{k,t}$ is the final amount of investment.

4.1.9 Labor market

There is a continuum of labor unions indexed by $l \in [0,1]$ that hire labor from the household at $\tilde{W}_t$ in perfect competition and sell labor to a labor packer at price $W_t(l)$ in monopolistic competition. These wages are updated with sticky price frictions a la Calvo (1983) with a probability of updating wages being $(1-\phi_w)$. The labor packer sells the bundle of labor to the wholesaler at a price W_t. The problem of the labor packer is analogous to the non-commodity assembler:

$$\max_{L_t(l)} W_t L_t - \int_0^1 W_t(l) L_t(l) \delta_l$$

subject to

$$L_t = \Big[\int_0^1 L_t(l)^{\frac{1}{1+\lambda_{l,t}}}\Big]^{1+\lambda_{l,t}}$$
$$log\lambda_{l,t} = (1-\rho_w)log\bar{\lambda_l} + \rho_w log\lambda_{l,t-1} + \epsilon_{w,t}.$$

As in the case of non-commodity assemblers, the demand for each union's product is:

$$L_t(l) = \Big[\frac{W_t(l)}{W_t}\Big]^{-\frac{1+\lambda_{l,t}}{\lambda_{l,t}}} L_t.$$

Using this demand, the unions (with monopolistic competition) face the following problem:

$$\max_{W_t(l)} E_t \sum_{s=0}^{\infty} \phi_w^s \Lambda_{t,t+s} \left[W_t(l) - \tilde{W}_t\right] L_t(l)$$

subject to

$$L_t(l) = \left[\frac{W_t(l)}{W_t}\right]^{-\frac{1+\lambda_{l,t}}{\lambda_{l,t}}} L_t$$

Finally, the observed real wage is computed as:

$$wp_t = \frac{w_t}{p_t^f}$$

4.1.10 Government

The government consists of two distinct entities: a fiscal authority and a monetary authority. The fiscal authority finances its activities through a combination of debt issuance and taxes paid by the household.[11] The authority allocates its revenue to purchase a portion of the final consumption good as government expenditure and to repay the debt from the previous period. Government expenditure is assumed to follow a stochastic process. The following equations characterize the behavior of the fiscal authority:

$$P_t^f G_t + R_{t-1} B_{t-1} = B_t + \tau P_t^f Y_t$$
$$G_t = \left[1 - \frac{1}{g_t}\right] Y_t^f$$
$$log(g_t) = (1-\rho_g) log(\bar{g}) + \rho_g log(g_{t-1}) + \epsilon_{g,t}$$

where $\epsilon_{g,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_g)$.

Meanwhile, the monetary authority fixes the interest rate by following a Taylor-type monetary policy rule:

$$log(R_{t+1}) = (1-\rho_r) log(\bar{R}) + \rho_r log(R_t) + (1-\rho_r)\theta_\pi [log(\pi_t) - log(\bar{\pi})] + (1-\rho_r)\theta_y [log(Y_t) - log(\bar{Y})] + \epsilon_{r,t}$$

where $\epsilon_{r,t}$ is $i.i.d \sim \mathcal{N}(0, \sigma_r)$.

4.2 Solution

I use the perturbation method of order one around the steady state as in Schmitt-Grohé and Uribe (2004).[12] I relegate the specification of the steady state and the equations that characterize the equilibrium to Appendix C.

[11] I assume that taxes are a constant proportion of the household's income derived from the non-commodity good.

[12] I use the software platform Dynare to solve the model and to estimate it.

4.3 Estimation

I employ Bayesian methods to estimate the posterior mean values and distributions of the model parameters. This approach integrates the likelihood function with the prior distribution of the parameters to conduct the estimation process.[13] The estimation uses quarterly data from 1964 to 2019 for nine key economic variables. Since the model does not account for long-term trends, I follow the detrending approach recommended by Liao and Chen (2023) and Born and Pfeifer (2021). Rather than applying the one-sided Hodrick-Prescott filter, I opt for polynomial detrending.[14]

4.3.1 Priors and fixed parameters

Following the approach of Justiniano et al. (2011), I fix a small set of parameters commonly used in the literature. Specifically, I set the depreciation rate, δ, to 0.025, the intertemporal elasticity of substitution parameter, σ, to 2.0, and the investment adjustment cost parameter, ψ_s, to 1.0. I fix the weight of the commodity sector in the consumption bundle $(1-\omega_f)$ to 0.177. This value aligns with the average share of food and energy in final private expenditure in the U.S. national accounts from 1947 to 2019, ensuring consistency with historical data.

Additionally, most of the priors for the estimated parameters follow the values proposed by Justiniano et al. (2011). For parameters specific to the commodity sector, I set the prior for the weight of commodities in the wholesale sector (β_o) to follow a beta distribution with a mean of 0.10, and the prior for the parameter governing the elasticity of substitution in the final production sector (λ_f) to follow a normal distribution with a mean of 10.0.[15]

4.3.2 Data

I estimate the model using the following data:

$$X_t = [gdp_t, C_t, I_{k,t}, rpi_t, p_t^f, r_t, w_t, L_t, \pi_t]$$

where gdp_t, c_t, and $I_{k,t}$ are the logs of GDP, consumption and investment per càpita used in Section 2. rpi_t is the log of the relative price of equipment. p_t^f is the log of the ratio between the price value of final private expenditure over the price value of final private expenditure without food and energy prices. r_t is the FED interest shadow rate from Wu and Xia (2016). w_t is the log of the ratio between the average hourly earnings of production and

[13]For a detailed explanation of Bayesian estimation methods, see An and Schorfheide (2007); for a review, refer to Fernández-Villaverde and Guerrón-Quintana (2021).

[14]The Hodrick-Prescott filter has been criticized for significant drawbacks in estimating cyclical components (Hamilton, 2018). Polynomial detrending has been used as an alternative by other documents, such as Uribe and Schmitt-Grohé (2017) and Canova (2020).

[15]A higher value of λ_f implies that the elasticity of substitution in this sector approaches 1.0.

the final private expenditure without food and energy prices. L_t is the total hours worked in the economy, and π_t is the quarterly change of the log of final private expenditure without food and energy prices.

4.3.3 Estimation results

Table 6 presents the estimated parameters, along with their prior distributions and posterior results. The posterior means are consistent with findings in the related literature, further validating the model's calibration.

The model can, qualitatively, replicate several well-known stylized facts from business cycle literature: (i) the correlation of GDP with consumption, and investment is positive; (ii) the standard deviation of consumption is smaller than that of GDP, while the standard deviation of investment is larger; and (iii) the correlation of consumption with investment is positive. However, the quantitative values of these correlations and standard deviations are different from those observed in the data. Moreover, the model fails to replicate the positive correlation between GDP and hours worked. Table 7 compares the moments from the data with those generated by the simulated model.

4.4 Model results

I organize the results into three main analyses. First, I present the IRFs of key macroeconomic variables in response to both the IST shock and the commodity good supply shock. Second, I assess the relative contribution of various shocks to the variance of these variables within the model. Finally, I simulate the model to determine whether it can replicate the responses observed in the empirical data.

The results can be summarized as follows: First, the model IRFs to IST shocks are broadly consistent with those observed in the empirical analysis of the IST shocks that control for oil and food price movements. Additionally, the IRFs to commodity good supply shocks show that a decrease in the price of the commodity good leads to an increase in the RPI, i.e. IST shocks are not the only shocks moving the RPI. Second, based on the model specification, estimation, and data used in this analysis, IST shocks account for only a small portion of the variance in consumption and GDP, though they explain a larger share of the variance in investment (explaining 13.3% of GDP variance, 1.4% of consumption variance, and 34.9% of investment variance). Finally, when computing the IRFs using the simulated data and applying the empirical methodology outlined in Sections 2.2 and 3.2, the results align with those observed in the actual data: using the RPI without any adjustments leads to short-run increases in price variables and a decrease in real wage. This reinforces the challenges associated with estimating the IST shocks with the RPE.

Figure A4 in Appendix A shows the model's IRFs to a positive IST shock ($\epsilon_{i,t}$): there is an increase in the real wage, a decrease in non-commodity inflation and the final consumption good inflation rate. At the same time, both GDP and investment initially rise, and then

Par.	P. Dist.	Prior M.	Post. M.	90% Low	90% High	Prior SD.
α	beta	0.20	0.1974	0.1951	0.1993	0.05
β^o	beta	0.10	0.0703	0.0698	0.0708	0.05
λ	normal	0.15	0.0861	0.0831	0.0889	0.10
ϕ_p	beta	0.66	0.6425	0.6410	0.6440	0.10
λ_f	normal	10.00	10.0396	10.0296	10.0466	0.50
h	beta	0.50	0.4517	0.4457	0.4576	0.10
χ_L	gamma	2.00	1.5125	1.4802	1.5416	0.75
$100(\beta^{-1}-1)$	gamma	0.25	0.2558	0.2546	0.2568	0.1
λ_l	normal	0.15	0.2186	0.2128	0.2238	0.10
ϕ_w	beta	0.76	0.9524	0.9485	0.9561	0.10
χ_u	gamma	5.00	6.1477	6.0924	6.2026	1.00
θ_π	gamma	1.500	1.8039	1.7896	1.8182	0.30
θ_y	gamma	0.500	0.4876	0.4869	0.4883	0.05
τ	beta	0.200	0.1668	0.1662	0.1676	0.10
ρ_a	beta	0.600	0.4450	0.4394	0.4502	0.20
ρ_i	beta	0.600	0.2859	0.2813	0.2911	0.20
ρ_m	beta	0.600	0.9619	0.9578	0.9648	0.20
ρ_o	beta	0.600	0.6092	0.6051	0.6140	0.20
ρ_g	beta	0.600	0.9179	0.9149	0.9206	0.20
ρ_r	beta	0.600	0.9690	0.9646	0.9730	0.20
ρ_w	beta	0.600	0.9698	0.9666	0.9728	0.20
ρ_p	beta	0.600	0.8938	0.8882	0.8993	0.20
ρ_b	beta	0.600	0.9697	0.9681	0.9712	0.20
σ_a	invgam	0.900	0.9200	0.8559	0.9898	1.00
σ_i	invgam	0.500	0.4763	0.4743	0.4782	1.00
σ_m	invgam	0.500	0.0664	0.0645	0.0685	1.00
σ_o	invgam	0.500	0.4262	0.4200	0.4326	1.00
σ_g	invgam	0.500	0.0655	0.0645	0.0667	1.00
σ_r	invgam	0.100	0.0266	0.0249	0.0290	1.00
σ_w	invgam	0.100	0.1337	0.1266	0.1436	1.00
σ_p	invgam	0.100	0.1302	0.1221	0.1405	1.00
σ_b	invgam	0.100	0.1362	0.1252	0.1443	1.00

Table 6: Estimation Results of parameters in the DSGE model.

Metric	Data	Model
S.D. Inv./S.D. GDP	3.280	5.048
S.D. Con/S.D. GDP	0.734	0.624
corr GDP-Inv	0.817	0.731
Corr GDP-Con	0.925	0.517
Corr Con-INV	0.661	0.087
Corr GDP-Labor	0.773	-0.124
Corr GDP-RPI	0.011	-0.247

Table 7: Comparison of moments between Data and Model

the shock vanishes some periods later. Consumption falls in the initial quarters as the economy funnels additional resources into investment, but begins to rise after some periods. Additionally, labor demand from wholesalers (ld) increases at first, followed by a decline after some quarters. These responses closely mirror those analyzed in Section 2.4, once IST shocks are adjusted for food and oil prices. Figure A5 in Appendix A, in contrast, illustrates the response of macroeconomic variables to a commodity price shock. A key observation here is that the increase in commodity prices decreases the relative price of investment (RPI) supporting that RPI contains information of fluctuations in the commodity sector. In fact, Notice that the inflation measures increase while real wages decrease after the shock.

Table 8 presents the variance decomposition from the DSGE model. The columns represent the shocks incorporated into the model, while the rows display the macroeconomic variables under analysis. The results indicate that the neutral technology shock accounts for a substantial share of the variance in price-related variables and a portion of the variance in investment consumption and GDP. In contrast, the IST shock plays a significant role in explaining the variance of the investment variable but contributes much less to GDP and consumption (explaining 13.3% of GDP variance, 1.4% of consumption variance, and 34.9% of investment variance).[16] Finally, the commodity price shock is a major contributor the variance in cpi, by explaining 25.8% of its variance.

Finally, I simulate time series for the same data used in Section 2, generating 10.000 draws of several macroeconomic variables, including GDP, consumption, investment, labor demand from wholesalers, interest rates, wages, CPI, core CPI inflation, the price of commodities, the relative price of investment (RPI), and the RPI relative to core prices.[17] Using the same identification strategy in Section 2, with the RPI measure which still reflects information

[16]These results show a similar pattern in comparison with empirical results of the FEVD in Table 3: IST explains more of investment's FEV and less of GDP and consumption for higher horizons, but the values are not similar.

[17]Note that the RPI relative to core prices is the inverse of the IST variable, defined as $\frac{1}{\gamma_t} = \frac{P_t^i}{P_t}$.

about commodity price shocks, the real variables behave qualitatively similar to the responses observed in the empirical analysis: GDP and investment increase immediately following the shock, while consumption initially decreases but rises after a few periods. Meanwhile, the price variables show an increase in CPI and commodity prices immediately after the shock (Figure A6 in Appendix A).

In contrast, when using the RPI relative to core prices (as in Section 3.2 with the empirical data), the IRFs of the real variables remain qualitatively the same, but the responses of the price variables differ. In this case, CPI inflation, and core CPI inflation decrease following the shock, aligning with the empirical findings. This distinction underscores the importance of properly accounting for commodity price influences when interpreting RPI and its relationship to IST shocks (Figure A7 in Appendix A).

	$\epsilon_{a,t}$	$\epsilon_{i,t}$	$\epsilon_{m,t}$	$\epsilon_{o,t}$	$\epsilon_{g,t}$	$\epsilon_{r,t}$	$\epsilon_{w,t}$	$\epsilon_{p,t}$	$\epsilon_{b,t}$
rpi	0.0	95.8	0.0	4.2	0.0	0.0	0.0	0.0	0.0
gdp	43.1	13.3	4.4	2.8	21.8	2.2	6.8	0.1	5.6
cons.	17.8	1.4	18.5	5.5	3.8	1.5	3.3	0.0	48.1
inv.	44.2	34.9	5.5	0.5	1.8	1.8	6.7	0.2	4.4
labor	90.0	1.2	1.2	1.8	3.0	0.3	1.1	0.0	1.3
wages	78.5	1.1	2.2	13.3	0.5	0.1	0.5	0.4	3.2
Inflation	72.9	0.1	0.5	25.8	0.2	0.0	0.2	0.1	0.1
c. Inflation	97.9	0.2	0.7	0.5	0.2	0.0	0.3	0.1	0.2
Com. Price.	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0

Table 8: Variance Decomposition in the DSGE model (%)

5 Conclusions

The RPE has been a significant focus in macroeconomic research, primarily due to its connection with IST. Empirical studies have suggested that IST shocks, identified through the RPE, play a crucial role in explaining the behavior of key macroeconomic variables during business cycle fluctuations. This paper aims to demonstrate that the estimated IST shocks are still influenced by exogenous movements in oil and food prices. Such exogenous price changes disproportionately affect the cost of non-durable consumption goods relative to equipment prices, leading to potential issues in the estimation of IST shocks.

After adjusting for the effects of both price indices, IRFs indicate that IST shocks lead to a decline in price levels, while GDP and investment exhibit an immediate increase, and consumption responds with a lag. Notably, the FEV attributable to IST shocks is reduced for GDP, consumption, and investment when compared to estimates that do not account for fluctuations in oil and food prices.

A medium-scale DSGE model with a rich stochastic structure can account for the empirical findings. The model includes a commodity good sector where the price is determined exogenously, and its output is used as input by the final consumption goods producer. This structure implies that the relative price of investment reflects information about the prices in the commodity sector. Simulations from the DSGE can qualitatively reproduce the empirical IFRs observed in the data.

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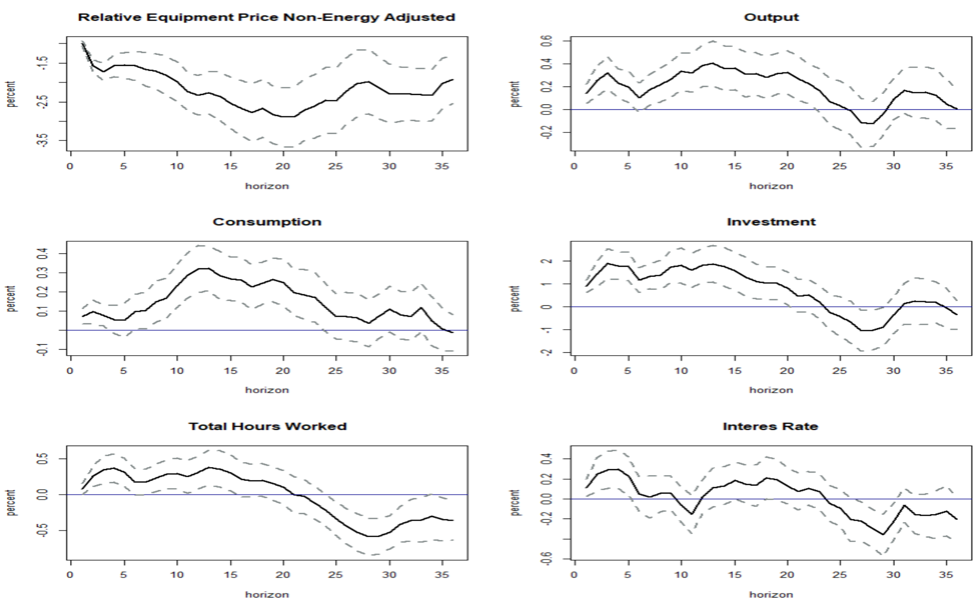
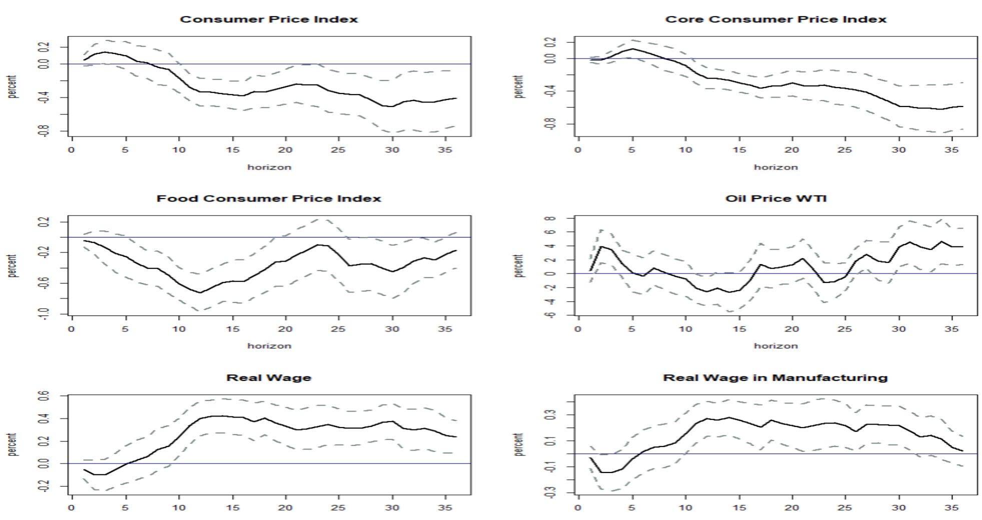
Appendices

A Figures

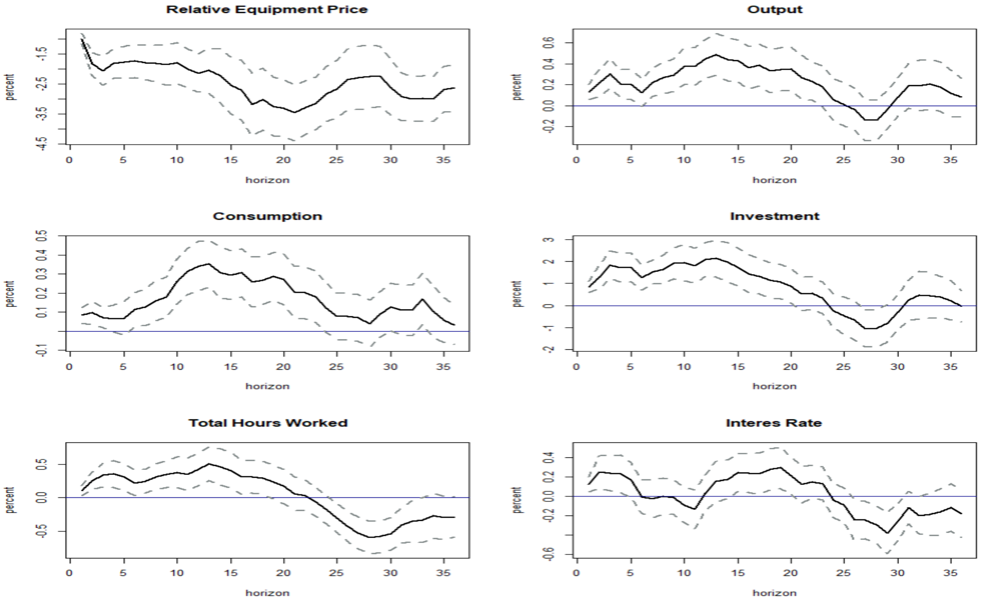


(a) Real Variables.

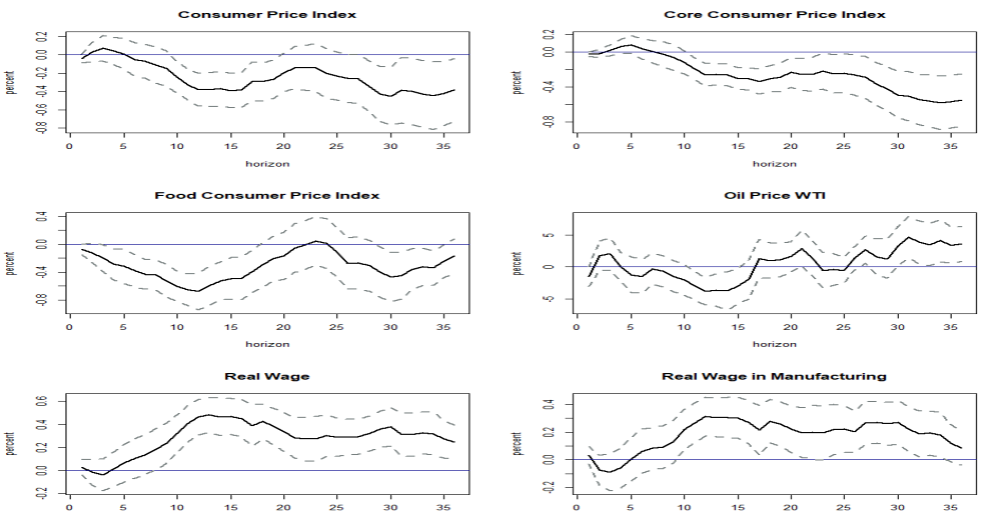


(b) Price Variables

Figure A1: Impulse response of macroeconomic variables to IST shocks estimated using RPENE. Dotted lines represent the 90,0% interval.

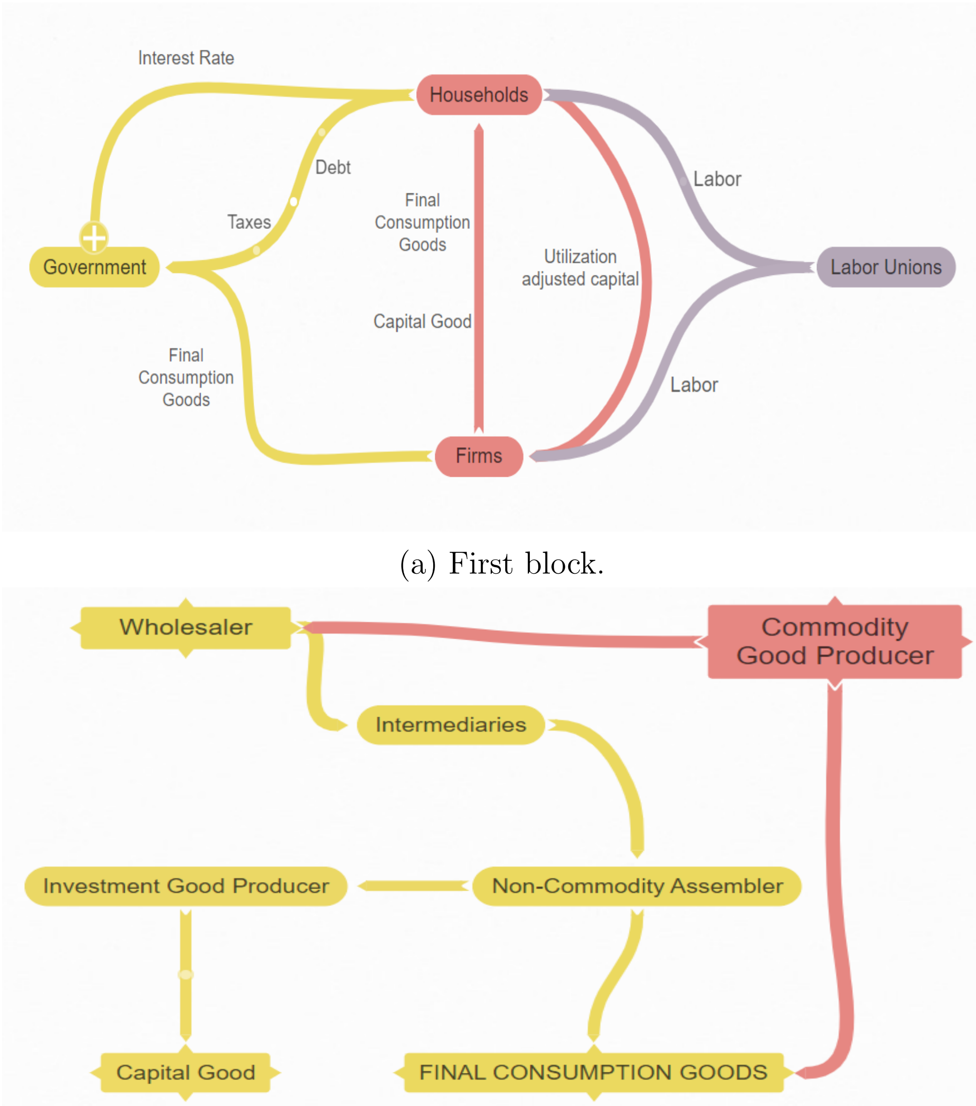


(a) Real Variables.



(b) Price Variables

Figure A2: Impulse response of macroeconomic variables to IST shocks estimated using PCEFE. Dotted lines represent the 90,0% interval.



(a) First block.

(b) Second block

Figure A3: Diagram of the flows in the model economy.

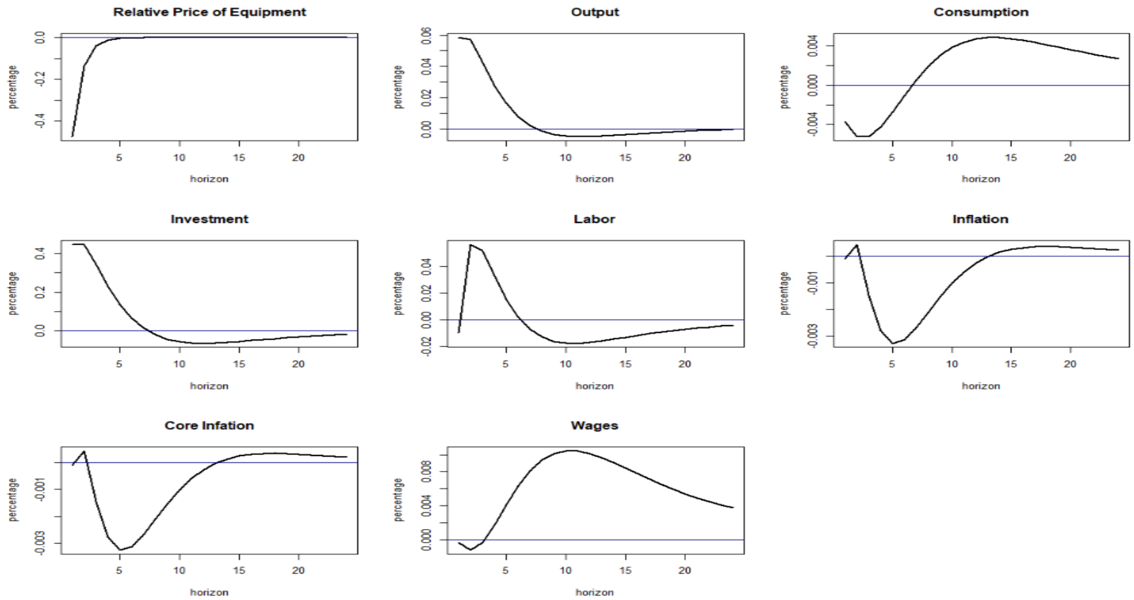


Figure A4: Impulse Response Function of main macro variables after an IST shock in the DSGE model.

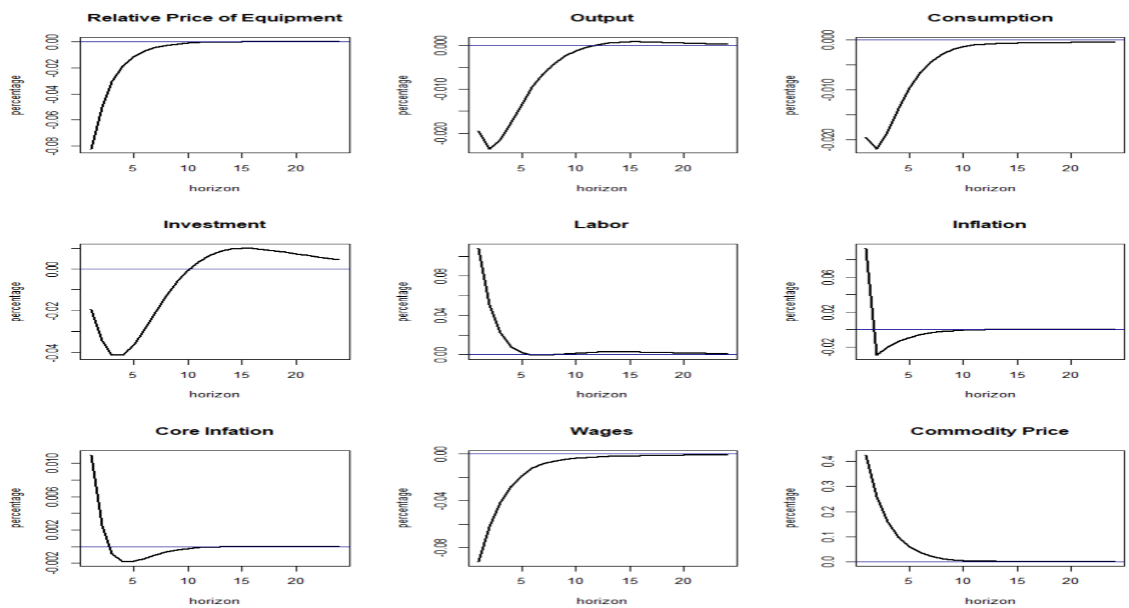
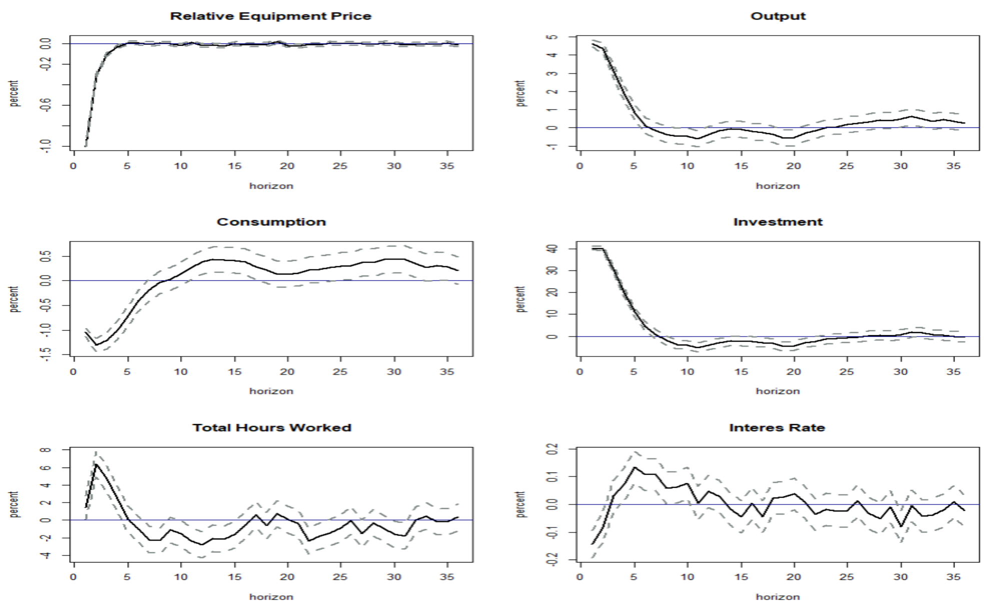
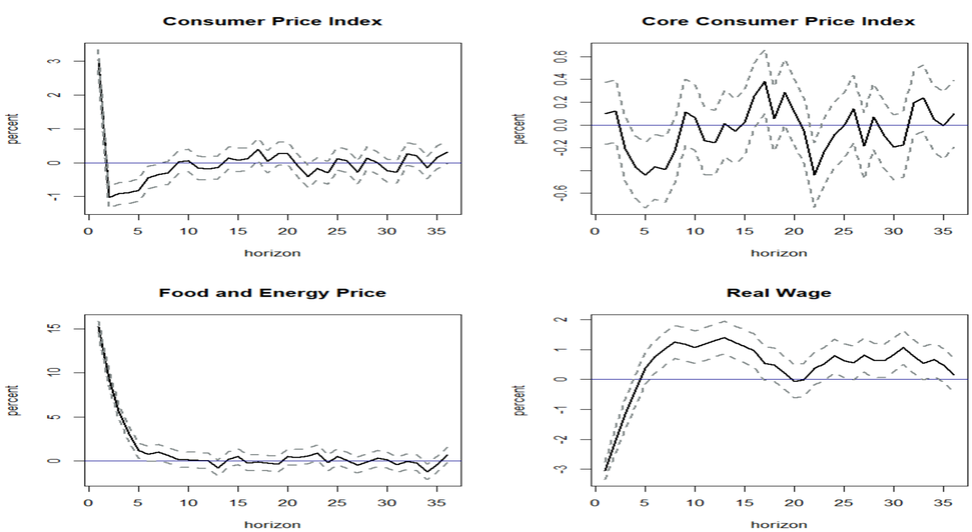


Figure A5: Impulse Response Function of main macro variables after a commodity supply shock in the DSGE model.

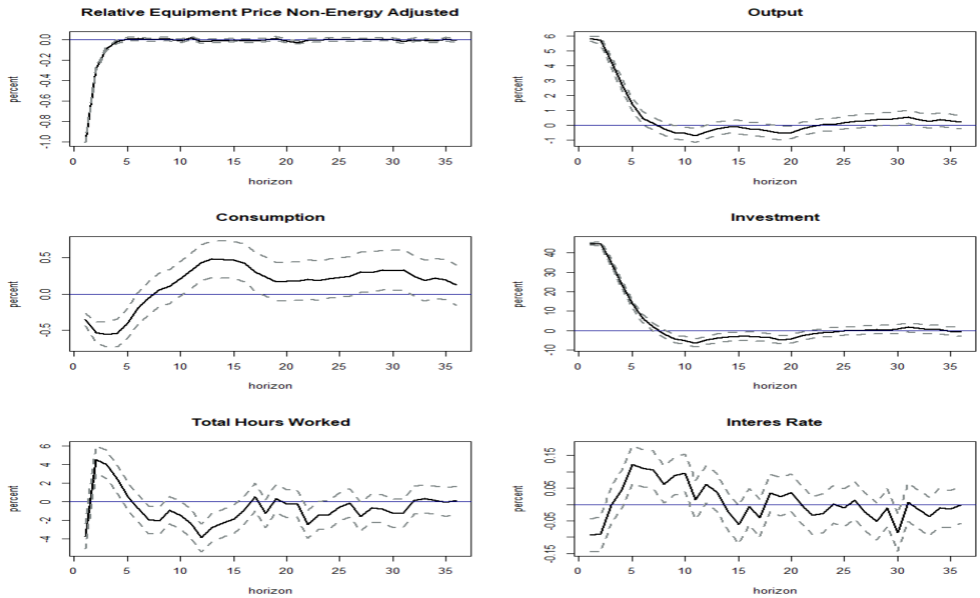


(a) Real Variables.

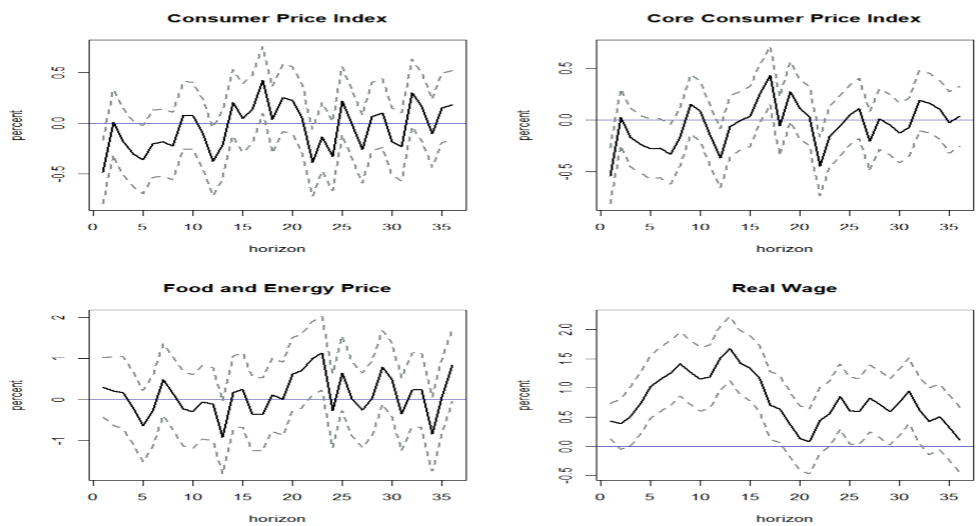


(b) Price Variables

Figure A6: Impulse response of macroeconomic variables to IST shocks estimated with the RPI using the simulated data from the DSGE model. The dotted lines represent the 90,0% interval.



(a) Real Variables.



(b) Price Variables

Figure A7: Impulse response of macroeconomic variables to IST shocks estimated with the RPI with respect to core price (analog to RPENE in the data), using the simulated data from the DSGE model. The dotted lines represent the 90,0% interval.

B Importance of BZK's IST news shocks

I compute the percentage of the forecast error variance explained by BZK's news shocks, both with and without the inclusion of oil and food price indexes. It is important to note that, according to the original document, the estimation already incorporates inflation (measured as the annual change in the CPI) into the system of equations, yet there is still a correlation with oil price shocks. To better account for the effects of food prices and WTI (West Texas

Intermediate crude oil prices), I remove inflation from the estimation and instead introduce three components that are part of the CPI: Core CPI, Food CPI, and WTI.

Since Core CPI data is only available after 1957, the forecast error variance decomposition (FEVD) is calculated using data from that period onward for both the adjusted system (the clean one) and the baseline model. This adjustment allows for a more accurate assessment of how food and oil prices contribute to the variance explained by BZK's news shocks, ensuring that the results account for key components of the CPI while isolating their effects.

Table 4 shows the estimation with (Clean) and without (Base) the variables in the system. Notice that there is decrease in the forecast error variance of GDP, consumption and hours worked explained by the IST news shocks once I introduce both variables in the system.

	GDP	GDP	Inv.	Inv.	Cons.	Cons.	Hours	Hours
h	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**	**Base**	**Clean**
1	0.115	0.056	0.125	0.233	0.403	0.086	0.94	0.119
5	0.543	0.225	0.506	0.492	0.602	0.258	0.605	0.296
10	0.573	0.244	0.488	0.440	0.635	0.290	0.678	0.348
15	0.562	0.226	0.444	0.389	0.629	0.270	0.621	0.281
20	0.593	0.221	0.475	0.391	0.644	0.256	0.609	0.258

Table 9: FEVD of IST news shock as in BZK

C Equilibrium Equations

To solve the model, I obtain the equations that characterize the equilibrium and redefine the nominal prices using the price of the non-commodity assembler as a numeraire. Nominal variables in lower case are the ratio of each price over the numeraire. The system of equations that characterize the equilibrium is as follows:

- Equations from the Wholesaler

$$p_t^w[1-\alpha-\beta_o]A_t^{1-\alpha-\beta_o}K_t^{\alpha}O_{p,t}^{\beta_o}L_t^{-\alpha-\beta_o} = w_t \tag{11}$$

$$p_t^w[\alpha]A_t^{1-\alpha-\beta_o}K_t^{\alpha-1}O_{p,t}^{\beta_o}L_t^{1-\alpha-\beta_o} = r_t^k \tag{12}$$

$$p_t^w[\beta_o]A_t^{1-\alpha-\beta_o}K_t^{\alpha}O_{p,t}^{\beta_o-1}L_t^{1-\alpha-\beta_o} = p_t^o \tag{13}$$

- Three Equations Phillips curve:

$$\tilde{p}_t = (1+\lambda_t)\frac{x_{2,t}}{x_{1,t}} \tag{14}$$

$$x_{1,t} = Y_t + E_t\Big[\phi_p \Lambda_{t,t+1} \pi^{\frac{1+\lambda_t}{\lambda_t}} x_{1,t+1}\Big] \tag{15}$$

$$x_{2,t} = p_t^w Y_t + E_t\Big[\phi_p \Lambda_{t,t+1} \pi^{\frac{1+\lambda_t}{\lambda_t}+1} x_{2,t+1}\Big] \tag{16}$$

- Equations from the final good producer

$$1 = p_t^f Y_{f,t}^{\frac{\lambda_f}{1+\lambda_f}} \omega_f Y_{c,t}^{\frac{-\lambda_f}{1+\lambda_f}} \tag{17}$$

$$p_t^o = p_t^f Y_{f,t}^{\frac{\lambda_f}{1+\lambda_f}} [1-\omega_f] O_{c,t}^{\frac{-\lambda_f}{1+\lambda_f}} \tag{18}$$

$$Y_t^f = \Big[\omega_f Y_{c,t}^{\frac{1}{1+\lambda_f}} + (1-\omega_f) O_{c,t}^{\frac{1}{1+\lambda_f}}\Big]^{1+\lambda_f} \tag{19}$$

- Equations from the investment producer

$$p_t^i \gamma_t = 1 \tag{20}$$

$$I_t = \gamma_t Y_{i,t} \tag{21}$$

- Equations from the capital producer

$$p_t^k \mu_t [1 - s_t - s_{p,t}\frac{I_t}{I_{t-1}}] + E_t\Big[\Lambda_{t,t+1}[p_{t+1}^k \mu_{t+1} s_{p,t+1} [\frac{I_t}{I_{t-1}}]^2 \pi_{t+1}]\Big] = p_t^i \tag{22}$$

$$I_{k,t} = \mu_t [1 - s_t] I_t \tag{23}$$

- Equations from the household

$$\lambda_t^c = \psi \frac{L_{s,t}^{\chi_l}}{\tilde{w}_t} \tag{24}$$

$$p_t^f \lambda_t^c = b_t[C_t - hC_{t-1}]^{\sigma} - E_t\Big[\beta_c h b_{t+1}[C_{t+1} - hC_t]^{\sigma}\Big] \tag{25}$$

$$\Lambda_{t,t+1} = E_t\Big[\beta_c \frac{\lambda_{t+1}^c}{\lambda_t^c}\Big] \tag{26}$$

$$1 = E_t\Big[R_{t+1}\Lambda_{t,t+1}\Pi_{t+1}^{-1}\Big] \tag{27}$$

$$r_t^k = p_t^f a_{up,t} \tag{28}$$

$$\lambda_t^{c2} = \lambda_t^c p_t^f \tag{29}$$

$$\lambda_t^{c2} = E_t\Big[\beta_c \lambda_{t+1}^c [r_{t+1}^k u_{t+1} - p_{t+1}^f a_{u,t+1}] + \beta_c \lambda_{t+1}^{c2}[1-\delta]\Big] \tag{30}$$

$$K_t = u_t \tilde{K}_t \tag{31}$$

$$\tilde{K}_t = [1-\delta]\tilde{K}_{t-1} + I_{k,t} \tag{32}$$

- Fiscal Authority Equations

$$P_t^f G_t + R_{t-1}B_{t-1} = B_t + \tau P_t^f Y_t \tag{33}$$

$$G_t = \Big[1 - \frac{1}{g_t}\Big] Y_t^f \tag{34}$$

- Wages Three Equations

$$\tilde{w}_t = [1 + \lambda_{l,t}] \frac{f_{1,t}}{f_{2,t}} \tag{35}$$

$$f_{1,t} = \tilde{w}_t [w_t^{\frac{1+\lambda_{l,t}}{\lambda_{l,t}}}] L_t + E_t\Big[\phi_w \Lambda_{t,t+1} \pi_{t+1}^{\frac{1+\lambda_{l,t}}{\lambda_{l,t}}+1} f_{1,t+1}\Big] \tag{36}$$

$$f_{2,t} = [w_t^{\frac{1+\lambda_{l,t}}{\lambda_{l,t}}}] L_t + E_t\Big[\phi_w \Lambda_{t,t+1} \pi_{t+1}^{\frac{1+\lambda_{l,t}}{\lambda_{l,t}}} f_{2,t+1}\Big] \tag{37}$$

- Aggregate price and dispersion

$$1 = [1-\phi_p]\tilde{p}_t^{-\frac{1}{\lambda_t}} + \phi_p \pi_t^{\frac{1}{\lambda_t}} \tag{38}$$

$$v_{p,t} = [1-\phi_p]\tilde{p}_t^{-\frac{1+\lambda_t}{\lambda_t}} + \phi_p \pi_t^{\frac{1+\lambda_t}{\lambda_t}} v_{p,t-1} \tag{39}$$

$$Y_{w,t} = v_{p,t} Y_t \tag{40}$$

- Aggregate wage and dispersion

$$w_t^{-\frac{1}{\lambda_{w,t}}} = [1-\phi_w]\tilde{w}_t^{-\frac{1}{\lambda_{w,t}}} + \phi_w w_{t-1}^{-\frac{1}{\lambda_{w,t}}} \pi_t^{\frac{1}{\lambda_{w,t}}} \tag{41}$$

$$v_{w,t} = [1-\phi_w][\frac{\tilde{w}_t}{w_t}]^{-\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} + \phi_w[\frac{w_t}{w_{t-1}}]^{\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} \pi_t^{\frac{1+\lambda_{w,t}}{\lambda_{w,t}}} v_{w,t-1} \tag{42}$$

$$L_{s,t} = v_{w,t} L_t \tag{43}$$

- Other Market Clearing Conditions

$$Y_t = Y_{c,t} + Y_{i,t} \tag{44}$$

$$e_{o,t} = O_{p,t} + O_{c,t} \tag{45}$$

$$Y_{f,t} = C_t + G_t + a_{u,t}\hat{K}_t \tag{46}$$

- Function Definitions

$$s_t = \frac{\psi_s}{2}\Big[\frac{I_t}{I_{t-1}} - 1\Big]^2 \tag{47}$$

$$s_{p,t} = \psi_s\Big[\frac{I_t}{I_{t-1}} - 1\Big] \tag{48}$$

$$a_{u,t} = \frac{1}{\gamma_{ss}\mu_{ss}} \frac{R_{ss} - (1-\delta)}{\chi_u}\Big[1 - e^{-\chi_u(u_t - 1)}\Big] \tag{49}$$

$$a_{up,t} = \frac{1}{\gamma_{ss}\mu_{ss}}[R_{ss} - (1-\delta)]e^{-\chi_u(u_t-1)} \tag{50}$$

- Law of motion of exogenous processes

$$logA_t = (1-\rho_a)log\bar{A} + \rho_a logA_{t-1} + \epsilon_{a,t} \tag{51}$$

$$log\lambda_t = (1-\rho_p)log\bar{\lambda} + \rho_p log\lambda_{t-1} + \epsilon_{p,t} \tag{52}$$

$$logP_t^o = (1-\rho_o)log\bar{P^o} + \rho_o logP_{t-1}^o + \epsilon_{o,t} \tag{53}$$

$$log\gamma_t = (1-\rho_i)log\bar{\gamma} + \rho_i log\gamma_{t-1} + \epsilon_{i,t} \tag{54}$$

$$log\mu_t = (1-\rho_m)log\bar{\mu} + \rho_m log\mu_{t-1} + \epsilon_{m,t} \tag{55}$$

$$logb_t = (1-\rho_b)log\bar{b} + \rho_b logb_{t-1} + \epsilon_{b,t} \tag{56}$$

$$log\lambda_{l,t} = (1-\rho_w)log\bar{\lambda}_l + \rho_w log\lambda_{l,t-1} + \epsilon_{w,t} \tag{57}$$

$$log(g_t) = (1-\rho_g)log(\bar{g}) + \rho_g log(g_{t-1}) + \epsilon_{g,t} \tag{58}$$

$$\begin{aligned} \log(R_{t+1}) = (1-\rho_r)\log(\bar{R}) + \rho_r\log(R_t) + (1-\rho_r)\theta_\pi[\log(\pi_t) - \log(\bar{\pi})] \\ + (1-\rho_r)\theta_y[\log(Y_t) - \log(\bar{Y})] + \epsilon_{r,t} \end{aligned} \tag{59}$$

C.1 Steady State

To compute the Steady State (SS) I need to assume the SS values of some of the endogenous variables in the model. In particular, the SS of the technology variables ($\bar{A}, \bar{\mu}$, γ), the core inflation ($\bar{\pi}$), the government expenditure exogenous variable ($\bar{g}$) and the labor demanded by the wholesaler ($\bar{L}$) are set to be 1. Using these restrictions I find the SS of all the other variables by finding their time-invariant values that satisfy the equilibrium equations, and the SS defined above.