Monetary Policy and Prices in Brazil: Insights by Income Level

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Abstract

We investigate the asymmetry effects of a monetary policy shock on prices by income level in Brazil. Using data from January 2010 to February 2020 and a sign-restricted BVAR model (controlling for the price puzzle), we find evidence that monetary policy could be socially desirable to reduce inequalities in a short period, mainly within the recessive cycles. Furthermore, implications are verified in a wide range of robustness tests, considering changes in the econometric model and expanded database (with subprime and Covid-19 crisis). Conclusively, an active Central Bank (sometimes named Hawkish) could contribute, at least partially, to reduce the loss of lower-income household purchasing power before wage adjustments.

Key-words: Monetary Policy; Income Level; Inflation.
JEL Classification: E31; E52; O23.

Resumo

Investigamos os efeitos assimetricos de um choque de política monetária sobre os preços por nível de renda no Brasil. Utilizando dados de janeiro de 2010 a fevereiro de 2020 e um modelo BVAR com restrição de sinal (controle para o price puzzle), encontramos evidências de que a política monetária pode ser socialmente desejável para reduzir as desigualdades em um curto período, principalmente dentro do ciclos recessivos. Além disso, as implicações são verificadas em uma ampla gama de testes de robustez, considerando mudanças no modelo econométrico e expansão da base de dados (com crises do subprime e Covid-19). Conclusivamente, um Banco Central ativo (as vezes classificado como Hawkish) poderia contribuir, pelo menos parcialmente, para reduzir a perda de poder aquisitivo das famílias de baixa renda antes de reajustes salariais.

Palavras-chaves: Política Monetária; Nível de Renda; Inflação.
Classificação JEL: E31; E52; O23.

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1 Introduction

Is it possible for the Central Bank to effectively act against inflation? Does the action of the monetary authority have effects on economic aggregates? How long does an interest rate shock last? These and other questions have aroused the interest of researchers and policy-makers over the past 50 years. From the New Keynesian perspective, inflation affects consumption and investment decisions and, consequently, is directly linked to their standard of living. Thus, monetary policy could be an instrument within business cycles (see Woodford (2003) and Gali (2008)). Notoriously, the relationship between interest rates, inflation, and economic activity goes beyond the simple intuition that higher interest rates reduce the amount of money in circulation and, therefore, prices. There are imperfections in the economy (price stickiness, heterogeneous goods, labor search, and even credit constraints, among others) that make transmission channels a little more complex.

After the Lucas (1976) critique, there was an increase in the development/refinement of theoretical monetary models with structural parameters (mainly based on contributions of Phelps e Taylor (1977), Fischer (1977) and Calvo (1983)) and in the search for empirical "stylized facts" related to monetary policy (see seminal papers by Sims (1992), Galí (1992) and Christiano et al. (1996)). However, an empirical puzzle (dubbed "price-puzzle" by Eichenbaum (1992)) emerged from the vector autoregression models. Opposite to theoretical advances, some empirical papers have found evidence that an exogenous monetary policy shock could induce a rise in the aggregate price level. Since then, several theoretical and methodological arguments have been constructed to explainthe price puzzle.

The common procedures are the commodity prices inclusion (Sims (1992)) and the impose of sign restrictions for identification (Uhlig (2005) and Fry e Pagan (2011)). Both alternatives have been discussed, tested and expanded by researchers such as Hanson (2004), Bernanke (2005), Sims e Zha (2006), Henzel et al. (2009), Tas (2011) and Estrella (2015). However, depending on the data frequency and time window of analysis, the results are not consensual.

Consequently, the effects of monetary policy on the average price level can be tricky. Some researchers (see Boivin et al. (2009), Coibion et al. (2017) and Cravino et al. (2020)) have investigated the heterogeneous effects of monetary shocks on disaggregated groups (by sector or income level). Most of the time, the motivation stems from the possible distributional/asymmetric effects on wealth. Specifically, Cravino et al. (2020) highlights that since there may be considerable inequality in consumption across income levels, monetary shocks could asymmetrically influence household inflation.

For Brazilian data, contributions by Cysne (2004), Luporini (2008), Guimaraes e Monteiro (2014), Filho (2017) and Silva et al. (2018) indicate that a contractionary shock in interest rate positively affects the price level (both monthly and quarterly data). While authors such as Minella (2003), Carvalho e Junior (2009),Tomazzia e Meurer (2009),Mendonça et al. (2010) and Bezerra et al. (2014) indicate that the inclusion of commodity prices, monetary policy costs, or signal restrictions for identification, can explain or solve the puzzle. However, there is a lack of empirical studies about the potential effects of monetary policy on prices for different income levels in Brazil and, consequently, that explore the validity of price puzzle across income ranges. Specifically, this point becomes relevant because it rise questions such as: Do monetary policy shocks have socially desirable effects for lower purchasing power population?

The main objective of this paper is to understand whether changes in interest rate asymmetrically affect the dynamics of prices for different income brackets in Brazil. In the specific contributions of this article, we provide a new look at Brazilian price dynamics, based on Cravino et al. (2020) framework, present and detail some procedures to account for this problem (see Uhlig (2005) and Fry e Pagan (2011)), and make some considerations about distributional effects of monetary policies in Brazil. The disaggregated evidence (six income-levels) can provide new insights to policymakers about the consequences and importance of monetary policy rules and contribute to the empirical debate about monetary asymmetries and effects.

The rest of the paper is organized as follows: In Section 2, we briefly expose a theoretical model and explore the empirical literature about the price puzzle in Brazil. Next, in Section 3, we detail the bayesian vector model with sign restrictions. Section 4 presents the preliminary statistical analysis and details of variables. Finally, in the last sections (5 and 6), we discuss the results and build the main conclusions.

2 References

In this section, we first present Cravino et al. (2020) model that support the the hypotheses explored in this research: monetary policy affects prices asymmetrically, according to the income levels. Then, we briefly explore some established contributions (Minella (2003),Cysne (2004),Luporini (2008),Tomazzia e Meurer (2009),Carvalho e Junior (2009),Mendonça et al. (2010),Bezerra et al. (2014),Guimaraes e Monteiro (2014) and Filho (2017)) on the causes and solutions of the Brazilian price puzzle.

2.1 *Theoretical Model*

The economy has a continuum of h-type households (according to income levels), with preferences given by a utility function (U^h) that depends on consumption (C_t^h) and labor supply (N_t^h). Then, for a given discount rate (β):

$$U^h = E_0 \sum_{t=0}^{\infty} \beta^t \left[lnC_t^h - N_t^h \right] \tag{1}$$

Households are subjected to a budget constraint:

$$P_t^h C_t^h + Q_{t,t+1} B_{t+1}^h = W_t A^h N_t^h + T_t^h + B_t^h \tag{2}$$

They respect a *No Ponzi Game* condition such that the amount spent on consumption ($P_t^h C_t^h$) plus the expected value of the bonds in the following period ($Q_{t,t+1} B_{t+1}^h$) must be equal to the current stock of bonds (B_t^h) plus labor income ($W_t A^h N_t^h$) and government/firm transfers (T_t^h) to households (A^h is related to the efficiency of labor). The bundle of goods consumed can be generically represented by the following equation:

$$C_t^h = \left[\sum_{j}^{J} \left[\overline{\omega}_j^h\right]^{\frac{1}{\eta}} \left[C_{j,t}^h\right]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{3}$$

Cravino et al. (2020) indicate that $C_{j,t}^h$ is assigned to household h's consumption of final goods from sector j and $\overline{\omega}_j^h$ is a parameter that represents the specific taste shifter for j-sector goods (which determines the cross-household differences). Therefore, within the set of goods supplied by firms, the percentage spent on varieties differs by income bracket. Consequently, from the potential differences of weights, the price index associated with the h-bundle can be defined as:

$$P_t^h = \left[\sum_{j}^{J} \overline{\omega}_j^h P_{j,t}^{1-\eta} \right]^{\frac{1}{(1-\eta)}} \tag{4}$$

Where $P_{j,t}$ is the price for j-sector good. Therefore, for $\overline{\omega}_j^h$ varieties, the demand function for the h-type household can be derived as:

$$C_{j,t}^h = \overline{\omega}_j^h \left[\frac{P_{j,t}}{P_t^h}\right]^{-\eta} C_t^h \tag{5}$$

The monopolist intermediate producers operate a linear technology ($Y_{j,t}(i) = \overline{N}_{j,t}(i)$ and $\overline{N}_{j,t}$(i) is the efficiency units of labor used by producer i),can set prices (with θ_j probability) and maximize the present value of profits:

$$\overline{P}_{j,t} = argmax \left\{\sum_{k=0}^{\infty}[1-\theta]^k E_t \left\{Q_{t,t+k}[\overline{P}_{j,t} - W_{t+k}]Y_{j,t+k}(i)\right\}\right\}$$

Subjected to the aggregate production of intermediate goods:

$$Y_{j,t}(i) = \left[\frac{P_{j,t}(i)}{P_{j,t}}\right]^{-\gamma} Y_{j,t} \tag{6}$$

Finally, the monetary authority sets nominal interest rate following a standard Taylor rule:

$$exp(i_t) = exp(\rho_i i_{t-1}) \left[\Pi_t^{\phi_\pi} \left[\frac{Y_t}{\overline{Y}}\right]^{\phi_y}\right]^{(1-\rho_i)} exp(\nu_i) \tag{7}$$

Where $i_t = -log(Q_{t,t+1})$ is the nominal interest rate, $\Pi_t = \frac{P_t}{P_{t-1}}$ is aggregate inflation, and $\overline{Y}$ is the efficient level of output. ν_t is the monetary shock and satisfies $\varepsilon_{\nu,t} \sim N(0, \sigma_{\varepsilon_\nu})$:

$$\nu_t = \rho_\nu \nu_{t-1} + \varepsilon_{\nu,t} \tag{8}$$

Following the New Keynesian framework (see Woodford (2003) and Gali (2008) for a deeper discussion), the connection between real and nominal variables also comes from the imperfect markets and price rigidity. It means that even though firms produce s consumed by different types of households, we can observe different persistence at each income level. Furthermore, the expected effects on prices by income levels differ. That is the hypothesis explored in our paper, considering what has already been done for the Brazilian economy (as we will see in the next section).

2.2 *The Brazilian Price Puzzle*

The Brazilian price puzzle (increase in the price level after a contractionary monetary policy shock) has been frequently reported in empirical papers and sowed many possibilities over the past few decades. Chronologically, we present the empirical evidence supporting the Brazilian price puzzle and discuss some solutions available.

Minella (2003) was one of the first authors to replicate the Eichenbaum (1992) analysis of the Brazilian economy. The author compares the power of a monetary policy shock on inflation and output over three different periods: (1975-1985), (1985-1994), and (1994-2000). The benchmark VAR model, using monthly data, contains four variables: industrial production, nominal interest rate, inflation rate, and the monetary base. Between 1975 and 1985 (a period characterized by moderately-increase inflation), Minella (2003) indicates that an interest rate shock did not affect prices. On the other hand, in the high inflation period (1985-1994), there was a positiveimpact, characteristically according to the price puzzle. The author overcomes the problem using a centered inflation rate to capture the acceleration between periods. Finally, after Real Plan, there is evidence that the instrument gained some power against price advances.

However, it is interesting to note that the results may be inconclusive due to the Brazilian transition to the inflation-targeting regime.

To better understand the Brazilian price-puzzle, Cysne (2004) contribution uses quarterly data from 1980/Q1 to 2004/Q2. Furthermore, the author illustrates the use of bootstrap bias-corrected confidence bands in the VAR estimation (motivated by Christiano et al. (1999) research). The basic model has output, price level, bank reserves, the monetary base (natural logarithm), and short-term interest rate, following Christiano et al. (1999). The Cholesky decomposition implies that output is not simultaneously affected by any other variable but affects them all. Next, the price level only responds to production (contemporaneously) but affects all others, and so on. Cysne (2004) concludes that although there is a statistically significant price puzzle for the Brazilian economy (looking at less than one year), its effect is quantitatively small and lasts for a short time horizon.

Using monthly data between 1990 and 2001, Luporini (2008) analyzes the effects of a reduction in the interest rate on inflation, exchange rate, and output. Using a classical Cholesky decomposition, the vector of autoregressions (VAR) results show that the effect on inflation is positive, matching the price puzzle, and occurs only after some time window. Furthermore, aggregate production declines, as expected, and there is an additional puzzle in the exchange rate. Luporini (2008) evidence is robust to the inclusion of international conditions, commodity prices, and various measures of inflation. However, it is interesting to note that while the price puzzle remains, even after informational controls in the model, the exchange rate puzzle disappears.

Tomazzia e Meurer (2009) execute a vector model with the following contemporary ordering: product, price level, interest rate, monetary aggregate, credit level, and exchange rate. The monthly data cover the period from 1999 to 2008. The main contribution of Tomazzia e Meurer (2009) is about understanding the effects of a monetary shock on industrial disaggregated production variables, advancing the understanding of the Brazilian economy. Even with a positive response of prices (after an interest rate shock), Tomazzia e Meurer (2009) shows that the price puzzle is not significant in the short term. Furthermore, the positive relationship disappears in the alternative models (expanded using commodity prices, swaps, and expectations).

Carvalho e Junior (2009) execute a factor-augmented vector autoregressive (FAVAR) model, replicating the Bernanke (2005) methodological framework. The main argument for applying the factorial approach is that it considers many indicators, coming closer to what is considered by the monetary authority. The benchmark database has 125 macroeconomic series. Contemplating the Post-Real period, from January 1995 to September 2009, Carvalho e Junior (2009) built a model with the following variables: production, price, money, consumption, income, credit, and employment. The results of the factorial model fit the stylized theoretical relation and reveal that (within the analyzed period) there is no price puzzle for Brazilian data.

Among the earliest authors to apply the Uhlig (2005) identification method, using Brazilian data, we have Mendonça et al. (2010). The procedure imposes signal restrictions, aiming to recover structural shocks alternatively, and enabling better control over the economic effects of the price puzzle. Using monthly data from July 1999 to May 2010, the results of the bayesian vector model (composed of production, interest rate, price level, exchange, and swap) indicate that the price level can fall by up to 0.1% in the six first months after the contractionary shock in monetary policy.

Bezerra et al. (2014) follow the same line as present in Mendonça et al. (2010), but use monthly and quarterly data between 1995 and 2010 and select a distinct set of variables: production, prices, commodities, total reserves, non-borrowed reserves, and interest rate. The authors justify the choice as a way to get closer to Uhlig (2005)'s contribution. The results show a price puzzle control, significantly higher than its predecessors. Furthermore, the price response is statistically significant and reflects persistence over an extensive period.

Using principal component analysis to disaggregate the economic dynamics of the five Brazilian regions, from January 2002 to December 2011, Guimaraes e Monteiro (2014) estimate a VAR model considering: prices, exchange rate, nominal interest rate, and output. They test the asymmetry in the response of regional cycles after monetary policy shocks. Guimaraes e Monteiro (2014) indicate that the particularities are not strong enough to generate asymmetric responses in the regions. Furthermore, the price puzzle occurs in some specifications, but there is no strategy to control it (or explain its structure).

Filho (2017) investigates transmission channels from new measures of monetary shocks using Brazilian Central Bank forecasts. Using quarterly data between 1999 and 2014, the authors build shock series through the yield curve. The estimated VARs, using output, inflation, and monetary shocks, reveal recessive effects on economic activity and a price puzzle. Furthermore, even after the inclusion of the commodity prices and exchange/fiscal expansions, the relationship still holds. Filho (2017) justify the price puzzle through the existence of a cost channel in which firms must finance their wage bill in advance.

As we can see, characteristic movements of the price puzzle occur in different periods in the Brazilian economy. Specifically, the commodity price inclusion and the development of identification strategies seem to lead to a fruitful path towards the solution. Both procedures are adopted: We estimate a BVAR model with signal restriction (following Uhlig (2005)) and use commodity prices (following Mendonça et al. (2010) and Bezerra et al. (2014)) for each income bracket. To reinforce our strategy, in the next section we present the motivation in choose a bayesian model with sign restrictions and some algebraic details on its empirical structure.

3 Econometric Framework

We intend to briefly explain why imposing sign restrictions on macroeconomic models can be helpful, but first, let us go back to Lucas's critique. In the late 1970s, Lucas (1976) presented new insights on the economic recommendations based on simultaneous equation models that assume the exogeneity of public policies. Since the execution of public policies can shift the relationship between economic variables (through expectations), the estimated parameters would not be structural, and many results were open to questioning.

Among the popular alternatives, the Dynamic Stochastic General Equilibrium (DSGE) and Vector of Autorregression (VAR) frameworks reach the first positions (see Sims (1986), Stokey et al. (1989), Canova (1995) and Ljungqvist e Sargent (2004) for a deeper discussion). However, while the DSGE models are fully specified (concerning the laws of motion for economic variables), the standard VAR models explore systematic endogeneity and data-driven process without requirements about prior theoretical relationships. It's in this gap that structural identification and sign restrictions are placed: they consider recursive expectations and allow for the inclusion of prior knowledge from economic theory.

From now on, to explain Uhlig (2005) framework, we represent a simple p-order Vector Autorregressions (VAR) as:

$$Y_t = C_1 Y_{t-1} + C_2 Y_{t-2} + ... + C_p Y_{t-p} + u_t \tag{9}$$

Where Y_t represents a $n \times 1$ vector of endogenous variables, C_i are $n \times n$ coefficient matrices and u_t is the $n \times 1$ one-step ahead prediction error, with zero mean and variance–covariance matrix equals to Σ. In the companion form:

$$\mathbf{Y} = \mathbf{XC} + \mathbf{U} \tag{10}$$

We are interested in estimating the parameters $(\mathbf{C}, \Sigma)$. According to Litterman (1986) and Koop e Korobilis (2010), since most macroeconomic time series present high persistence or trend, the Bayesian approach is a feasible alternative without loss of information. Bayesian estimation provides probability distributions rather than point estimates, allowing us to think directly about the distributions of possible effects and considering the uncertainty built into the process. Then, using the maximum likelihood:

$$\hat{\mathbf{C}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Y} \tag{11}$$

$$\hat{\boldsymbol{\Sigma}} = \frac{1}{T} (\mathbf{Y} - \mathbf{X}\hat{\mathbf{C}})^\top (\mathbf{Y} - \mathbf{X}\hat{\mathbf{C}}) \tag{12}$$

The prior and posterior distribution for $(\mathbf{C}, \boldsymbol{\Sigma})$, with $\nu \geq 0$ degrees-of-freedom, are the Normal–Wishart centered around $(\overline{\mathbf{C}}, P)$, considering $\overline{\mathbf{C}}$ the $np \times n$ mean coefficient matrix, P a $n \times n$ positive definite matrix and N an $np \times np$ positive definite matrix. This specification implies that:

$$\Sigma^{-1} \sim \mathcal{W}_m(P^{-1}/\nu, \nu) \tag{13}$$

$$vec(\mathbf{C}) \sim \mathcal{N}(vec(\overline{\mathbf{C}}), \Sigma \otimes N^{-1}) \tag{14}$$

From Uhlig (1994) indicate that if the prior is characterized by the set of parameters $(\overline{C}_0, N_0, P_0, \nu_0)$, the posterior can be described by $(\overline{C}_T, N_T, P_T, \nu_T)$:

$$\nu_T = T + \nu_0 \tag{15}$$

$$N_T = N_0 + \mathbf{X}^\top \mathbf{X} \tag{16}$$

$$\overline{\mathbf{C}}_T = N_T^{-1}(N_0 \overline{\mathbf{C}}_0 + \mathbf{X}^\top \mathbf{X} \hat{\mathbf{C}}) \tag{17}$$

$$\overline{P}_T = \frac{\nu_0}{\nu_T} P_0 + \frac{T}{\nu_T} \hat{\Sigma} + \frac{1}{\nu_T} (\hat{\mathbf{C}} - \overline{\mathbf{C}}_0)^\top N_0 N_T^{-1} \mathbf{X}^\top \mathbf{X} (\hat{\mathbf{C}} - \overline{\mathbf{C}}_0) \tag{18}$$

Considering a weak prior, if $N_0 = \nu_0 = 0$ and both P_0 and C_0 are arbitrary chosen. Then:

$$\nu_T = (T + 0) = T \tag{19}$$

$$N_T = (0 + \mathbf{X}^\top \mathbf{X}) = \mathbf{X}^\top \mathbf{X} \tag{20}$$

$$\overline{\mathbf{C}}_T = \left(N_T^{-1} 0 \overline{\mathbf{C}}_0 + \left\{ \mathbf{X}^\top \mathbf{X} \right\}^{-1} \mathbf{X}^\top \mathbf{X} \hat{\mathbf{C}}) \right) = \hat{\mathbf{C}} \tag{21}$$

$$\overline{P}_T = \left(\frac{0}{\nu_T} P_0 + \frac{T}{T} \hat{\Sigma} + \frac{1}{T} (\hat{\mathbf{C}} - \overline{\mathbf{C}}_0)^\top \{0\} \left\{ \mathbf{X}^\top \mathbf{X} \right\}^{-1} \mathbf{X}^\top \mathbf{X} (\hat{\mathbf{C}} - \overline{\mathbf{C}}_0) \right) = \hat{\Sigma} \tag{22}$$

As we know, $\hat{\mathbf{C}}$ and $\hat{\Sigma}$ are also functions of the observed data, therefore we can proceed to the final details. To calculate the impulse response, we need first define an *impulse vector*, s.

Following Uhlig (2005) proposition, considering a matrix S such that the decomposition of one-step ahead prediction error is $u_t = S v_t$. Given that v represents fundamental innovations, independent and normalized, $E[v_t v_t^\top] = I_n$, and a Cholesky decomposition of Σ

is $\Sigma = E[u_t u_t^\top] = E[S v_t v_t^\top S^\top] = S E[v_t v_t^\top] S^\top = S I_n S^\top = S S^\top$. If and only if, α is a n-dimensional vector of unit length and s is a column of S, we can define an *impulse vector*, called s as the following:

$$s = \tilde{S}\alpha \tag{23}$$

Moreover, let $\mathbf{s}$ be the prjection:

$$\mathbf{s} = [s^\top, 0_{1,n(p-1)}]^\top \tag{24}$$

as well as:

$$\Gamma = \begin{bmatrix} & \mathbf{C}^\top & \\ I_{n(p-1)} & & I_{n(p-1),n} \end{bmatrix} \tag{25}$$

Then, we can finally move to calculate the appropriate responses of variable j to s impulse for k periods:

$$r_{k,j} = (\Gamma^k \mathbf{s}) \tag{26}$$

The Uhlig (2005) identification process involves to impose *ex-post* sign restrictions (≥ 0 or ≤ 0) on S, which last for a chosen period $K \geq 0$, on a set of orthogonalized impulse response functions. Basically, we have $\mathcal{A}(C, \Sigma, K)$ as the set of all monetary policy impulse vectors. Since the s vector is obtained using this inequality constraints, $\mathcal{A}(C, \Sigma, K)$ can contain a lot of elements or even be empty. Consequently, we need to supplement the identification assumptions.

The rejection method consists in: first estimate an BVAR model without restrictions and obtain $\hat{\mathbf{C}}$ and $\hat{\Sigma}$, arbitrarily draw $\hat{P}_T$ and $\hat{\mathbf{C}}_T$ from posteriors, extract orthogonal innovations and then calculate impulse responses $r_{k,j}$. Here, Uhlig (2005) and Rubio-Ramirez et al. (2010) procedures differ: while Uhlig (2005) suggests an *impulse vector* generation based on a given rotation, Rubio-Ramirez et al. (2010) use a QR decomposition. Then, after s generation, both authors multiply the *impulse vector* by responses and verify if the imposed signs match (if they don't match, we drop the drawn and start again). Unfortunately, rejection method find only the s vectors that exactly satisfy the sign restrictions. Then, if the set of possibilities is small range, the identification process may be compromised. To this issue, the penalty method can be used (see Uhlig (2005)). It differs from rejection by minimizing a penalty function concerning an orthogonal *impulse vector*. The method penalizes wrong signal responses in linear proportion and we can handle the previous problem.

Let J be the number of sign restrictions and K the periods for which the restriction is active. The response of j variable to a impulse in s for k periods is:

$$min_s \ \Psi(s) = \sum_{j=0}^{J} \sum_{k=0}^{K} g\left(l_j \frac{r_{j,s}(k)}{\sigma_j}\right) \tag{27}$$

Whereas $l_j = -1$ if the sign restriction is positive and $l_j = 1$ if it's negative. Furthermore, $f(.)$ can be defined as:

$$f(x) = \begin{cases} x & \text{if } x \leq 0 \\ 100x & \text{if } x \geq 0 \end{cases}$$

But even using the penalty function, there are some limitations about sign restrictions. The main issue occurs because models identified by sign restrictions are only set-identified and, consequently, may not generate a unique set of impulse responses. One way to diagnose identification problems, that will be used in this paper, is the Fry e Pagan (2011) Median-Target method [1].

4 Data and Insights

Our basic model uses available monthly data (January 2010 to February 2020) for economic activity, price level by income range, commodity price, interest rate, total reserves, and non-borrowed reserves (following Uhlig (2005), Mendonça et al. (2010) and Bezerra et al. (2014)), for Index variables the bases are adjusted to June 2010 = 100. This time window allows us to analyze a period with the prevalence of the inflation target regime in Brazil (considering Lucas' critique). From the Central Bank of Brazil (BCB), we use the Economic Activity Index seasonally adjusted (IBCBr, code 24364), Interest Rate (12-month accumulated Selic, code 4189), Total Bank Reserves (TotRes, code 1784), Non-Borrowed Reserves, Rediscount (NBRes, code 12484) and Commodity Index (CommP, code 29042).

Prices, by income range, come from the Institute for Applied Economic Research, see Lameiras et al. (2017), and were transformed into an index to better fit the theoretical and empirical models. The sub-indices are developed similarly to the logic behind Cravino et al. (2020) model: the weights are different according to income levels. Using the Household Budget Survey (POF) in 2008/2009, income levels are separated as: Very Low (less than R$900), Low (between R$900 and R$1350), Medium-Low (between R$ 1350 and R$ 2250), Medium (between R$2250 and R$4500), Medium-High (between R$4500 and R$9000) and High (greater than R$ 9000). Furthermore, note that the indicators are limited to the items surveyed by the National Consumer Price Index System (SNIPC) from Brazilian Institute of Geography and Statistics (IBGE).

Table 1 – Descriptive Statistics for Level Variables

Description	Code	Min	$1^{th}Q$	Median	Mean	$3^{th}Q$	Max	Std	A_s
Economic Activity	$IBCBr$	97.085	100.281	101.887	102.781	105.564	109.120	3.156	0.850
Prices - Very Low Income	$IPCA_{VL}$	97.085	112.771	134.178	136.262	159.867	174.475	24.828	0.251
Prices - Low Income	$IPCA_{L}$	97.520	112.361	133.426	135.426	158.333	173.043	24.315	0.247
Prices - Middle-Low Income	$IPCA_{ML}$	97.568	112.002	132.518	134.584	156.747	171.794	23.798	0.260
Prices - Middle Income	$IPCA_{M}$	97.859	111.520	131.130	133.423	154.448	169.888	22.963	0.301
Prices - Middle-Upper Income	$IPCA_{UM}$	97.938	111.084	130.172	132.647	153.261	169.268	22.659	0.328
Prices - High Income	$IPCA_{H}$	97.811	114.268	133.824	135.812	156.897	173.492	23.462	0.254
Commodity Price	$ComP$	79.058	108.703	130.105	132.603	153.863	189.277	29.135	0.257
Interest Rate	$Selic$	4.190	7.153	10.160	9.806	11.888	14.15	2.812	−0.377
Total Reserves	$TotRes$	3.271	3.749	4.032	4.022	4.252	5.414	0.403	−0.080
Non-Borrowed Reserves	$NBRes$	−0.080	0.000	0.000	0.000	0.000	00.053	0.009	−0.015

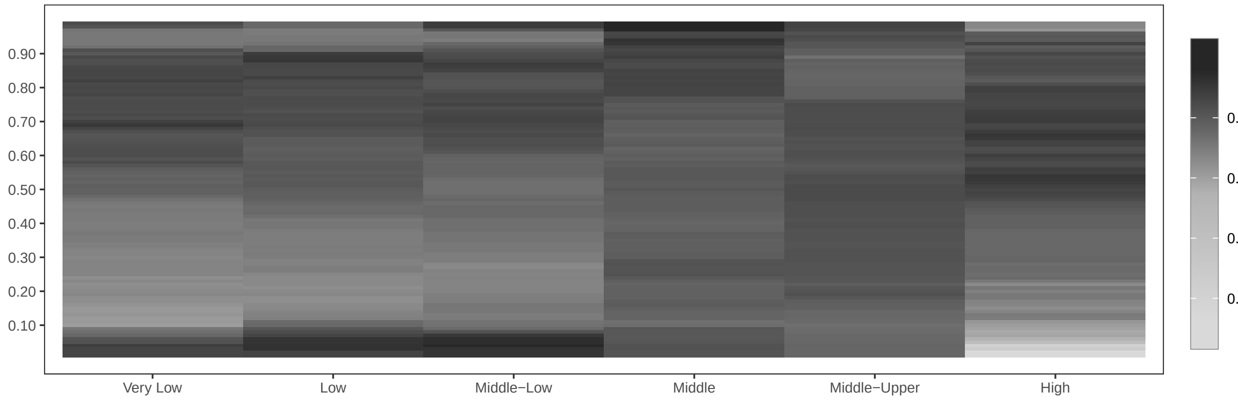
Note: Elaborate by the author. Min = Minnimun; $1^{th}Q$ = First Quartile; $3^{th}Q$ = Third Quartile;Max = Maximun; Std. = Standard Deviation; A_s = Asymmetry.

For IBCBr, Selic, TotRes, and NBRes we observed a low interquartile range and negative asymmetry (concentration of values above the median). The commodity price index (ComP) is positively asymmetric and has a high interquartile range. Focusing on price indexes by income bracket, we notice that the standard deviation of prices decreases as the income level increases, from very low to middle-upper, and then rises at the high-income level. Consequently, the extreme brackets are more disperse than average levels in our time window.

[1] The goal is to find a single s such that responses are nearest to the median responses.

Furthermore, to better understand the main differences between price series and bring some *insights* into the dynamics of these variables, we explore a Quantile Unit Root test. We analyzed the persistence of general positive/negative random shocks (see Koenker e Xiao (2004)) in price indexes by income level. In Figure 1, the lines (from bottom to top) represent the conditional quantiles of inflation, from 1% to 99%, and the columns (from left to right) are related to the analyzed income level. Finally, the higher the coefficient (of the autoregressive term) the darker the cells:

Figure 1 – Persistence of Price Shocks



Note: Elaborate by the authors.

The results indicate that the persistence of negative shocks is more intense in lower-income groups. In other words, even with high coefficients in all quantiles (above 0.89), we expect general downward price movements to be more lasting for Very Low, Low, and Middle-Low groups. It reveals some potential patterns of price dynamics in Brazil. Initially, exogenous (stochastic) factors pushing prices up appear are more severe at higher income levels. This evidence does not mean that upper-income brackets face more accentuated inflation, but that bad changes are usually longer. In contrast, stochastic shocks that reduce the price level are more persistent at lower income levels.

Even though relatively simple test (univariate), these patterns suggest that: if monetary policy is a good instrument to control prices, it may be more effective for the lowest income levels in Brazil and interventions can have socially desirable consequences. However, as the quantile split is affected by values resulting from various channels (such as market structure, price adjustment, and interest rates, among others, see Woodford (2003) and Gali (2008) for a broader exposition), an investigation focused on specific variations in interest rate/monetary policy is essential and will be explored in the next section.

5 Results

5.1 Benchmark Model

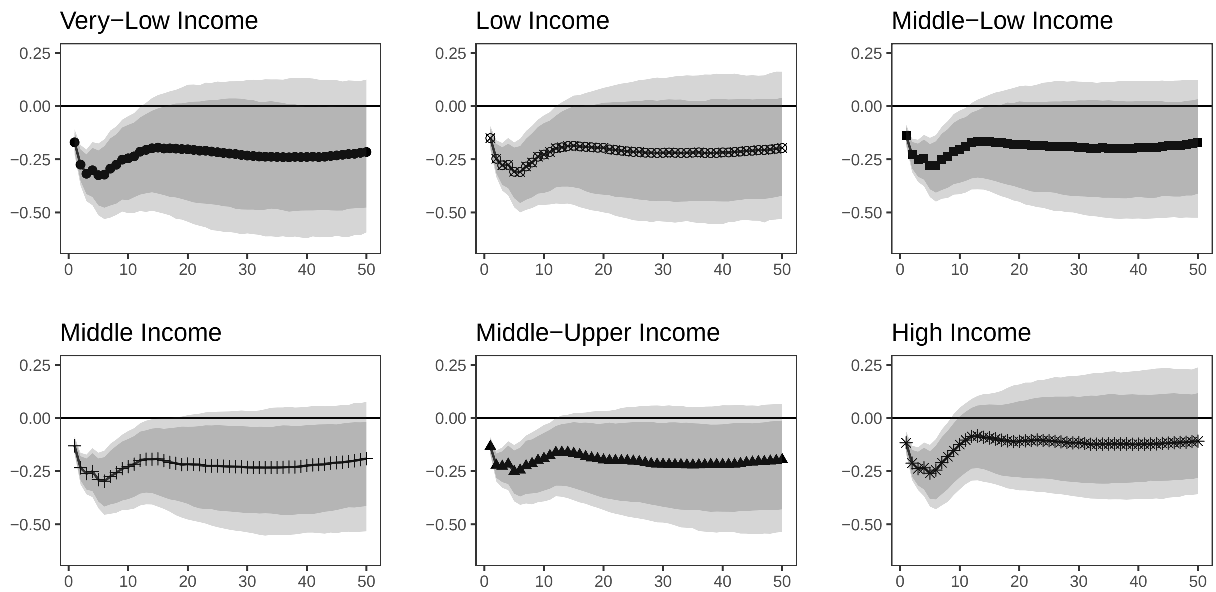
To understand how monetary policy shocks can affect prices by income level, we start with a baseline model using five variables ($IBCBr$, $IPCA_j$,$ComP$,$Selic$,$TotRes$ and $NBRes$). As we follow Uhlig (2005), some details about the lag order, sign restrictions, and set of priors are necessary [2]. We focus on the monetary policy shock for strategy building. All variables are

[2] Since the unconstrained model suffers from severe bias in the estimates, we correct the signal bias and compare the effects of the monetary policy shock (which may differ in magnitude and significance). Similar to the sensitivity analysis of theoretical models, from an established economic relationship, we verified how the impulse response functions react to different persistence levels for prices.

in logs times 100 (except for interest rate), and the lag order is selected based on traditional information criteria, which indicate 5 lags in our case. To identify the impulse vector, we assume that a contractionary shock does not conduct to an increase in prices, increase in non-borrowed reserves and decrease in interest rate. This restrictions apply from the moment of impact until six months after the shock (in line with Bezerra et al. (2014)). Finally, following Uhlig (2005), the Normal–Wishart prior is adopted.

Since we are mainly interested in the parameters estimation, we use data until February 2020 [3]. Below we present the impulse response functions[4] of the Bayesian estimation after a shock of one standard deviation in the monetary policy (about 2.8%), using the penalty method, with 68% and 90% confidence bands:

Figure 2 – Impulse Response Functions



Note: Elaborate by the authors. The y-axis indicates the effects on price levels and the x-axis specify the months after the shock. Black pointed lines and shaded areas represent the impact for 68% (gray) and 90% (light gray) confidence intervals. The horizontal line represents x-axis (or when y = 0).

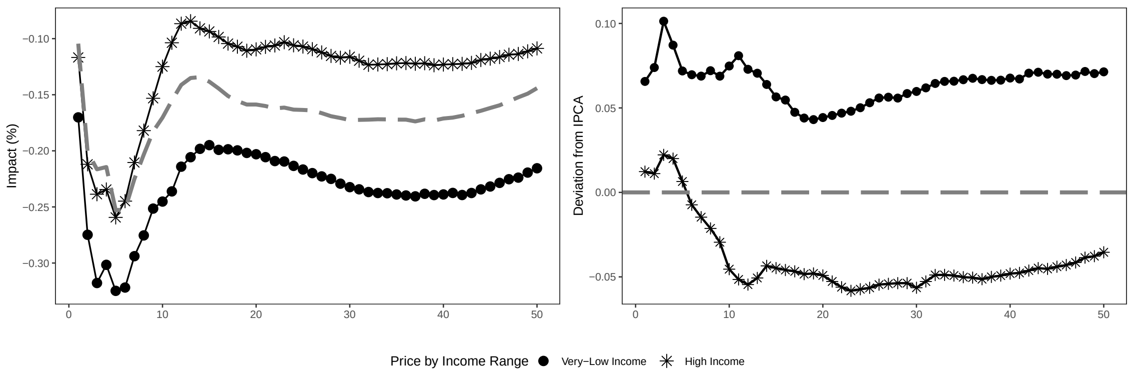
First, matching the Bezerra et al. (2014) and Mendonça et al. (2010) contributions, it seems that the Brazilian "price-puzzle" is properly controlled for all proxies used. Furthermore, monetary policy shocks (one standard deviation) have negative and statistically significant effects on prices, which can persist for up to seven (High Income) and ten months (Very-Low Income), seeming more persistent/strong in the lower income brackets (aligned to the Quantile Unit Root test presented in Figure 1).

Following, we compare the impulse-response functions (by income level) to a model with aggregate IPCA, focusing on the extreme brackets (Very-Low and High). Once again, we turn our interest to relative deviations as they allow for a better understanding of heterogeneity between income levels.

3 There is no consensus on the best strategies to estimate VAR models with pandemic data. Lenza e Primiceri (2022) and Huber et al. (2020) suggest that dropping these observations may be acceptable for parameter estimation, but it is inappropriate for forecasting purposes because it underestimates uncertainty. In the robustness subsection we estimate the model with alternative time window.

4 In order to reinforce the existence of the Brazilian price puzzle in recent data, in Appendix 1 we present the impulse response functions using the standard BVAR estimator with Minnesota priors.

Figure 3 – Impulse Response Deviations from IPCA



Note: Elaborate by the authors. The graph on left side shows the impulse response functions and the right one shows deviations ($IRF_{Dev,t} = IRF_{Income,t} - IRF_{IPCA,t}$), by income levels, considering the entire period.

In the figures above, the patterns are even clearer: the effect of an interest rate shock is more intense for the lower income groups. For high income levels, there is evidence that shocks are milder and in some cases the relative difference is even negative (again compared to the IPCA). Additionally, we perform Wilcox test for each point in the IRFs to reinforce the statistical differences[5] and there is evidence of statistical significance for the first year after shock. These results are in line with the evidence presented by Cravino et al. (2020) for United States.

The 12-month cumulative effects are larger and significant for lower income levels (considering 68% and 90% confidence intervals). For 18 months after the shock, the significance of the accumulated effect occurs only for middle and middle upper brackets at 68%. Therefore, in addition to the higher accumulated effect at low income levels, a monetary policy shock may be more lasting (persistent) for middle groups. Finally, we can notice that for the 24-month time horizon, no accumulated effect remains significant.

Table 2 – Cumulative Median Effects (After 2.8% Selic Shock)

Resp. → / **Impulse ↓**	**12 Months**				**18 Months**				**24 Months**			
	IPCA$_{VL}$	**Sgfnt**	**IPCA$_{L}$**	**Sgfnt**	**IPCA$_{VL}$**	**Sgfnt**	**IPCA$_{L}$**	**Sgfnt**	**IPCA$_{VL}$**	**Sgfnt**	**IPCA$_{L}$**	**Sgfnt**
$Selic_{\alpha=68\%}$	-3.227	Yes	-2.998	Yes	-4.423	No	-4.139	No	-5.665	No	-5.361	No
$Selic_{\alpha=90\%}$	-3.227	Yes	-2.998	No	-4.423	No	-4.139	No	-5.665	No	-5.361	No

Resp. → / **Impulse ↓**	**12 Months**				**18 Months**				**24 Months**			
	IPCA$_{ML}$	**Sgfnt**	**IPCA$_{M}$**	**Sgfnt**	**IPCA$_{ML}$**	**Sgfnt**	**IPCA$_{M}$**	**Sgfnt**	**IPCA$_{ML}$**	**Sgfnt**	**IPCA$_{M}$**	**Sgfnt**
$Selic_{\alpha=68\%}$	-2.686	Yes	-2.880	Yes	-3.702	No	-4.082	Yes	-4.804	No	-5.406	No
$Selic_{\alpha=90\%}$	-2.686	No	-2.880	Yes	-3.702	No	-4.082	No	-4.804	No	-5.406	No

Resp. → / **Impulse ↓**	**12 Months**				**18 Months**				**24 Months**			
	IPCA$_{MU}$	**Sgfnt**	**IPCA$_{H}$**	**Sgfnt**	**IPCA$_{MU}$**	**Sgfnt**	**IPCA$_{H}$**	**Sgfnt**	**IPCA$_{MU}$**	**Sgfnt**	**IPCA$_{H}$**	**Sgfnt**
$Selic_{\alpha=68\%}$	-2.461	Yes	-2.166	No	-3.492	Yes	-2.745	No	-4.681	No	-3.388	No
$Selic_{\alpha=90\%}$	-2.461	No	-2.166	No	-3.492	No	-2.745	No	-4.681	No	-3.388	No

Note: Elaborate by the authors. In the lines, we present the variable that receives the shock (impulse) for full sample. In the columns, we highlight the proxies by income level and accumulation time.

[5] The test captures the differences in the median between two samples from different populations. As the samples over time are not independent, we compare the impulse response functions point by point.

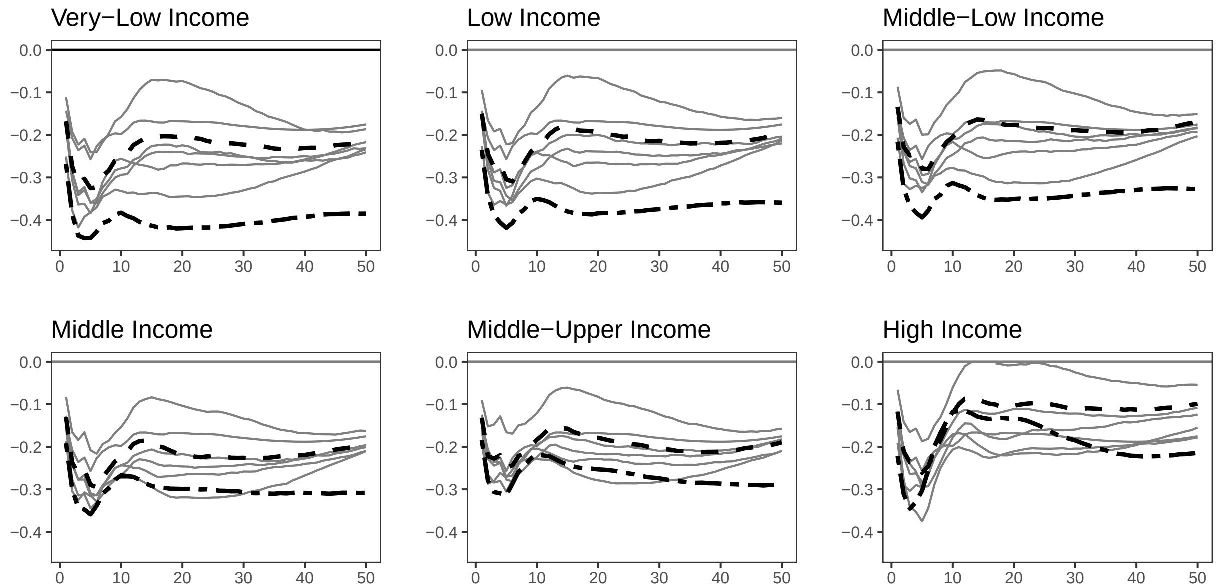
Our results indicate an intuitive possibility: monetary policy is more effective for low income households in short periods. However, before we explore these patterns further, we executed robustness tests to confirm these findings.

5.2 Robustness

We analyse how the results change from seven modifications in the framework: (i) Implement the Fry e Pagan (2011) procedure; (ii) Increase $K = 9$ periods; (iii) Decrease $K = 3$ periods; (iv) Variable Replacement: Commodity Prices by Exchange Rate; (v) Variable Inclusion: Inflation Expectations Volatility; (vi) Variable Inclusion: Uncertainty; and (vii) Subprime and Covid Data (from July 2006 to February 2022). Basically, with tests (i) and (ii) we tried to understand the sensitivity of the estimated impulse response functions to changes in the estimation procedure. In items (iii) to (vii), we tested the stability of the parameters against changes in the structure of the database.

The impulse response functions (condensed) for the Bayesian model with sign-restrictions are present in Figure 4:

Figure 4 – Impulse Response Functions - Robustness



Note: Elaborate by the authors. The y-axis indicates the effects on price levels and the x-axis specifies the months after the shock. Black dashed lines represent the original sample and two dashed the extended sample. Gray solid lines are robustness tests, from (i) to (vi).

The gray lines represent the medians of the impulse response functions from tests (i) to (vi), the black dashed line represents the benchmark model, and the black two dashed line the model with extra data, test (vii). All tests performed showed stability, reinforcing the robustness of the findings.

Additionally, it is interesting to observe the differences when we include data for the Subprime and Covid-19 crisis. It seems that for the lower income brackets, the central bank's effectiveness enhances, while for higher income levels, the gap is smaller. These results differ from the contemporaneous Brazilian literature (Mendonça et al. (2010) and Bezerra et al. (2014)) and reinforce the importance of monetary policy at critical moments, smoothing the cycles for the low-income population, matching the evidence presented by Cravino et al. (2020) using US data.

6 Conclusion

The nominal rigidity and the effectiveness of monetary policy in Brazil are topics of great public appeal, intensely discussed during electoral periods and moments of recession. It happens because only thirty years ago, the country was successful in controlling hyperinflation and getting rid of many monetary problems (with the implementation of the Real Plan, see Franco (2017)). However, with the sanitary crisis, instability of public accounts, pressure on the exchange rate, and uncertainty, the price level reached two digits and returned to attention.

We follow the theoretical model proposed by Cravino et al. (2020) to analyze the effects of monetary policy shocks on prices (by income level) in Brazil, which considers the heterogeneity in consumption baskets by income level. In our application, we use the time series presented by Lameiras et al. (2017) and made available by the Institute of Applied Economics Research (Ipea). As a strategy to control the price puzzle, following Mendonça et al. (2010) and Bezerra et al. (2014), we use Uhlig (2005) Bayesian vector autoregression model with sign restrictions.

The preliminary/univariate analysis, using Quantile Unit Root test by Koenker e Xiao (2004), shows that the persistence of negative shocks is more intense in lower-income groups. In other words, we expect the general downward price movements (from multiple stochastic channels) to be more lasting in lower income brackets. Moving on to vector analysis, we try to identify monetary shocks using a signal constraint process, as suggested by Uhlig (2005) and Fry e Pagan (2011), to understand the net effects of changes in the interest rate on the prices of consumer baskets from different income brackets.

Our findings indicate that the decisions of the Brazilian Central Bank could be socially desirable to reduce inequalities within the economic cycles of recession. In other words, different from the evidence present in the national literature (see Mendonça et al. (2010) and Bezerra et al. (2014)), our results indicate that the transmission of monetary policy shocks to prices seems to be conditional to the degree of nominal rigidity of the income bracket in question, which is related to the composition of the consumption basket. The implications are verified in a wide range of robustness, considering changes in the econometric model and database. Finally, during the Covid-19 pandemic, our results suggest that the recent sequential increases in the interest rate (hawkish posture) could contribute, at least partially, to reduce the inequality before price adjustments.

These results are of practical importance for policymakers and economic agents. First, they allow the government to understand the heterogeneous effects of monetary shocks on disaggregated income levels, contributing to the search for socially desirable paths. Second, because the decomposed response could expand the understanding of hawkish/dovish postures in critical moments, improving investment decisions.

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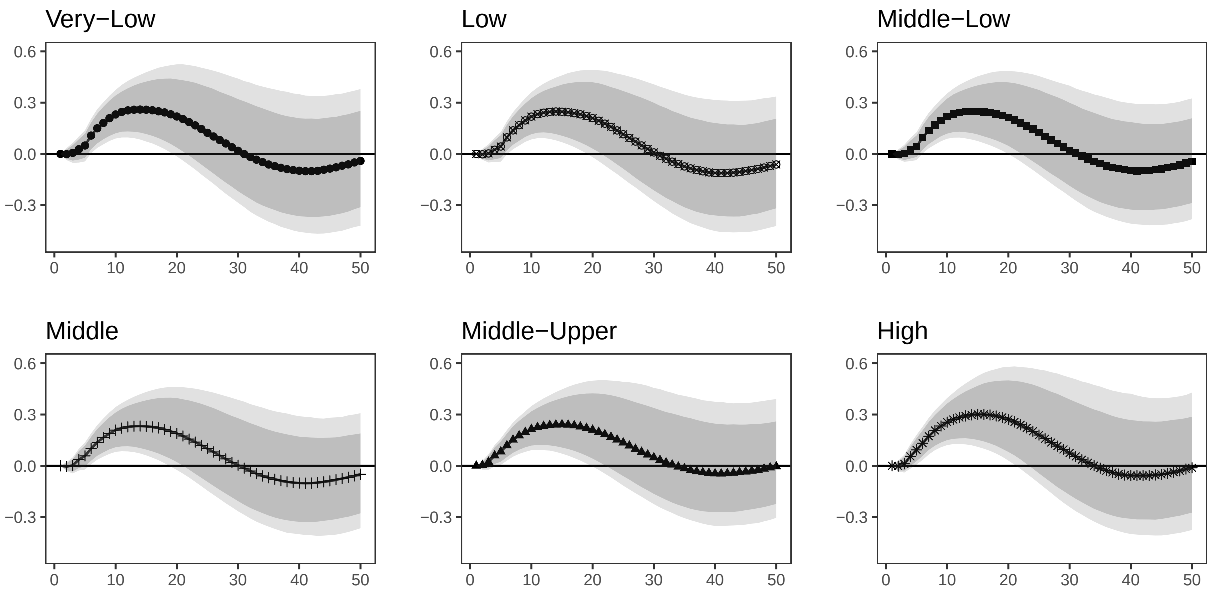
Appendix 1 Impulse Response Functions - Standard BVAR

Figure 5 – Impulse Response Functions - Standard BVAR



Note: Elaborate by the authors. The y-axis indicates the effects on price levels and the x-axis specify the months after the shock. Confidence bands are constructed for 68% and 95%.