Redistribution effect of monetary policy: evidence from Brazil.

G. V. Moura* and A. V. Schmidt†

July, 2018

Abstract

Brazil is ranked among the world's most unequal countries and has high income disparities. Recent research shows that the effect of changes in the interest rates is non-homogeneous across individuals, implying a redistribution effect of monetary policy. More specifically, in addition to the traditional channels, interest rates will also affect people depending on their income composition, price levels and on the maturity of their assets and liabilities. In order to investigate the redistributive effects of monetary policy in Brazil, we used the capital-labor ratio, as well as monthly data for GDP, inflation rate, exchange rate and interest rate in a Bayesian autoregressive vector model with Wishart stochastic volatility. The results show a positive and significant response of the capital-labor ratio to monetary shocks, which lasts more than a year, i.e., a contractionary shock shifts income from labor to capital, implying an income distribution effect. This result is robust to different periods, which suggests that interest rate shocks have a non negligible redistributive effect.

Key-words: Income distribution. Conventional Monetary Policy. Bayesian TVP-VAR. Stochastic volatility.
JEL classification: E52; E25; E64; C11.

*Economics Department, Universidade Federal de Santa Catarina.
†Graduate program in Economics from Universidade Federal de Santa Catarina.
Contact: aishameriane.schmidt@posgrad.ufsc.br

Preliminary Version: please, do not cite nor quote.

Introduction

The distribution of income has been an important subject in the economic debate and there is an ever-growing literature trying to address what are the macroeconomic factors that have an impact on how income are distributed among individuals (see, for example, Jones, 2015; Anand & Segal, 2008; Areosa & Areosa, 2016; Benhabib, Bisin & Luo, 2017). Regarding the monetary policy, before the Great Recession in 2008, the predominant idea was that expansionary monetary policy could reduce inequality in the short run, but for long lasting results, it would be better for the monetary authority to aim for inflation control and stability of the aggregate demand (ROMER; ROMER, 1998). This view started to be challenged after the crisis, leading to theoretical and empirical studies relating conventional and unconventional monetary policy with income distribution and inequality. However, there is no consensus about the direction of this relationship, i.e., it remains to be decided whether increases (or decreases) in interest rates increase or decrease inequality (FURCERI; LOUNGANI; ZDZIENICKA, 2018).

Theoretically, there are different channels proposed in the literature through which the changes in the interest rates can affect inequality. The main channels are: (i) the income composition channel, (ii) the earnings heterogeneity channel, (iii) the interest rate exposure channel, (iv) the savings redistribution channel and (v) the inflation tax channel (AUCLERT, 2017). The first one works on the assumption that it is likely that households will have their income coming from a combination of different sources (capital, labor or transferences) and, at the same time, the relative importance from each income source for a given household will vary depending on the percentile of income distribution they are located at (CASIRAGHI et al., 2017). While people within the lowest deciles of income tend to have a large fraction of their earnings coming from government transfers, people around the median will rely mostly on wages and people in the highest deciles of income will have a larger share of income stemming from capital, which depends on the interest rates. Interest rate also affects people from the lowest deciles who depend on wages, since it has a direct impact on unemployment. At the same time, people depending on transfers will be less affected, which makes difficult to assess the overall impact of the monetary shocks on inequality through the income composition channel.

The second channel is related to labor market: depending on whether a household have a more or less skilled job, they will be unevenly affected by changes in the hourly wages or changes in hours worked and unemployment rate (COIBION et al., 2017). In the interest rate exposure channel, accordingly to Auclert (2017), the monetary policy will have different effects on the households, conditional to the maturity of their assets and liabilities. Long term borrowers tend to benefit from decrease in interest rates while long term lenders lose. The savings channel, although also related to wealth, operates differently. Its effect is directly on the instant price of assets, since there is an inverse relation between interest rates and asset nominal prices. Finally, the inflation tax channel is linked to the direct effect of monetary policy over inflation. Since people from the lowest deciles of income tend to have less access to financial markets and rely mostly in money, they see their purchase power diminishing more when inflation rates goes up (AMARAL, 2017).

From the empirical side, there is also no consensus on whether monetary policy has an effect on income distribution. Bivens (2015) argues that FED's expansionary policy, if the economy is near full employment, will diminish income inequality, although the effect is small. Still for the American economy, the work from Coibion et al. (2017) also suggests that contractionary shocks in the interest rate increase inequality, while expansionary shocks are related with inequality reduction. For the Italian economy, Casiraghi et al. (2017) found a negligible effect of monetary policy on income inequality whilst Guerello (2017), using data from the Euro area, encountered a negative association between inequality and interest rates: an increase in interest rates leads to a decline in employment, prompting the rise of inequality. On the opposite direction, the study of O'Farrell, Rawdanowicz & Inaba (2016) for the OECD member countries indicates that a 100 basis points reduction in interest rates is associated with a 0.02% boost of the Gini Index.

Mumtaz & Theophilopoulou (2015) used a Bayesian mixed-frequency structural vector autoregressive model (mixed-frequency SVAR) to explore the role of monetary policy shocks on inequality observed in the UK in the 1968-2008 period. The authors used microdata from national surveys to build annual indexes of inequality for wages and income. Their model showed that contractionary monetary policy shocks leads to a significant increase in inequality in both wages and income. This observed effect was higher in the period before the inflation target policies and was higher in income inequality than wages inequality. Similar results were found in a later paper also by Mumtaz & Theophilopoulou (2017): using quarterly data, they estimated a structural VAR for the period between 1969 and 2012 to see the response of four different Gini indexes (total consumption and consumption of non durables, disposable income and gross wage). Furthermore, they investigated if there was some changes in the VAR coefficients when estimating a TVP-VAR for the period of unconventional monetary policies that followed after the 2008 financial crisis. From this last model, they found out evidence that the quantitative easing policy in UK played a role in increasing the inequality on the period of the Great Recession. Davtyan (2017) employed a vector error correction methodology with data from the 1% richest in United States to investigate the effect of contractionary monetary shocks. However, differently from Mumtaz & Theophilopoulou (2017), this study concludes that contractionary shocks decreased inequality.

Regarding the growth in empirical studies relating monetary policy and income distribution, there are no such studies for the Brazilian economy. Thus, this paper investigates the magnitude, significance and persistence of monetary policy shocks on the capital-labor ratio ($^K/_L$), which accounts for the ratio between the capital income share and the labor income share using data from Brazil. The idea behind is that given an uneven composition of income, shifts in the share of national income allocated to wages or to profits, imply a redistribution effect. We estimated a Bayesian TVP-VAR(2) with Wishart innovations, adopting the model first proposed by Uhlig (1997). Results show that the effect of monetary shocks over $^K/_L$ is positively significant and lasts at least fifteen months, suggesting that there is a non-negligible redistributive effect of monetary policy over income distribution: expansionary monetary shocks lead to the increase of the capital-labor ratio, which can signify either the increase in the share of capital income or the reduction of the share of labor income.

The remainder of the paper is organized as follows. Section 1 presents the data and section 2 has the empirical model and schematics of the estimation procedure. Then, the results are shown in section 3, followed by the final remarks in section 4.

1 Data

Empirical studies relating monetary policy to income distribution or inequality like Mumtaz & Theophilopoulou (2017) and Davtyan (2017) used microdata from national surveys to construct the Gini indexes for one or more variables. However, there is no such data for Brazil: even though the Brazilian Institute of Geography and Statistics (IBGE) has at least two surveys involving household consumption and/or income (Consumer Expenditure Survey and Continuous National Household Sample Survey), one is very infrequently (was executed just 4 times in the last decade) and the other, although occurs in a monthly basis, was initiated in 2012 and the sample is not sufficient large yet (to be used in a TVP-VAR). It is also not possible to obtain data from other sources: there are just a few data series of income inequality or distribution for Brazil, like Gini index, and they are annual. Since monetary decisions are made more than once in a year, it is important to use monthly data to capture the impact of fluctuations in the interest rate.

Our proposal is to use the ratio between the capital income and the labor income - both are monthly series made available to general public by Brazil's IRS. The capital income is related to all declared income in form of profit and interests from an individual own capital or from other people, financial applications in stocks or investment funds, rents and fixed income investments. On other hand, the income labor is related only to wages. Thus, we are calling as *capital-labor ratio* ($^K/_L$) the quotient between those two series. The $^K/_L$ ratio can be seen as a measure of distribution of income between two factors: labor and capital. Since capital is not evenly distributed among individuals, shifts in $^K/_L$ imply a redistribution of income.

Besides the capital-labor ratio, the other four variables used in the model are the annual variation *per capita* GDP, inflation rate index (in last 12 months), 3-month treasury bill as interest rate and the monthly variation of the real effective exchange rate. Data used range from January, 2006 to February, 2018, but the first forty eight observations were used only to obtain the prior hyperparameters, which left 217 data points to estimate the model.

The variables used in the model before and after all transformations are shown in Figure 1 and the descriptives of the final series are reported on Table 1.

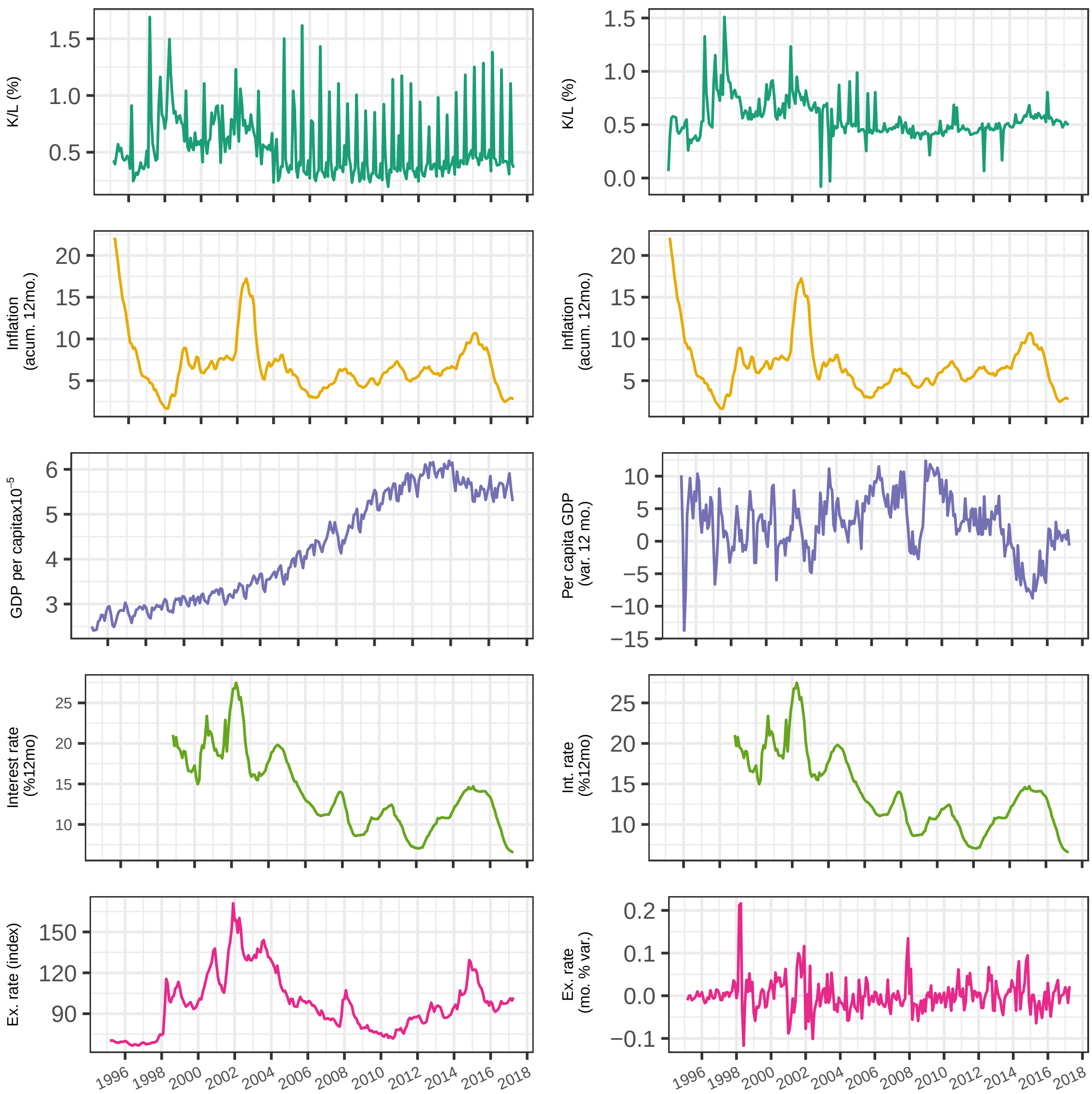
Table 1 – Descriptive statistics of the series used in the model.

	K/L	Interest rate	Per capita GDP	Exchange rate	Inflation rate
Minimum	-0.0814	6.5400	-13.7417	-0.1169	1.6456
1st quartile	0.4482	10.7125	-0.1639	-0.0195	4.8092
Mean	0.5577	13.9905	2.5755	0.0014	6.8280
Median	0.5124	13.1600	2.5618	-0.0016	6.2707
3rd quartile	0.6369	17.3900	5.8039	0.0144	7.6704
Maximum	1.5100	27.4900	12.3665	0.2167	21.9876
Stand. Dev.	0.1907	4.7089	4.6299	0.0388	3.4314

The 3-month treasury bill rate series (used as interest rate) begins in September, 1999 and was completed with 44 values from the basic interest rate (Selic) annualized and deseasonalized. The remaining series start on January, 1996 and finish on February, 2018, totalizing 266 time periods. K/L means the capital-labor ratio and is the quotient between the capital income by the labor income. Both K/L and GDP had their seasonality component removed using the X-13ARIMA-SEATS algorithm. The inflation rate index used is the IPCA. GDP per capita is the annual variation, while the exchange rate is the monthly variation of the real effective exchange rate.

Source – Own construction using data from BCB-Depec, Sisbacen PTAX800, IBGE, BM&FBOVESPA and BCB-DSTAT.

Figure 1 – Data series used in the TVP-VAR, before (left) and after (right) transformations. Brazil, 1996-2018.



Comparison between the five series used in the model before (left) and after (right) the seasonal adjustment and other transformations. The vertical divisions marks the November month of each year indicated in the horizontal axis. The series where a seasonal treatment were made are the capital-labor ratio and the interest rate. GDP per capita is the annual variation and exchange rate is the monthly variation of the real effective rate. The 3-month treasury bill rate series starts on 1999, so the first values used to complete the series are from the Selic rate, transformed from yearly to 12-month rate and deseasonalized.

Source – Own construction using data from BCB-Depec, Sisbacen PTAX800, IBGE, BM&FBOVESPA and BCB-DSTAT.

2 Empirical Model

In order to explore the impact of the monetary shocks on the K/L ratio, we estimated a Bayesian VAR (BVAR) with Wishart stochastic volatility (SV), following the specification from Uhlig (1997) and the proposed method for filtering, backward smoothing and posterior sampling from Windle & Carvalho (2014). The state-space representation of the model is given by:

$$
\begin{aligned}
y_t &= Z_t \cdot \beta_t + \epsilon_t, \text{ with } \epsilon = \mathscr{U}(\Omega_t^{-1})'\xi_t \text{ and } \xi_t \sim \mathcal{N}(0, \mathbb{I}_m), && (1)\\
\beta_t &= \beta_{t-1} + u_t, \text{ with } u_t \sim \mathcal{N}(0, Q^{-1}), && (2)\\
\Omega_{(t+1)} &= \frac{\mathscr{U}(\Omega_t)'\Theta_t\mathscr{U}(\Omega_t)}{\lambda}, \text{ with } \Theta \sim \mathcal{B}_m\left(\frac{\nu + c + km}{2}, \frac{1}{2}\right). && (3)
\end{aligned}
$$

In the equation system (1)-(3), it is assumed that there are m variables observed in t periods ($t = 1, \ldots, T$); $\lambda > 0$ and $\nu > m-1$ are parameters; c is the number of deterministic regressors (like the intercept or tendency); the shocks Θ are independent; $\mathscr{U}(\cdot)$ is the superior Cholesky decomposition and $\mathcal{B}_m(p, q)$ is the multivariate Beta distribution. The parameter ν allows variation in the precision matrix Ω_t: the lesser ν, highest the variation of H_t across time and vice-versa. Asymptotically, when $\nu \to \infty$, the model converges to a VAR without SV, because the multivariate Beta density from (2) goes, in this case, to a identity matrix of order m (KIM, 2014).

The prior distributions choice for the parameters and innovations of the model made by Uhlig (1997) explores the conjugacy between the Beta and Wishart distributions, allowing a closed-formula solution for the Bayesian update of the unobserved states whilst confers important properties to the model . According to Kim (2014), this structure is not subject to the same limitations from Cogley & Sargent (2005) and Primiceri (2005) model: using a Wishart density to model the SV component of the model allows that variances and covariances evolve freely, without the necessity of modeling them apart. The Wishart density ensures that the precision matrix Ω_t will be always positive definite. The prior hyperparameters were calculated by OLS using data from January, 1996 to December, 1999, comprising 48 months. This period was short after the implementation of the new currency (Brazilian Real), which stabilized the economy, but was marked by large volatility in the macroeconomic aggregates. Also, in this period the Brazilian's Central Bank adopted the floating exchange rate regime, which was substituted by the inflation target regime in the beginning of 2000s. Therefore, the data used to estimate the model consists of data only from the inflation target period (2000-2018) Prior distributions are described in Table 2.

A major issue incurs in the estimation of the model defined in (1)-(3): differently from the model from Cogley & Sargent (2005) or the one from Primiceri (2005), where it is possible to reduce the problem of estimating Ω_t in a series of univariate simpler problems, there is no transformation in the measurement equation (1) that will simplify the problem. Uhlig (1997) proposed an extended Kalman filter for the innovations and an importance sampling scheme to obtain estimates of the coefficients. Although functional, this method cannot be directly applied to a TVP-VAR framework.

To estimate a version of Uhlig (1997) with time-varying coefficients, one could generalize the extended Kalman filter, following a maximum likelihood with closed formula approach, such as proposed by Noriller & Moura (2017). Or, for a Bayesian flavor, one could employ the method from Windle & Carvalho (2014) to forward the filter, do the backward sampling and to sample from the posterior distribution, which was our choice. Then, to close the blocks from the Gibbs sampler, we draw the coefficients β_t, conditional to the innovations using the algorithm from Carter & Kohn (1994).

2 .0.1 Gibbs sampler structure

The blocks of the Gibbs sampler are described below. Denote as B^T the collection of all values of $\{\beta_t\}_{t=1}^T$ (the same for Ω^T).

1. **Initialize Ω^T, B^T, Q, set the hyperparameters and initial values.**
2. **Draw B^T conditional on Ω^T and the other parameters:** In this part we employed the algorithm by Carter & Kohn (1994).
3. **Draw Q^T from a inverse Wishart distribution**
4. **Draw jointly ν Ω^T conditional on B^T:** After estimating the coefficients, we begin the volatility block. Propositions 1, 2 and 3 from Windle & Carvalho (2014) are used in a sequential manner to run the forward filter, backward sampler, predict one step ahead and estimate n, k and m. For the next results, consider the following notation: the collection of data until time t is $\mathcal{D}_t \equiv \{y_t\} \cup \mathcal{D}_{t-1}$ for $t \in \{1, \ldots, T\}$ with $\mathcal{D}_0 \equiv \{\Omega_0\}$, where Ω_0 is an arbitrary covariance matrix. The prior for the data in the first period, $(Z_1|\mathcal{D}_0)$ follows a Wishart distribution and it is given by $\mathcal{W}_m\left(n, (k\Omega_0)^{-1}/\lambda\right)$. All three propositions implicitly conditions the results to the parameters n, k, λ.

   a) (WINDLE; CARVALHO, 2014, Proposition 1) **Forward filtering:** Suppose $(Z_t|\mathcal{D}_{t-1}) \sim \mathcal{W}_m\left(n, (k\Omega_{t-1})^{-1}/\lambda\right)$. After observing y_t, the updated distribution is
   $$(Z_t|\mathcal{D}_t) \sim \mathcal{W}_m\left(n, (k\Omega_{t-1})^{-1}\right) \tag{4}$$
   with
   $$\Omega_t = \lambda\Omega_{t-1} + y_t. \tag{5}$$
   To make 1-step ahead predictions, we use
   $$(Z_{t+1}|\mathcal{D}_t) \sim \mathcal{W}_m\left(n, \frac{(k\Omega_t)^{-1}}{\lambda}\right) \tag{6}$$

   b) (WINDLE; CARVALHO, 2014, Proposition 2) **Backward sampling:** The joint density of all data until time T conditional to $\mathcal{D}_T$, $(\{Z_t\}_{t=1}^T|\mathcal{D}_T)$, with respect to the T-fold product of S_m^+ embedded in $\mathbb{R}^{m(m+1)/2}$ with Lebesgue measure, can be decomposed as,
   $$p(\{Z_t\}_{t=1}^T|\mathcal{D}_T) = p(Z_T|\mathcal{D}_T)\prod_{t=1}^{T-1} p(Z_t|Z_{t+1}, \mathcal{D}_t). \tag{7}$$
   The last term in (7) is a shifted Wishart distribution given by
   $$p(Z_t|Z_{t+1}, \mathcal{D}_t) = \lambda \cdot Z_{t+1} + U_{t+1}, \quad U_{t+1} \sim \mathcal{W}(k, (k\Omega)^{-1}). \tag{8}$$

   c) (WINDLE; CARVALHO, 2014, Proposition 3) **Marginalization:** The joint density of the observables $\{y_t\}_{t=1}^T$ is given by
   $$p(\{y_t\}_{t=1}^T|\mathcal{D}_0) = \prod_{t=1}^{T} p(y_t|\mathcal{D}_{t-1}), \tag{9}$$
   where $p(y_t|\mathcal{D}_{t-1})$ is defined both for the full-rank case and rank-deficient case. See Windle & Carvalho (2014) for more details.

We used 50.000 replications as *burn-in* and the posterior results are based on a sample size of 10.000 replications.

2 .0.2 Prior

We employed a Normal-Wishart independent prior with an inflation factor in the prior variances. This was a choice made to give less importance to the prior values since the period pre 2000s in Brazil is known for its fluctuations in the economy and was marked by a higher volatility than the one observed in more recent periods.

Table 2 – Model Priors, initial values and parameters

Parameter	Description	Prior family (or value)♠	Coefficient(s)
β_0	**Initial Coefficients**	$\mathcal{N}(\hat{\beta}_{OLS},\ k_\alpha \cdot \hat{V}(\hat{\beta}_{OLS}))$	$k_\beta = 4$
Q	**Covariance matrix of shocks in β_t**	$\mathcal{IW}(1/4\ k_Q^2 \cdot p_Q \cdot \hat{V}(\hat{B}_{MQO}),\ p_Q)$	$k_Q = 0.01$, $p_Q = 48^{☆}$
Ω_1	**Initial Covariance**	$\mathcal{W}_m(\nu_\Omega, \Sigma_0^{-1}/\lambda_\Omega)^{✣}$	$k_\Omega = 0.01$, $p_\Omega = 6^{❄}$
ν_{H0}	**Parameter**	$\nu_{H0} = 20$	-
λ	**Parameter**	$\lambda = \frac{\nu}{\nu+1}$	-

Notes:
✣ - Initial value Σ_0 will be estimated based on a Wishart conjugate prior.
♠ - Variables with a hat ând subscript OLS are the ordinary least squares estimates, which were evaluated using the first 48 observations from the sample. $\mathcal{N}(\mu, \theta)$ e $\mathcal{IW}(\Psi, \nu)$ denote the Normal distribution with mean μ e variance θ and the Inverse-Whishart distribution with scale Ψ and ν degrees of freedom, respectively. $\mathbb{I}_n$ denotes the identity matrix of rank n.
☆ - 48 refers to the number of total observations used to calculate the prior parameters.

Source – Own construction.

2 .0.3 Identification of the shocks

Since our interest lies in investigating the impact of interest rate shocks, it is necessary to compute impulse response functions (IRF). In this paper, the scheme proposed by Primiceri (2005) to compute the IRF for a time-varying parameter model were employed, where, for each time t, the coefficients from B_t and Ω_t were used. Since the results obtained will depend on the order of the variables, we are assuming the following identification scheme: the capital-labor ratio has a structural characteristic (see Herran, 2005), therefore, it is not contemporaneously affected by any other shock; inflation and GDP affect contemporaneously the interest rate, which affects the exchange rate. This last relation is due to the assumption of the impossible trinity: it is not possible to the monetary authority to answer shocks from GDP, inflation and exchange rate at the same time (AIZENMAN; CHINN; ITO, 2013). We selected some specific dates to verify if there is some change in the IRF functions, which would indicates that the relationship between the model variables is not stable over time.

3 Results and Discussion

To verify the impact of monetary shocks, we calculated the impulse response functions (IFR) for each period, considering the estimated values of β_t, Ω_t and a time horizon of 25 periods. Figure 2 presents the median of the IRF using the estimated values at t equal to December, 2017 (the last period of the sample) with the intervals from the 5th to 95th percentile (light area) and 25th to 75th percentile (darker area). Although small in magnitude (0.011 at the spike in the fourth month), the effect from the rise of the interest rate over the capital-labor ratio is positive and lasts at least one year, suggesting that in fact there is a redistributive effect of monetary policy over income. It is not possible to tell if the increase is due to a rise in the capital income, a diminution of the labor income or both. Either way, considering the existing heterogeneity in the economy with respect to capital owners and workers, it is most likely that the first group is benefiting more from a contractionary policy, which could ultimately lead to an increase in inequality.

To verify whether this relation between monetary policy and K/L is stable or varies across time, we estimated the FIR medians for the periods of January, 2000 (beginning of the sample used for estimation); July, 2008 (the period where Brazil was most affected by the international financial crisis) and December, 2017 (end of the sample), presented in Figure 3. Again, the values are significantly different from zero from the second month after the initial shock and lasts for at least 10 months, for all three periods, using the interval between the 5th and the 95th percentiles. The median of the FIR in July, 2008 is higher than the ones evaluated in 2000 and 2017, suggesting that the effect of monetary shocks on the capital-labor ratio was a slightly higher during that period, in line with the results found by Mumtaz & Theophilopoulou (2017) for the Great Recession. However, when considering the 90% confidence interval, there are no differences between the curves.

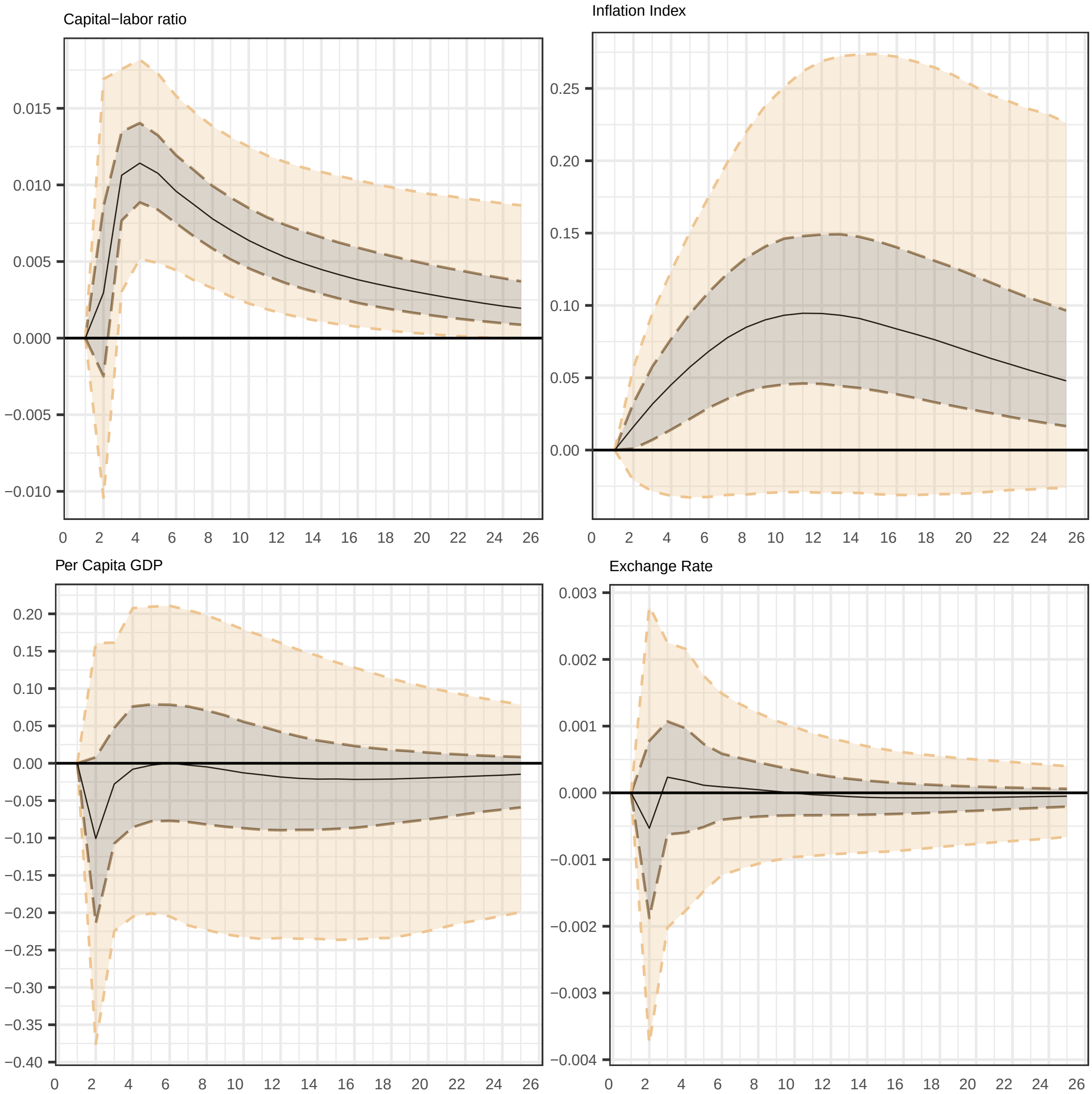
The estimated volatilities of the model are shown in Figure 4. There is a strong evidence of changes in the volatility pattern, specially for the capital-labor ratio and the interest rates. Both annual variation of per capita GDP and monthly variation of the exchange rate (third and fourth graphs, respectively) present a similar pattern, at least with respect to the regions of volatility increase and decrease.

4 Final remarks

In this paper, we investigated whether there is a redistributive effect of the monetary policy in Brazil. Our main contribution is to bring new empirical results to the debate. Using a TVP-VAR with Wishart innovations we found out a suggestion that contractionary shocks in the interest rates leads to a rise in the capital-labor ratio, meaning that monetary shocks induce a redistribution between capital and labor income, favoring capital owners at cost of people who relies on income from labor.

Further developments goes in two fronts: econometric and economic. In the econometric side, we intend to further investigate the use of drifting coefficients. Although there is a strong argument in favor of the use of time-varying coefficients when modeling macroeconomic aggregates, this approach can lead to overfitting and a decrease in predictive power. Thus, our model can benefit of shrinkage techniques in the prior coefficients, like the ones developed by Bitto & Frühwirth-Schnatter (2018) and Eisenstat, Chan & Strachan (2016). On the economic front, our aim is to study what theoretical redistribute channel can explain the empirical results that we have found.

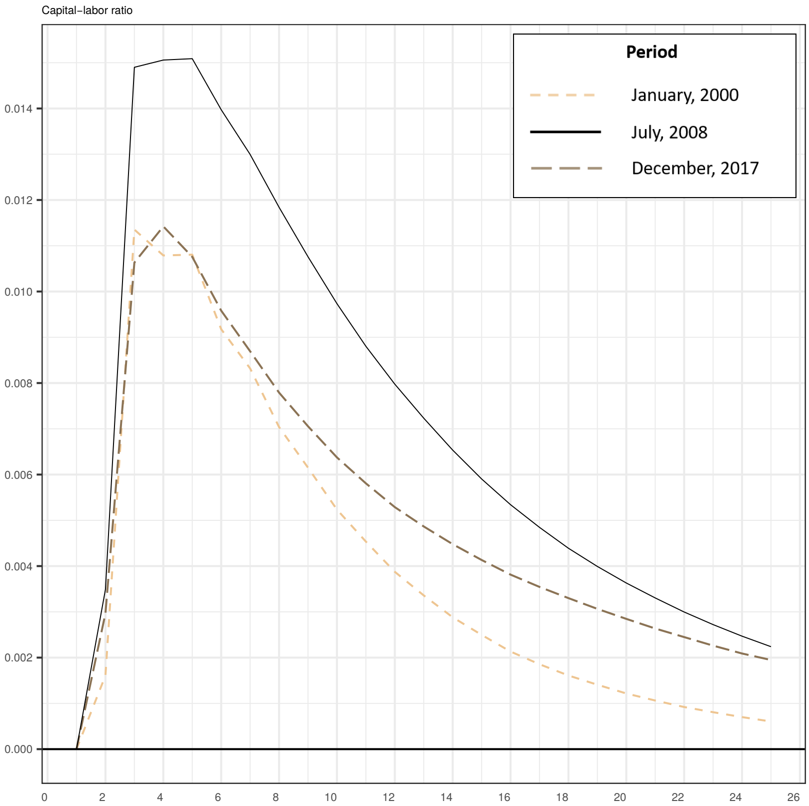
Figure 2 – Impulse response functions of the model variables to monetary shocks on the capital-labor ratio using the estimated values for December, 2017.



Impulse response functions (FIR) of K/L (%), Inflation (% in 12 months), per capita GDP (annual % variation) and Exchange rate (monthly % variation) to monetary shocks using the estimated coefficients and volatilities for December, 2017. With exception of the FIR of the capital-labor ratio, the remaining functions are not significantly different from zero considering the interval between the 5th and 95th percentiles (yellow area). For the Capital-Labor ratio, this interval does not include zero from the second month until the 15th month after the initial shock. The dark area corresponds to the interval between the 25th and the 75th percentile.

Source – Own construction.

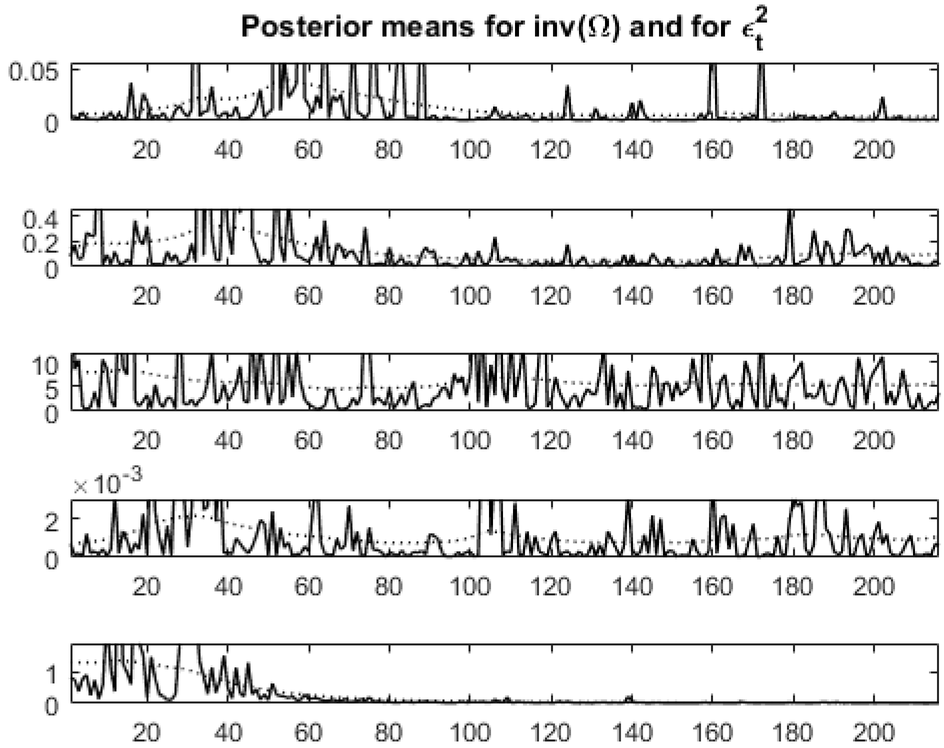
Figure 3 – Medians of the impulse response functions of the model variables to monetary shocks at different periods.



Medians of the impulse response functions (FIR) from the Capital-Labor ratio (K/L) to monetary shocks at January, 2000; July, 2008 and December, 2017. For all three curves the interval does not include zero until the 15th month after the initial shock.

Source – Own construction.

Figure 4 – Estimated volatilities of the model.



Means of the precisions for each VAR equation and respective squared-errors. From top to down, the graphs refer to the capital-labor ratio, inflation index, per capita GDP, exchange rate and interest rate.
Source – Own construction.

Bibliography

AIZENMAN, J.; CHINN, M. D.; ITO, H. The “impossible trinity” hypothesis in an era of global imbalances: Measurement and testing. *Review of International Economics*, Wiley Online Library, v. 21, n. 3, p. 447–458, 2013. Cited on page 8.

AMARAL, P. Monetary policy and inequality. *Economic Commentary*, Federal Reserve Bank of Cleveland, n. 01, 2017. Cited on page 2.

ANAND, S.; SEGAL, P. What do we know about global income inequality? *Journal of Economic Literature*, v. 46, n. 1, p. 57–94, 2008. Cited on page 2.

AREOSA, W. D.; AREOSA, M. B. The inequality channel of monetary transmission. *Journal of Macroeconomics*, Elsevier, v. 48, p. 214–230, 2016. Cited on page 2.

AUCLERT, A. Monetary policy and the redistribution channel. *NBER Working Paper*, 2017. Cited on page 2.

BENHABIB, J.; BISIN, A.; LUO, M. Earnings inequality and other determinants of wealth inequality. *American Economic Review*, v. 107, n. 5, p. 593–97, 2017. Cited on page 2.

BITTO, A.; FRÜHWIRTH-SCHNATTER, S. Achieving shrinkage in a time-varying parameter model framework. *arXiv preprint arXiv:1611.01310*, 2018. Cited on page 9.

BIVENS, J. Gauging the impact of the fed on inequality during the great recession. *Hutchins Center Working Papers*, Brookings Institution Press, 2015. Cited on page 2.

CARTER, C. K.; KOHN, R. On gibbs sampling for state space models. *Biometrika*, Oxford University Press, v. 81, n. 3, p. 541–553, 1994. Cited 2 times on pages 6 and 7.

CASIRAGHI, M. et al. A "reverse robin hood"? the distributional implications of non-standard monetary policy for italian households. *Journal of International Money and Finance*, Elsevier, 2017. Cited 2 times on pages 2 and 3.

COGLEY, T.; SARGENT, T. J. Drifts and volatilities: monetary policies and outcomes in the post wwii us. *Review of Economic dynamics*, Elsevier, v. 8, n. 2, p. 262–302, 2005. Cited on page 6.

COIBION, O. et al. Innocent bystanders? monetary policy and inequality. *Journal of Monetary Economics*, Elsevier, v. 88, p. 70–89, 2017. Cited on page 2.

DAVTYAN, K. The distributive effect of monetary policy: The top one percent makes the difference. *Economic Modelling*, Elsevier, v. 65, p. 106–118, 2017. Cited on page 3.

EISENSTAT, E.; CHAN, J. C.; STRACHAN, R. W. Stochastic model specification search for time-varying parameter vars. *Econometric Reviews*, Taylor & Francis, v. 35, n. 8-10, p. 1638–1665, 2016. Cited on page 9.

FURCERI, D.; LOUNGANI, P.; ZDZIENICKA, A. The effects of monetary policy shocks on inequality. *Journal of International Money and Finance*, Elsevier, v. 85, p. 168–186, 2018. Cited on page 2.

GUERELLO, C. Conventional and unconventional monetary policy vs. households income distribution: An empirical analysis for the euro area. *Journal of International Money and Finance*, Elsevier, 2017. Cited on page 3.

HERRAN, C. A. *Reduzindo a pobreza e a desigualdade no Brasil.* [S.l.]: BID, 2005. Cited on page 8.

JONES, C. I. Pareto and piketty: The macroeconomics of top income and wealth inequality. *Journal of Economic Perspectives*, v. 29, n. 1, p. 29–46, 2015. Cited on page 2.

KIM, D. Maximum likelihood estimation for vector autoregressions with multivariate stochastic volatility. *Economics Letters*, Elsevier, v. 123, n. 3, p. 282–286, 2014. Cited on page 6.

MUMTAZ, H.; THEOPHILOPOULOU, A. *Monetary Policy and Inequality in the UK.* [S.l.], 2015. Cited on page 3.

MUMTAZ, H.; THEOPHILOPOULOU, A. The impact of monetary policy on inequality in the U.K. - an empirical analysis. *European Economic Review*, Elsevier, v. 98, p. 410–423, 2017. Cited 2 times on pages 3 and 9.

NORILLER, M.; MOURA, G. V. Maximum likelihood estimation of a TVP-VAR. In: *Proc. 28th (EC)2 on Tîme-varying Parameter Models*. Amsterdam: European Conferences of the Econometric Community, 2017. Cited on page 6.

O'FARRELL, R.; RAWDANOWICZ, Ł.; INABA, K.-I. Monetary policy and inequality. OECD Publishing, 2016. Cited on page 3.

PRIMICERI, G. E. Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, Wiley-Blackwell, v. 72, n. 3, p. 821–852, 2005. Cited 2 times on pages 6 and 8.

ROMER, C. D.; ROMER, D. H. *Monetary policy and the well-being of the poor*. [S.l.], 1998. Cited on page 2.

UHLIG, H. Bayesian vector autoregressions with stochastic volatility. *Econometrica: Journal of the Econometric Society*, JSTOR, p. 59–73, 1997. Cited 3 times on pages 3, 5, and 6.

WINDLE, J.; CARVALHO, C. M. A tractable state-space model for symmetric positive-definite matrices. *Bayesian Analysis*, International Society for Bayesian Analysis, v. 9, n. 4, p. 759–792, 2014. Cited 3 times on pages 5, 6, and 7.