Assessing the impact of conventional monetary policy on the capital-labor ratio in Brazil

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Abstract

To empirically investigate redistributive effects of conventional monetary policy in Brazil, we used the series of 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 time-varying parameters and Wishart stochastic volatility. The data used for posterior computations comprises the monthly observations between March 2000 to October 2018, which corresponds to the inflation targeting regime in the Brazilian economy. The results show a positive and significant response of the capital-labor ratio to contractionary monetary shocks, which lasts at least a semester, i.e., a contractionary monetary policy shock shifts income from labor to capital, which suggests that interest rate shocks have a non-negligible redistributive effect. Moreover, this effect is not constant across periods and changes in the impulse response functions across the sample were observed due to a time-varying behavior of some of the model parameters, implying that the relationship between the monetary policy and distribution of income between production factors has changed over time.
Keywords: Income distribution. Conventional Monetary Policy. Bayesian TVP-VAR. Stochastic volatility.
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1 Introduction

In this paper, we investigate the magnitude, significance and persistence of conventional monetary policy shocks on the capital-labor ratio (K/L, the ratio between the time series of capital income by labor income) using data from Brazil for the period between 2000 and 2018. To do so, we use a time-varying parameter extension of the Wishart bayesian VAR from Uhlig (1997). The time-varying coefficient model allow us to examine whether there were changes in the behavior of the monetary authority that led to changes in the relationship between the interest rate and K/L, at the same time that the presence of stochastic volatility in the model permits changes in the shocks behavior. Our model 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 benefits the capital owners.

There is an ever-growing literature that addresses what are the impacts that macroeconomic factors, including interest rates, have on inequality and distribution of income, wealth and consumption (see, for example, Lucas, 2000; Anand and Segal, 2008; Areosa and Areosa, 2016; Benhabib, Bisin and Luo, 2017). Specifically regarding monetary policy, the predominant idea before the Great Recession in 2008 was that an expansionary policy could reduce inequality in the short run, but for long lasting results in the well-being of the poor it would be better for the monetary authority to aim for inflation control and stability of the aggregate demand Romer and Romer (1998). This view was challenged after the crisis, leading to theoretical and empirical studies investigating the redistributional aspects of conventional and unconventional monetary policy. However, there is no consensus regarding what are the redistributional channels, about the direction of the effects and neither the magnitude of this relationship, i.e., it remains to be decided whether increases (or decreases) in interest rates can rise or shrink inequality or even significantly affect distribution of income and wealth among different groups of individuals (Furceri, Loungani and Zdzienicka, 2018).

From the empirical side, there is also no consensus on whether monetary policy has an effect on income distribution (or, in the cases where there is an effect, the magnitude and direction is not the same depending on the study). 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. On other hand, Ludvigson, Steindel and Lettau (2002) found that the wealth channel had a minor role in transmitting the FED policy to household consumption. 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 and 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. Bunn, Pugh and Yeates (2018) evaluated the effect of the monetary policy easing that followed the 2008 crisis using household panel data and concluded that the overall effect of the policy on wealth and income inequality was relatively small, but there were important differences between households when analyzing the results in cash terms.

Mumtaz and 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 and 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 and Theophilopoulou (2017), this study concludes that contractionary shocks decreased inequality.

If one wants to investigate the relationship between the monetary policy, income and wealth distribution for Brazil, there are monthly series of capital and labor income based on the tax revenues from individuals and firms collected by the Brazilian tax authority. This series represents an aggregate measure (only the total incomes considering all population are available, there is no possibility to divide in deciles), thus it can be seen as the functional income distribution between the two production factors, capital and labor. More specifically, if we divide the income from capital by the income from labor (obtaining the capital-labor ratio, K/L), what we have is the share of the capital with respect to the national income divided by the share of labor w.r.t. the national income.

In this work, we investigate the effect of conventional monetary policy shocks on K/L by estimating a bayesian time-varying parameter VAR model using Brasilian monthly data. In addition to the interest rate and the capital-labor ratio, we included GDP, exchange rate and unemployment rate. The sample period goes from 1996 to 2018, where the first 4 years were used to compute the prior hyperparameters. The model is based on the Wishart bayesian VAR from Uhlig (1997), which was modified to allow for the time variation in the coefficients. A Gibbs-sampler scheme is used for posterior estimation: the method from Windle and Carvalho (2014) is used for the stochastic volatility components in the measurement equations; the time varying coefficients are estimated in a separate using the algorithm from Carter and Kohn (1994), and a final block has a conjugate prior for the volatility of the coefficients.

The remaining of this paper is organized as follows: section two has details the data. Section three covers the details of the econometric model, whilst section four has the results and discussion. Section five concludes.

2 Data

To assess the aggregate impact of monetary policy on income distribution that would be resultant from the channels described in the previous session, 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, interests, 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, which represents the share of the capital with respect to the national income divided by the share of labor w.r.t. the national income. The $^K/_L$ ratio can be seen as a measure of distribution of income between two production factors: labor and capital: since capital is not evenly distributed among individuals, shifts in $^K/_L$ imply a redistribution of income.

The interaction between interest rate and $^K/_L$ is two-fold. Concerning the capital income, monetary policy can affect the capital invested in the production (which generates dividends) by unbalancing the opportunity cost of the capital and its marginal product. On other hand, both short term base rate and the term structure of interest rate influence the present value of financial assets. And, with respect to labor income, the interest rate has an impact on unemployment, which directly impact wages and salaries.

Besides the capital-labor ratio, the other four variables used in the model are the annual variation of the *per capita* GDP, cumulative inflation rate (in last 12 months), 3-month treasury bill as interest rate[1] (annualized) 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. All series were tested for the presence of seasonality and, when needed, the ARIMA-X13 filter was used. The variables used in the model before and after all transformations are shown in Figure 7 (see Appendix).

[1]The 3-month treasury bill series (in portuguese the *Swap DI 90 dias*) is smoother than the actual series of the interest rate SELIC, therefore it was our choice for this work. However, the former is available only from 1999 onward. To "complete" the series from 1996 we used the raw data from the SELIC series, since the period from 1996 to 2000 were used in the prior determination.

3 Empirical model

Extending Uhlig (1997)'s model to a TVP setting can be done by changing the measurement equation and adding a second state evolution equation to the system:

$$y_t = Z_t\beta_t + \epsilon_t, \text{ with } \epsilon = \mathscr{U}(\Omega_t^{-1})'\xi_t \text{ and } \xi_t \sim \mathcal{N}(0, \mathbb{I}_m), \tag{1}$$

$$\beta_t = \beta_{t-1} + u_t, \text{ with } u_t \sim \mathcal{N}(0, Q^{-1}), \tag{2}$$

$$\Omega_{t+1} = \frac{\mathscr{U}(\Omega_t)'\Theta_t\mathscr{U}(\Omega_t)}{\lambda}, \text{ with } \Theta \sim \mathcal{B}_m\left(\frac{\nu}{2}, \frac{1}{2}\right), \ \nu > m-1, \lambda > 0, \tag{3}$$

where there are m variables observed during t periods ($t = 1, \dots, T$); $\lambda > 0$ and $\nu = m-1$ are (constant) parameters; c is the number of deterministic regressors (for example, the constant or drift); the iid shocks in the volatility are represented by Θ and they come from a multivariate Beta distribution, $\mathcal{B}_m(p, q)$. The term $\mathscr{U}(\cdot)$ denotes the superior Cholesky decomposition. In here, the parameter of the multivariate Beta distribution was changed from ${}^{\nu+c+km}/_{2}$ to $\frac{\nu}{2}$, following the specification that is used by Windle and Carvalho (2014).

For estimation, one can exploit the conjugacy between the Wishart and the multivariate Beta distribution to derive closed formula for the latent covariance states. This reduces the number of parameters to be estimated, in comparison, for example, to the TVP-VARs from Cogley and Sargent (2005) or Primiceri (2005). Another advantage of the Wishart MSV specification, according to Philipov and Glickman (2006), is that the model from Uhlig (1997) and the model defined in (1)-(3) are natural extensions of the univariate case, giving a direct interpretability of the covariance matrices. This structure also allows for the conditional volatility to be dependent of the past volatility and the past covariances, something that Kim (2014) refers as contagion among variables being incorporated into the covariance structure. Finally, the model is invariant to permutations of the variables and it is more parsimonious in the number of parameters of the stochastic volatility component, in comparison to Primiceri (2005) (even in the case where one prefers to estimate ν and λ).

Assuming that ν and λ are given, remains open how to estimate, at each point in time, the vector of coefficients β_t, the (fixed) matrix Q and the covariance matrices Ω_t. This could be done in a frequentist manner by a generalization of the Kalman filter and writing the likelihood function, like in the work from Moura and Noriller (2019). Their specification, however, ties up the matrix Q to the states Ω_t and has the challenges that an optimization on a highly non-linear likelihood function imposes. A more flexible way would be to implement a Gibbs-sampler, which allows to take advantage of the modular characteristic of the method. Furthermore, in comparison to the ML estimator, the procedure from Windle and Carvalho (2014) allows to obtain filtered and smoothed trajectories for all states. The next section explains in detail the proposed scheme for estimating (1)-(2).

3.1 Estimation

Let $D_{0:t}$ denote a collection $\{D_0, \ldots, D_t\}$, $f_\theta(a|b)$ denote the conditional density of a given b and $p(\cdot)$ denote a prior density. Then, the joint posterior density π for the model (1)-(2) has the form:

$$\pi(\beta_{0:T}, \Omega_{1:T}, \lambda, Q, \nu | y_{1:T}) \propto f_\theta(y_{1:T}|\beta_{1:T}, \Omega_{1:T}) f_\theta(\beta_{1:T}|Q) f_\theta\,(\Omega_{1:T})\, p(\beta_0)p(\Sigma_0)p(\lambda)p(\nu),$$

where Σ_0 and β_0 are initialization values. The conditional densities $f_\theta(y_{1:T}|\beta_{1:T}, \Omega_{1:T})$ and $f_\theta(\beta_{1:T}|Q)$ are given by equations (1) and (2), respectively, while equation (3) describes the density $f_\theta\Omega_{1:T}$ (together with an initial condition for Ω_1). By using a Gibbs-sampler, we can break the estimation procedure in different parts, one for the coefficients β_t, one for the covariance Q and one for the states Ω_t.

Starting with the β_t coefficients, assuming known the other parameters, we can Kalman filter with the Carter and Kohn (1994) algorithm to obtain the estimates. Then, given β_t could employ a conjugate prior to estimate the covariance matrix Q.

The blocks of the Gibbs sampler for the model (1)-(3) 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 and Kohn (1994).

3. **Draw Q from a inverse Wishart distribution**.

4. **Draw jointly (ν, Ω^T) conditional on B^T:** for such, propositions 1-3 from Windle and Carvalho (2014) are needed for the filtering, smoother and marginalization.

3.2 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, as explained bellow.

The prior hyperparameters were calculated by OLS using data from January, 1996 to December, 1999, comprising 48 months. This period was shortly after the implementation of the new currency (Brazilian Real), which stabilized the economy, but was marked by large fluctuations 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 (January 2000 to October 2018). Prior distributions are described in Table 1. The number of lags (2) was chosen accordingly the AIC criteria.

The prior distributions follow the specification needed to employ the method of Windle and Carvalho (2014) and Carter and Kohn (1994) for the variances and coefficients of the measurement equation, respectively, as well as the conjugate prior for the state transition equation for the coefficients. This means that the initial coefficients β_0 follows a multivariate normal distribution, the prior for the covariance matrix of the shocks over the β_t is an inverse wishart and the prior for the covariance Ω_t is a wishart. The initial coefficients and covariance in the measurement equation were inflated by the multiplication of a scalar and the prior hyperparameters were obtained through the OLS quantities from the first 48 observations (that were not included in the period used to compute the posterior).

Choosing the first 48 observations for the prior was not a coincidence. This period corresponds to the subsequent years after the stabilization of the economy through the real plan, that, among other things, implemented the a new currency (Brazilian reais) that at first had a fixed exchange rate. For the first years (1995 to 1998), inflation was still high and the Central Bank spent many resources trying to maintain the exchange rate fixed. The fixed exchange rate started to consume the country's dollar reserves, which was aggravated with the Asian and Russian crisis in 97-98, causing pressure for changes in the conduction of the monetary policy. This happened in 1999, when the government officially committed to the inflation targeting regime. Given that, the period from January 1996 to the beginning of 2000 was marked by shocks from various sources which increased volatility during that time. This implies that the removal of the first 48 observations and subsequent inflation of the prior distributions was a necessary action to account for the high uncertainty of the period.

Table 1: Model Priors, initial values and parameters

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

Notes:
✣ - The initial value Σ_0 is estimated based on a Wishart conjugate prior.
♠ - Variables with a hat $\hat{a}$nd 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.
✳ - ν_{H0} is an equally-spaced grid with values ranging from 4 to 70.

3.3 Identification of the shocks

We here are imposing a Cholesky decomposition of the shocks in order to isolate structural effects. 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 a consequence of the assumptions on our small open economy: the monetary authority will have to choose as nominal anchor either the exchange rate or the interest rate. Considering that Brazil adopts the inflation targeting regime, the latter seems to be more realistic in our application, since it is not possible to have an active monetary policy with a fixed exchange rate for a small open economy.

TVP-VARs such as the ones from Cogley and Sargent (2005), Primiceri (2005) or even the one defined in system (1)-(3) have the common characteristic that the law of movement for the coefficients is a random walk. This means that we are accepting the possibility of a non-stationary process in the sense that these coefficients can lead to explosive trajectories, which would imply unbounded impulse response functions. Cogley and Sargent included in the model their belief that the Fed follows a meaningful rule through the adoption of a stability condition. In practice, their Gibbs Sampler has a rejection sampling algorithm to discard explosive draws from the posterior. Koop and Potter (2011) proposes an alternative algorithm to avoid the explosive trajectories, arguing that methods such as Cogley and Sargent (2005) could perform poorly and approximate some results, whereas their method is exact. In this work we followed Primiceri (2005)'s approach and did not include restrictions in the model. None of our impulse response functions presented explosive behavior. Given that the sample excludes the Brazilian hyperinflation period prior to 1994 and all series were pre-treated to eliminate any non-stationary behavior, we considered that the restrictions were not essential in our case.

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.

4 Results

At any given time t, the system of equations presents 55 of the α coefficients, which correspond to five intercepts, 25 first lag coefficients and another 25 second lag coefficients. For each one of them, we could draw a whole trajectory from $t = 1$ to $t = 266$. Figure 1 shows the first and second lag coefficients of each variable in their own equations, i.e., the first two graphs from top line are the coefficients that multiplies the capital-labor ratio in $t-1$ and $t-2$ in the capital-labor ratio equation. The third column on the right contains the estimated standard deviations for each VAR equation.

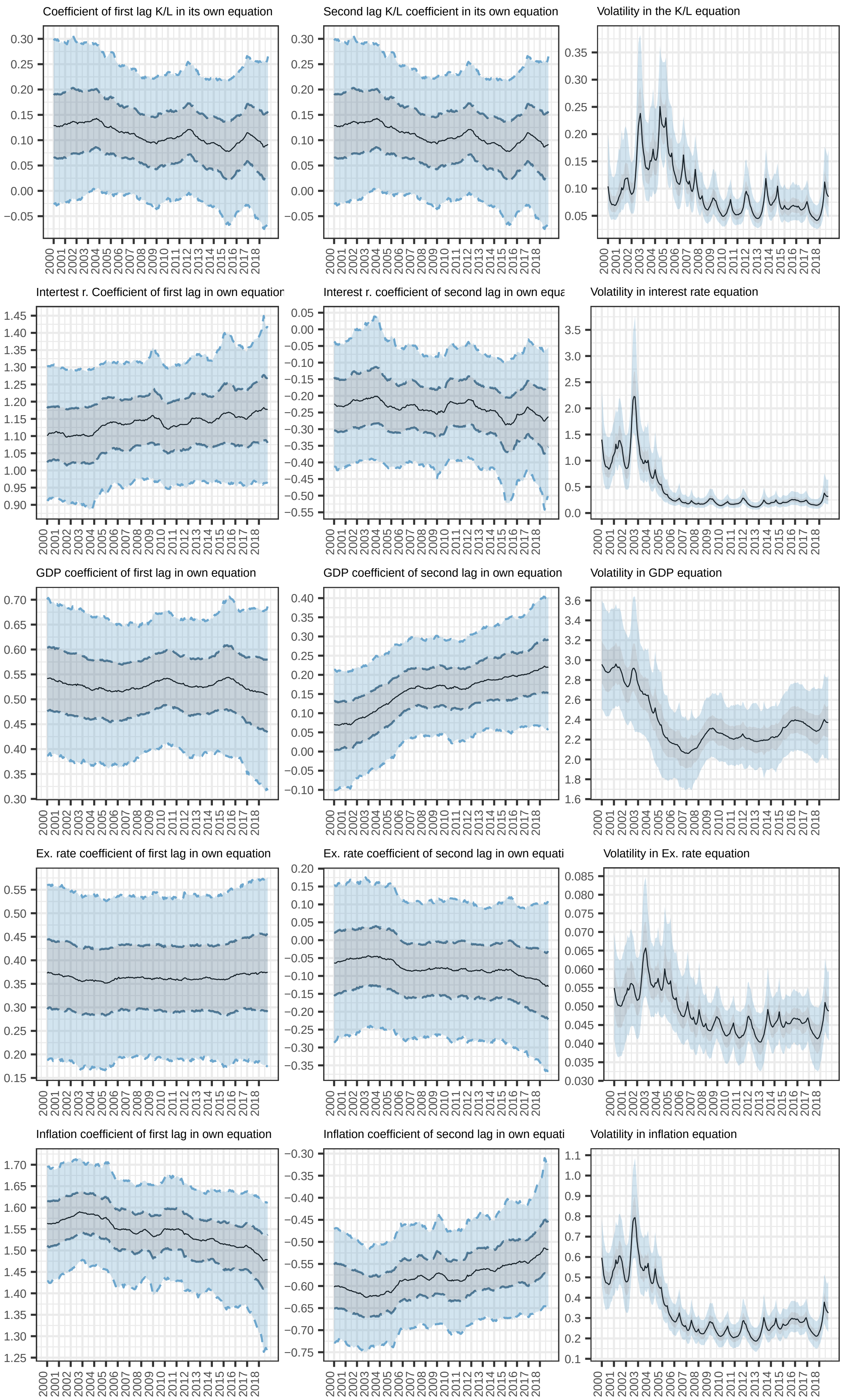
The solid black line is the median of 2500 posterior draws for each one of the parameters, at each given time. The gray area comprises the interval between the 25th and 75th percentiles, while the blue area ranges from 5th to 95th percentile. The coefficient for the second lag of the capital labor ratio has zero included in the 95% credible interval and the same happens for the second-lag coefficient of the exchange rate. In general, all ten coefficients plotted in the figure have low to nonexistent time variation. The exception are three coefficients that show some signs of moving patterns, namely the second lag of GDP in GDP's equation, which has an ascending behavior from 2000-2008, and ceases to include zero in the credible intervals. In other words, from 2008 onward, the annual variation of GDP at t starts to depend more from the annual variation two months before, increasing the autoregressive pattern. One possible explanation could be the increase in public spending in form of government stimulus, one of former President Lula's promises from his campaign (elections took place in 2002).

Sill analyzing Figure 1, from the bottom row we see that both coefficients of the inflation index in its own equation show some changes across time: the first lag is descending, meaning that the immediate effect from last month inflation in current inflation has been decreasing (it is important to note, however, that this movement is very small when analyzing the scale). At the same time, the second lag of inflation decreased in module (it is upward inclined but negative). This means that the inflation from two months ago is penalizing less the current inflation or, current inflation is being less affect by both first and second lag. If one thinks in terms of prices stickiness, may be the case that prices can be update more easily, which could cause a diminishing in the autoregressive effect. Nevertheless, the first lag coefficient is still higher than one, which implies a strong persistence in the price level.

All volatilities in Figure 1 present higher peaks in the first five to six years, but the GDP volatility presents a slightly different pattern. This could be due to the fact that the series was transformed to inform the annual variation or because GDP is a more structural aggregate and does not fluctuate much (not to mention that the monthly series is obtained by extrapolation from quarterly data). There is a 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.

The coefficients of all other variables in the capital equation labor are in Figure 2. It is possible to observe that many coefficients are not different from zero, when the 95% credible interval. This suggests that, at least in the capital-labor ratio, the coefficients are non time-varying and have values statistically non-different from zero.

Figure 1: First and second lag coefficients of each variable in its own equation and estimated volatilities (median, 50% and 90% centered around the median credible intervals) for 2000-2018.



First and second coefficients of each variable in their own equations (first and second columns) and standard deviation for each VAR equation (third column on the right). Due to lack of space, the interpretation is in the text only.

To verify the impact of monetary shocks over the other model's variables, we calculated the impulse response functions (IRF) for each period, considering the estimated values of β_t, Ω_t and a time horizon of 25 months. Figure 3 presents the median of the IRF using the estimated values at t equal to October 2018 (the last period of the sample) with the intervals from the 5th to 95th percentile (yellow light area) and 25th to 75th percentile (brown 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.

In order to assess whether the relation between monetary policy and K/L is stable or varies across time, we estimated the FIR from a monetary shock in the capital-labor ratio for different periods. The values are significantly different from zero from the second month after the initial shock and lasts for at least 10 months, for all periods, using the interval between the 5th and the 95th percentiles. The median of the FIR in July, 2008 is slightly higher than the others, suggesting that the effect of monetary shocks on the capital-labor ratio was a higher during that period, in line with the results found by Mumtaz and Theophilopoulou (2017) for the Great Recession. However, when considering the 90% confidence interval, there seems to exist no differences between the curves. The periods elected as the ones to recalculate the FIR are described in Table (2).

Table 2: Selected periods for the FIR calculation in Figures 4 and 6

	Date	t	Context		Date	t	Context
01	Jan/00	1	Beginning of the data series[1]	06	Jul/05	66	Political crisis[6]
02	Jun/01	18	Electrical crisis[2]	07	Jun/08	102	International economic crisis
03	Jun/02	30	Economic Expansion period[3]	08	Jun/10	126	Economic Expansion period[3]
04	Oct/02	34	Presidential elections[4]	09	Mar/16	195	Impeachment process [7]
05	Jan/03	37	Presidential Inauguration[5]	10	Oct/18	217	Last observation period

Notes:
[1] - Although we have data since January 1995, due to the use of the first 48 observations for the prior, the model just starts in January 2000.
[2] - The electrical crisis in Brazil occured from July 2001 to February 2002 and affected the power supply all over the country.
[3] - This classification is nade by the Brazilian Business Cycle Dating Committee (CODACE).
[4] - There was great political instability with spillovers to the economy due to Lula's (the candidate from the Worker's Party to presidency of the country) rise in the pools.
[5] - Luis Inácio Lula da Silva, the elected president in the 2002's elections, was nominated the $35th$ Brazil's president in January 1st, 2003.
[6] - The political crisis in 2005 is called *Mensalão Crisis* and was a scandal envolving many parties, including the President's. It culminated, later, with the trial and prison of several politicians acused of corruption.
[7] - The impeachment process of Dilma Rousseff started in December 2015.

The next exercise involves checking the reactions of the model variables to monetary shocks considering changes in the presidency of the Central Bank and/or in the head of the Finance Ministry during the sample period (2000-2018). The idea here is that different combinations of monetary-fiscal policies could have different outcomes in the income distribution. The dates used to compute the IRFs with the respective names of the central bank president and minister of finance are shown in Table (3). As control, we included the period of June 2008 (Great Recession).

Table 3: Selected periods for the impulse response calculation TVP-VAR from Figure 5

	Month, Year	t	CB[1] president & Min.[2] of Finance
01	January, 2003	37	Meirelles and Palocci
02	March, 2006	75	Meirelles and Mantega
03	June, 2008	102	Financial crisis*
04	November, 2011	133	Tombini and Mantega
05	January, 2015	183	Tombini and J. Levy
06	December, 2015	192	Tombini and N. Barbosa
07	June, 2016	197	Goldfajn and Meirelles

Notes:
1 - *Central Bank.*
2 - *Minister of Finance.*
* - In the thunderstorm of the Great Recession the Central Bank's head was Henrique Meirelles and the Minister of Finance was Guido Mantega. The international financial crisis, also called "subprime crisis" begun in the United States and had a global impact. Brazil was considered a success case because the effects of the crisis were not severe there as they were in other economies.

Source: Based on information from the Brazil's Central Bank (2018) and Ministry of Economy (2018).

Figure 5 shows a median change in the responses in both inflation and GDP to monetary shocks, while the median responses of the capital-labor ratio and exchange rate remained the same. It is interesting to note that in these latter, the peak occurred in June 2008, the middle of the crisis. Could be the case that the central-bank changed its behavior in a way that indirectly affected these two quantities. Nevertheless, this is a slight higher median value and considering the credible intervals there is no difference between the curves in different periods.

As for the inflation, the highest response to monetary shocks were in March 2006. In this period the inflation was in a decrease trajectory since 2005 and by the end of 2006 it was bellow the target. The interest rate reached its maximum in September 2005 (19.51% p.y.) and entered in a declining trajectory ever since, whilst inflation was kept under control (Banco Central do Brasil, 2006). This can be seen in Figure 7. The remaining periods were similar with the exeption of January 2015 and 2016. This period was marked by a turmoil in Brazilian politics and economy, which culminated in the Impeachment of the then President Dilma Roussef. Upon a close inspection to Figure 7, it is clear that a peak in inflation occurred during this time. This increase in prices was resulting from the frozen administrated prices in energy and oil that were practiced in the previous years and become unsustainable when the international scenario became less favorable. By the end of the first quarter in 2006, the President was removed from office to wait the Impeachment process to come to an end, and an interim government, led by the then vice-president Michel Temer, was established. Mrs. Roussef had replaced the Finance Minister Joaquim Levy by Nelson Barbosa, who stayed until June of 2016 where Mr. Temer replaced both by Mr. Ilan Goldfajn and Mr. Henrique Meirelles, respectively (see Table 3). These findings are supported by Mumtaz and Surico (2015)'s work, where they found that there are asymmetries in the propagation mechanism across good (such as 2006) and bad (2015, 2016) times. When the economy is in expansion (above its long-term average), the estimates of the degree of forward-lookiness and interest rate semi-elasticity are significantly larger than the estimates in recessions (below-average periods), which suggests that monetary policy is more effective during periods of expansions.

Regarding the annual variation of the per capita GDP's response to monetary shocks, we see that is responds negatively to monetary contractions (as one would expect, since raise in interest rates will discourage the firms to make investments in their productions. The exceptions were in January 2010 and January 2015. We can observe in Figure 7 that there was an abrupt decrease in the GDP variation exactly in the end of 2009, beginning of 2010 (the gridlines represent the months of November in each year). This means that the level of GDP in January 2010 was way bellow it was one year before (it recovered a few months later). Accordingly to the Brazilian Bureau of Geography and Statistics, 2009 had a major decrease in the GDP which was followed by an overheated economy during the last three quarters of 2010. This movements in the economy help to explain the rise in prices that followed in the upcoming years, due to a combination of excessive fiscal stimulus, heated economy and international trade retraction.

Table 4: Percentage of types of income (of total income) from the annual household tax declarations, 2007-2016.

Type of income	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Non-taxable income	*29,3*	*37,7*	*36,4*	*38,2*	*39,7*	*38,4*	*39,3*	*40,1*	*41,1*	*41,0*
Tax-exempt	21,4	28,7	28,1	29,2	29,4	29,1	29,6	30,7	31,3	30,7*
Profit and dividend	10,4	10,3	9,9	10,7	10,9	10,7	10,8	10,7	10,0	9,8
Pensions	2,2	3,9	3,9	3,8	3,5	3,5	3,6	3,6	3,8	4,0
Donations and bequests	2,3	3,8	3,5	3,3	3,1	2,8	2,8	3,1	4,0	5,6
Others	6,5	10,8	10,9	11,4	12,0	12,1	12,4	13,3	13,5	10,6
Taxable at the source	7,9	9,0	8,3	9,0	10,3	9,3	9,7	9,4	9,8	10,2
13o wages	2,2	3,0	3,3	3,2	3,1	3,1	3,2	3,2	3,1	3,2
Financial applications	2,4	2,8	2,5	2,5	2,9	2,6	2,1	2,1	2,7	3,0
Capital Gains	2,5	2,4	1,6	2,0	2,9	2,3	2,0	1,5	1,5	1,4
Others	0,8	0,9	0,9	1,3	1,5	1,3	2,4	2,6	2,5	2,7
Taxable income	*70,7*	*62,3*	*63,6*	*61,9*	*60,3*	*61,5*	*60,6*	*59,9*	*58,9*	*59,0*

* - the data for 2016 has disparities between the total tax-exempt income and presented in more than the report. It is possible that this value is a little overestimated.

Source: Based on BRASIL. Ministério da Fazenda. Receita Federal do Brasil (2018).

By analyzing the pattern of the impulse response functions of the capital-labor ratio in both Figures 4 and 5, there is no apparent evidence of changes in the behavior of the curves for different periods, indicating that the contemporaneous impact of shocks in the interest rates were fairly homogeneous across time. One possible explanation would be the stable composition between the tax-exempt incomes, incomes taxed "exclusively at the source" and the taxable income. Since there was no big shifts in the shares of each one of these categories with respect to the total amount of declared taxes, it is natural that little or no changes in its response to interest rates would be observed. Table 4 has the share of different taxed exclusively at the source and non-taxable personal income for the period of 2007-2015. Note, however, that this does not correspond entirely to the capital income series used in this paper, since it does not contains the taxes from firms.

One additional source of changes in the capital-labor ratio could be the inflation channel. Inflation can hurt those with labor income in comparison to those with capital income, since households who exclusively depend on labor and are located in the lowest deciles of the income distribution may not have access to financial markets, which would protect their purchase power. Adam and Zhu (2015) studied the relationship between price level changes and the redistribution of nominal wealth for the Euro Area and one conclusion is that middle class households, due to their negative net nominal positions, are losers with respect to increases in the price level, whilst richer households are winners. This result is in line with the findings of Auclert (2017), although the inequality was with respect to consumption and he used a microfounded model. In the present work we are investigating income and not wealth, but those two are intrinsically tied: households who have more income can accumulate more, which generates wealth. If they have financial wealth, this will generate an income stream for the following periods, creating a cycle between wealth and income.

From Figure 6, we conclude that there is no evidence of significant impact of the inflation shocks in the capital-labor ratio. This could be due to the specification of the shocks, since we are using a Cholesky decomposition and further discussion about the precedence of the shocks would be needed, but also can mean that the capital-labor ratio is not responding to inflation after all. By looking at the stable composition of the types of income described in Table (4), this second explanation is more plausible. If there is no changes in the structure of flows, then the inflation will not play a role. Note, however, that this is not the same for the interest rates: when the interest rate goes up, the capital gains also rise. It is different than the nominal value of money: if there is inflation and the money flow from capital is hurt, also is the nominal value of labor income, which does not affects the proportion between them.

Figure 2: First (left column) and second (right column) lags coefficients of the interest rate, per capita GDP annual variation, exchange rate and inflation rate in the capital-labor ratio (median, 50% and 90% centered around the median credible intervals), estimated for the 2000-2018 period.

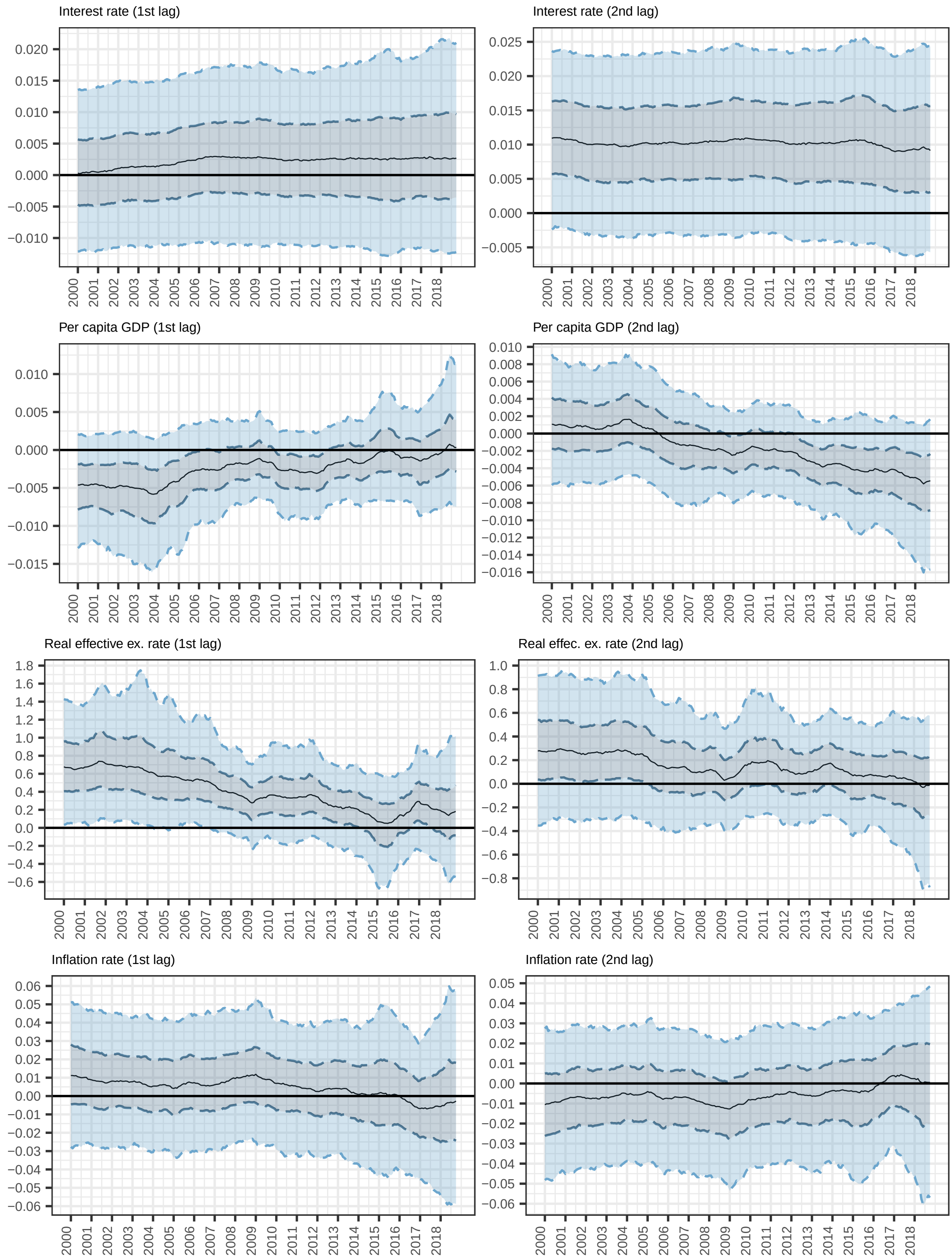
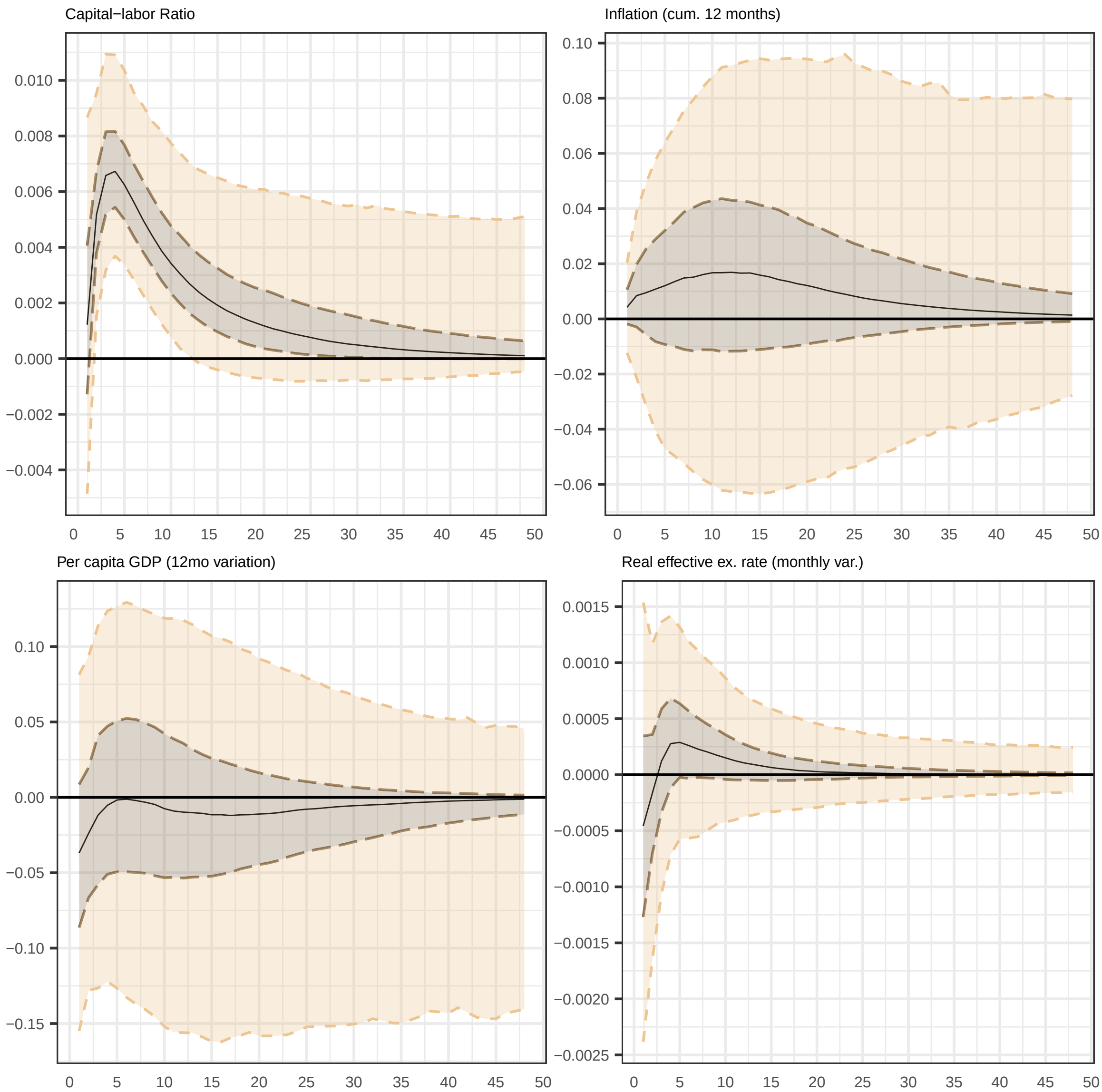
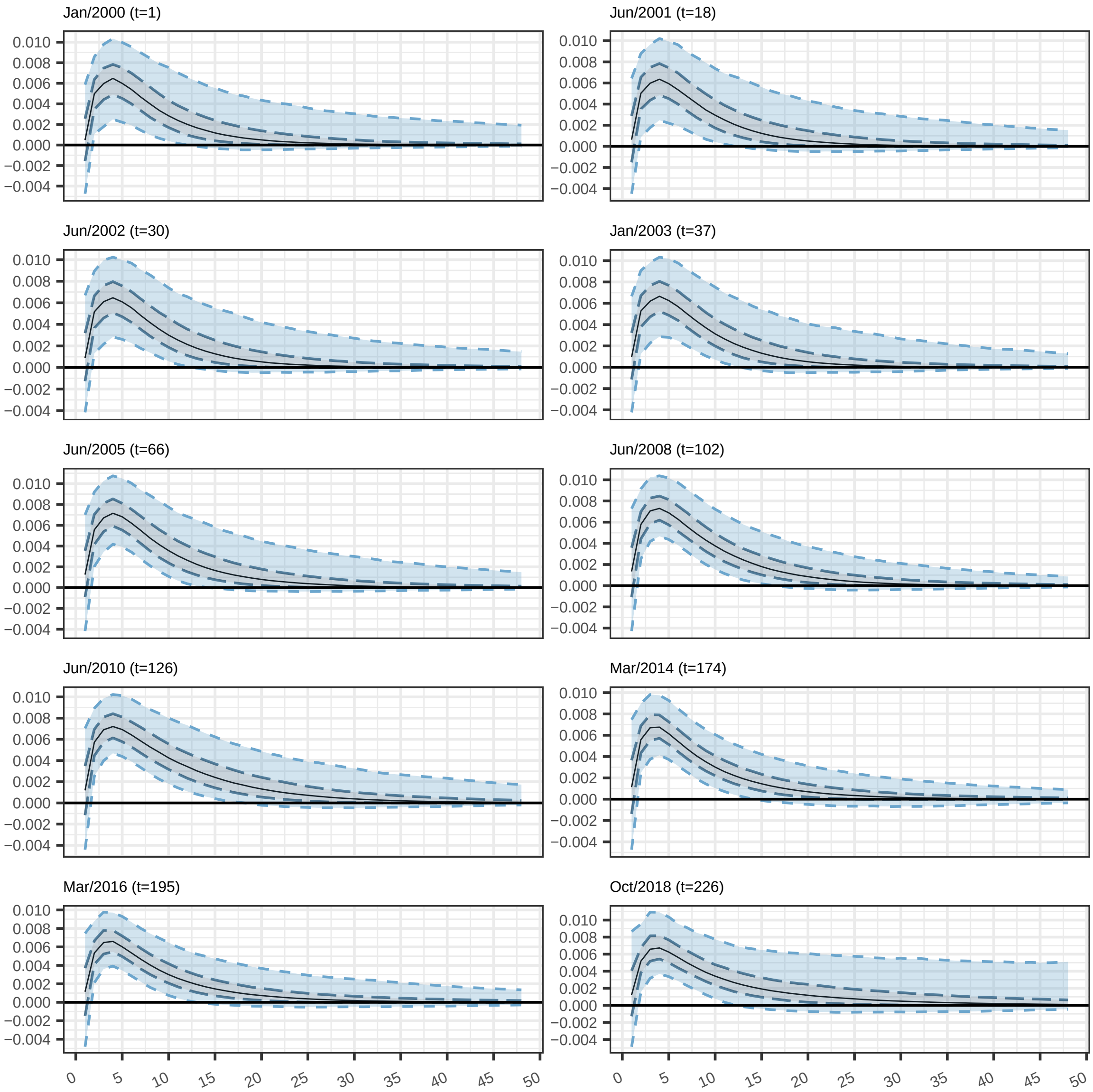


Figure 3: Impulse response functions (median, 50% and 90% centered around the median credible intervals) of the model variables to monetary shocks using the estimated values for October, 2018.



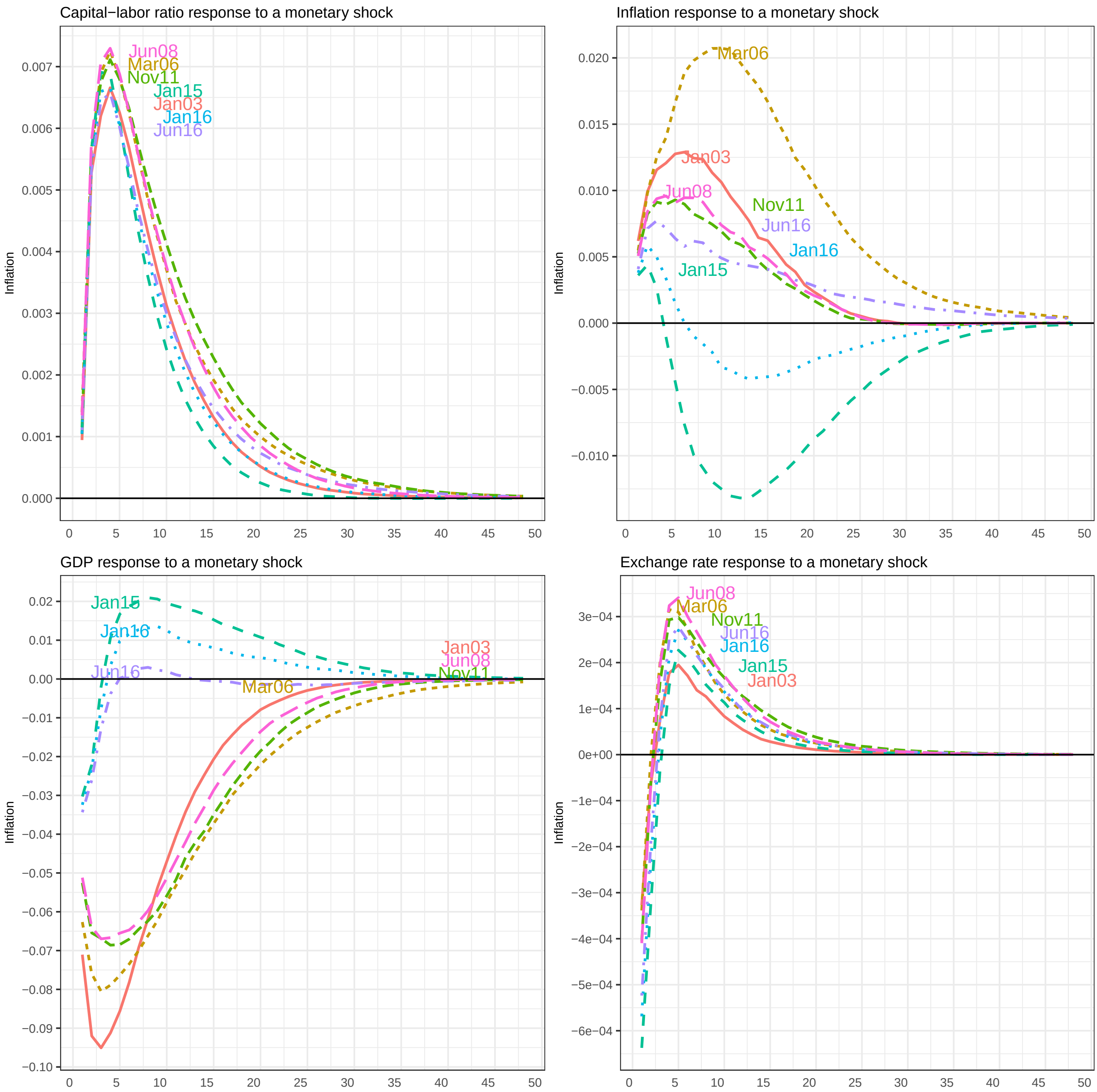
Impulse response functions (FIR) of K/L (%), Inflation (% in 12 months), per capita GDP (annual % variation) and Exchange rate (monthly % variation) to monetary shocks using the estimated coefficients and volatilities for December, 2017. With exception of the FIR of the capital-labor ratio, the remaining 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.

Figure 4: Impulse response functions (median, 50% and 90% centered around the median credible intervals) of the capital-labor ratio to monetary shocks for selected periods.



Impulse response functions (IRF) of K/L to a 1% monetary shock using the estimated coefficients and volatilities for each indicated time, selected accordingly to major political and/or economical events that occured between 2000-2018 in Brazil. The blue area corresponds to the interval between the 5th and 95th percentiles, whilst the gray area corresponds to the interval between the 25th and 75th percentiles, based in 2500 posterior draws. For the Capital-Labor ratio, these intervals do not include zero from the second month until the 15th month after the initial shock.

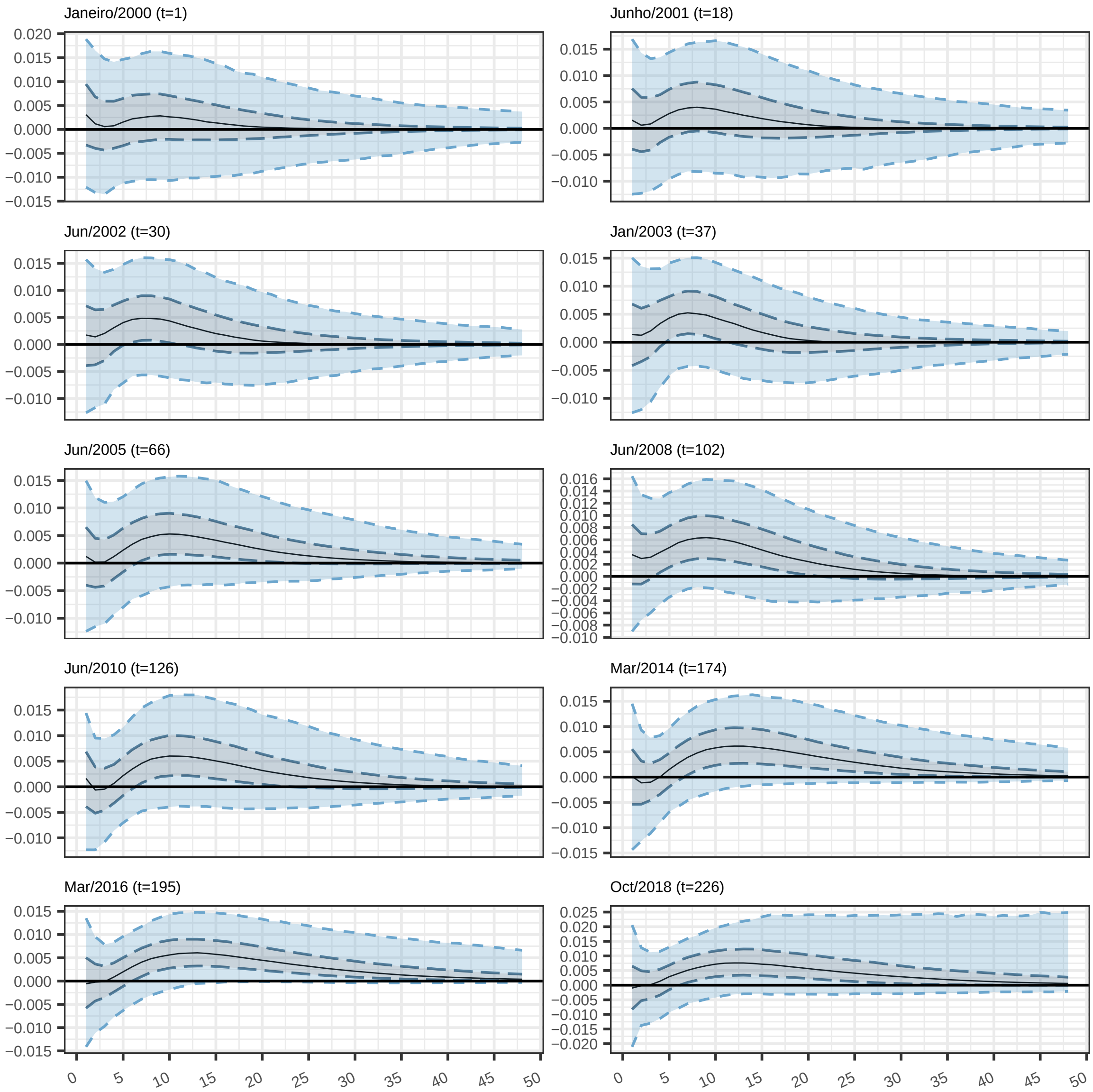
Figure 5: Medians of the impulse response functions to monetary shocks at different selected periods.



Medians of the impulse response functions (IRF) of the capital-labor ratio (K/L) to monetary shocks at six different times, where the combination between the President of the Central Bank and the Ministry of Finance changes from one to another. Plus, there is a 7th line correspondingly to June, 2008 (period of the Great Recession). For all curves at the botton left graph (corresponding to the response of the capital-labor ratio), the 95th percent interval dos not include zero until the 15th month after the initial shock.

Source: Own construction.

Figure 6: Impulse response functions (median, 50% and 90% centered around the median credible intervals) of the capital-labor ratio to inflation shocks for different periods. Brazil, 2000-2018.



Impulse response functions (IRF) of K/L to a 1% inflation shock using the estimated coefficients and volatilities for each indicated time, selected accordingly to major political and/or economical events that occured between 2000-2018 in Brazil, as described in table (2). The blue area corresponds to the interval between the 5th and 95th percentiles, whilst the gray area corresponds to the interval between the 25th and 75th percentiles, based in 2500 posterior draws. For the Capital-Labor ratio, all intervals include zero in the 48 periods after the initial shock.

5 Concluding 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.

As far as we know, this empirical exercise was not done before for the Brazilian economy. In particular, the relationship between monetary policy and inequality, despite the crescent tide of studies for other countries, appears to have not been not fully investigated using Brazil's data. One possible explanation for this is the lack of microdata for Brazilian households: the surveys that has data on consumption, wealth and income that would allow to estimate inequality measures are from the beginning of the last decade and were collected on an annual basis (Morgan, 2017). In 2016 a new monthly survey covering a representative sample of the country residents was started, but there is not enough data to be used in an econometric model yet. Therefore, this paper contributes to shed some light on the question.

A future extension of the econometric model would be to include a shrinkage algorithm in the coefficients of the TVP-VAR, following the method from Bitto and Frühwirth-Schnatter (2018). There is evidence that not all coefficients estimated in our application are time-varying (or different from zero) and using a procedure to eliminate non-relevant parameters could improve the convergence of our MCMC algorithm.

References

Adam, Klaus, and Junyi Zhu. 2015. "Price-level changes and the redistribution of nominal wealth across the Euro Area." *Journal of the European Economic Association*, 14(4): 871–906. [Cited on page 14.]

Anand, Sudhir, and Paul Segal. 2008. "What do we know about global income inequality?" *Journal of Economic Literature*, 46(1): 57–94. [Cited on page 2.]

Areosa, Waldyr Dutra, and Marta BM Areosa. 2016. "The inequality channel of monetary transmission." *Journal of Macroeconomics*, 48: 214–230. [Cited on page 2.]

Auclert, Adrien. 2017. "Monetary policy and the redistribution channel." *NBER Working Paper.* [Cited on page 14.]

Banco Central do Brasil. 2006. "Relatório de Inflaão, volume 8." [Cited on page 12.]

Banco Central do Brasil. 2018. "Composição Histórica da Diretoria." [Cited on page 12.]

Benhabib, Jess, Alberto Bisin, and Mi Luo. 2017. "Earnings inequality and other determinants of wealth inequality." *American Economic Review*, 107(5): 593–97. [Cited on page 2.]

Bitto, Angela, and Sylvia Frühwirth-Schnatter. 2018. "Achieving shrinkage in a time-varying parameter model framework." *arXiv preprint arXiv:1611.01310.* [Cited on page 20.]

Bivens, Josh. 2015. "Gauging the impact of the Fed on inequality during the Great Recession." *Hutchins Center Working Papers.* [Cited on page 2.]

BRASIL, Ministério da Fazenda. 2018. "Galeria de Ministros." [Cited on page 12.]

BRASIL. Ministério da Fazenda. Receita Federal do Brasil. 2018. "Grandes números - DIRPF (anos-calendário 2007-2013)." [Cited on page 13.]

Brooks, Stephen, and Andrew Gelman. 1998. "Some issues for monitoring convergence of iterative simulations." *Computing Science and Statistics*, 30–36. [Cited on page 25.]

Bunn, Philip, Alice Pugh, and Chris Yeates. 2018. "The distributional impact of monetary policy easing in the UK between 2008 and 2014." Bank of England Bank of England working papers 720. [Cited on page 3.]

Carter, Chris K, and Robert Kohn. 1994. "On Gibbs sampling for state space models." *Biometrika*, 81(3): 541–553. [Cited on pages 4, 6, and 7.]

Casiraghi, Marco, Eugenio Gaiotti, Lisa Rodano, and Alessandro Secchi. 2017. "A "reverse Robin Hood?" The distributional implications of non-standard monetary policy for Italian households." *Journal of International Money and Finance.* [Cited on page 2.]

Cogley, Timothy, and Thomas J Sargent. 2005. "Drifts and volatilities: monetary policies and outcomes in the post WWII US." *Review of Economic dynamics*, 8(2): 262–302. [Cited on pages 5 and 8.]

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia. 2017. "Innocent Bystanders? Monetary policy and inequality." *Journal of Monetary Economics*, 88: 70–89. [Cited on page 2.]

Davtyan, Karen. 2017. "The distributive effect of monetary policy: The top one percent makes the difference." *Economic Modelling*, 65: 106–118. [Cited on page 3.]

Furceri, Davide, Prakash Loungani, and Aleksandra Zdzienicka. 2018. "The effects of monetary policy shocks on inequality." *Journal of International Money and Finance*, 85: 168–186. [Cited on page 2.]

Guerello, Chiara. 2017. "Conventional and unconventional monetary policy vs. households income distribution: An empirical analysis for the Euro Area." *Journal of International Money and Finance.* [Cited on page 2.]

Herran, Carlos Alberto. 2005. *Reduzindo a pobreza e a desigualdade no Brasil.* BID. [Cited on page 8.]

Kim, Dukpa. 2014. "Maximum likelihood estimation for vector autoregressions with multivariate stochastic volatility." *Economics Letters*, 123(3): 282–286. [Cited on page 5.]

Koop, Gary, and Simon M Potter. 2011. "Time varying VARs with inequality restrictions." *Journal of Economic Dynamics and Control*, 35(7): 1126–1138. [Cited on page 8.]

Lucas, Robert E. 2000. "Some macroeconomics for the 21st century." *Journal of Economic Perspectives*, 14(1): 159–168. [Cited on page 2.]

Ludvigson, Sydney, Charles Steindel, and Martin Lettau. 2002. "Monetary policy transmission through the consumption-wealth channel." *FRBNY Economic Policy Review*, 5: 117–133. [Cited on page 2.]

Morgan, Marc. 2017. "Extreme and persistent inequality: New evidence for Brazil Combining National accounts, surveys and fiscal data, 2001-2015." *WID. World Working Paper Series*, 12. [Cited on page 20.]

Moura, Guilherme V, and Mateus R Noriller. 2019. "Maximum likelihood estimation of a TVP-VAR." *Economics Letters*, 174: 78–83. [Cited on page 5.]

Mumtaz, Haroon, and Angeliki Theophilopoulou. 2015. "Monetary Policy and Inequality in the UK." Working Paper, School of Economics and Finance, Queen Mary, University of London. [Cited on page 3.]

Mumtaz, Haroon, and Angeliki Theophilopoulou. 2017. "The impact of monetary policy on inequality in the U.K. - an empirical analysis." *European Economic Review*, 98: 410–423. [Cited on pages 3 and 11.]

Mumtaz, Haroon, and Paolo Surico. 2015. "The transmission mechanism in good and bad times." *International Economic Review*, 56(4): 1237–1260. [Cited on page 13.]

O'Farrell, Rory, Łukasz Rawdanowicz, and Kei-Ichiro Inaba. 2016. "Monetary policy and inequality." [Cited on page 2.]

Philipov, Alexander, and Mark E Glickman. 2006. "Multivariate stochastic volatility via Wishart processes." *Journal of Business & Economic Statistics*, 24(3): 313–328. [Cited on page 5.]

Primiceri, Giorgio E. 2005. "Time varying structural vector autoregressions and monetary policy." *The Review of Economic Studies*, 72(3): 821–852. [Cited on pages 5, 8, and 25.]

Romer, Christina D, and David H Romer. 1998. "Monetary policy and the well-being of the poor." National bureau of economic research. [Cited on page 2.]

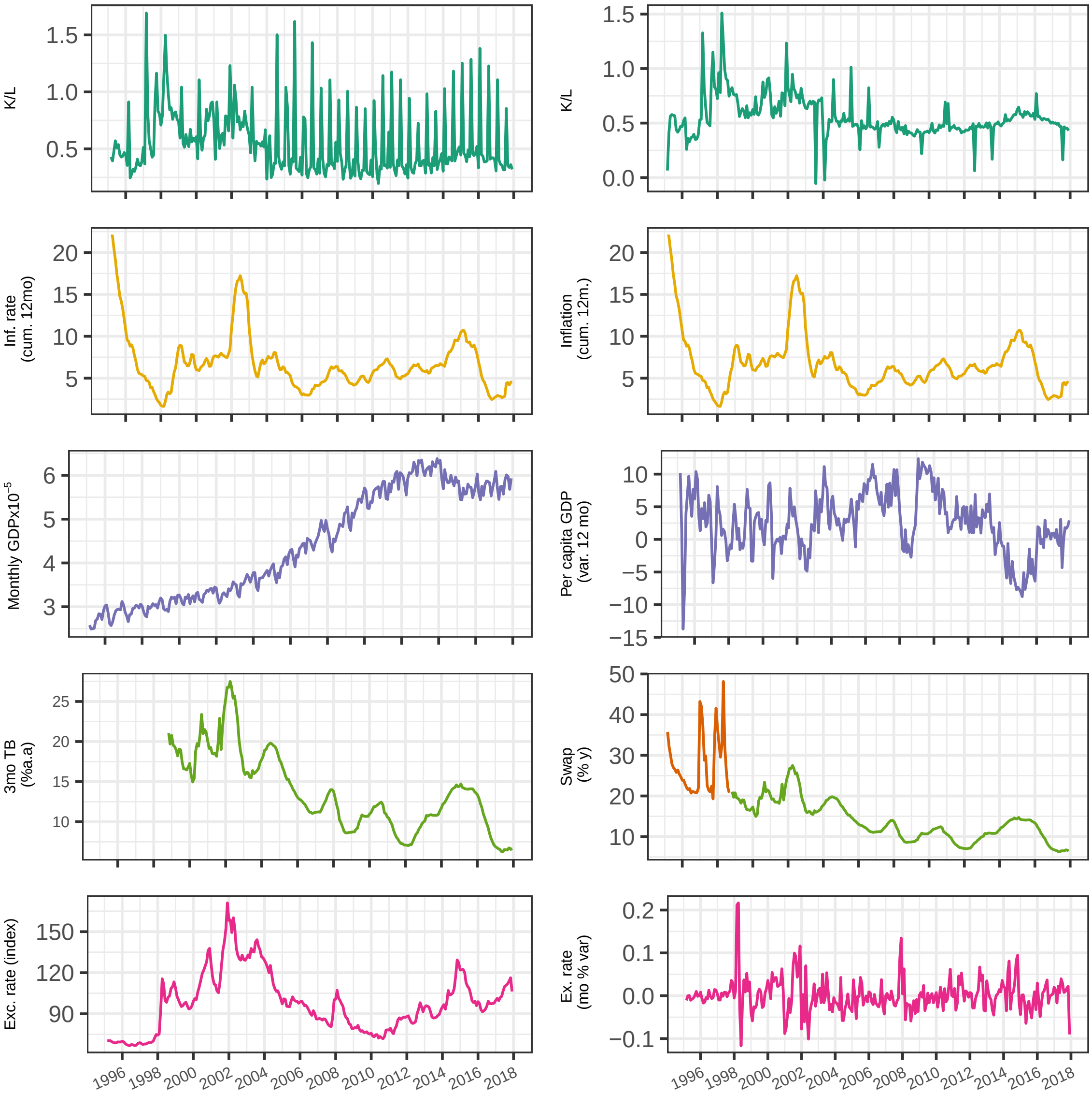
Uhlig, Harald. 1997. "Bayesian vector autoregressions with stochastic volatility." *Econometrica: Journal of the Econometric Society*, 59–73. [Cited on pages 2, 3, and 5.]

Windle, Jesse, and Carlos M Carvalho. 2014. "A tractable state-space model for symmetric positive-definite matrices." *Bayesian Analysis*, 9(4): 759–792. [Cited on pages 3, 5, 6, and 7.]

Appendix

Series used in the model

Figure 7: 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: Data from BCB-Depec, Sisbacen PTAX800, IBGE, BM&FBOVESPA and BCB-DSTAT.

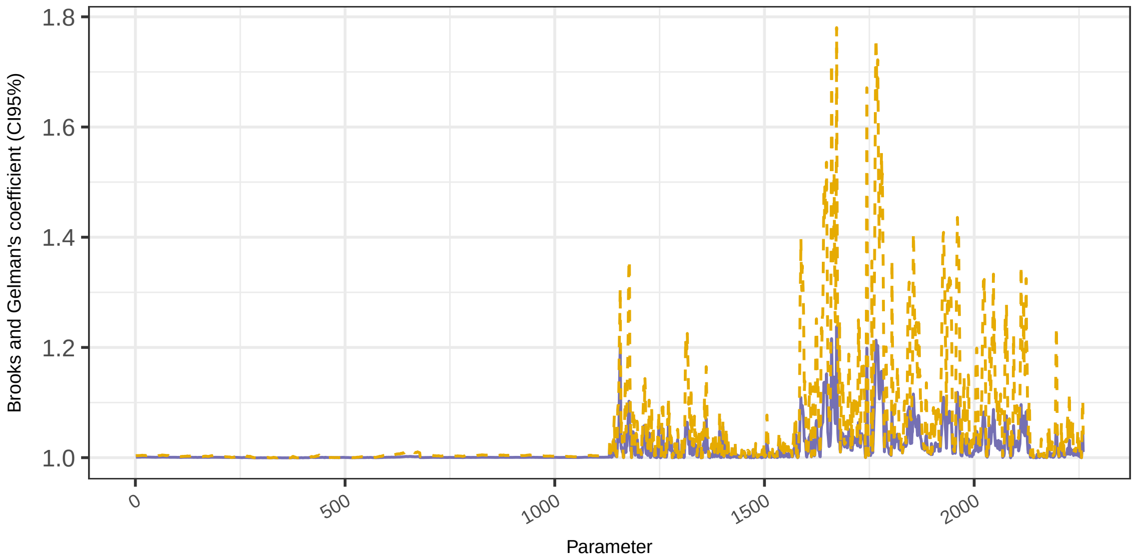
Convergence diagnosis

We obtained 10 thousand posterior draws for each parameter after a burn-in of 5 thousand iterations and kept one in four draws. In other words, we ran the model 5000 times and discarted this initial values. After that, we generated more 10000 values for each parameter but saved only 2500. The burn-in procedure is necessary to enforce that the draws come from the real full conditional posterior, whilst the discard of one in four values helps to prevent autocorrelation between draws.

Since the models is highly parametrized, diagnosis poses a challenge. Here we are following Primiceri (2005) and exhibiting the graph for the partial autocorrelation function (paf) considering the first difference parameters of the variable in its own equation (for example, the β upfront the K/L value at $t-1$ in the K/L equation) and the volatility of each VAR equation. The lags considered for the ACF were 20, 100 and 1000. The graphic in Figure 9 shows the ACF evaluated for these three lags, for each selected parameter.

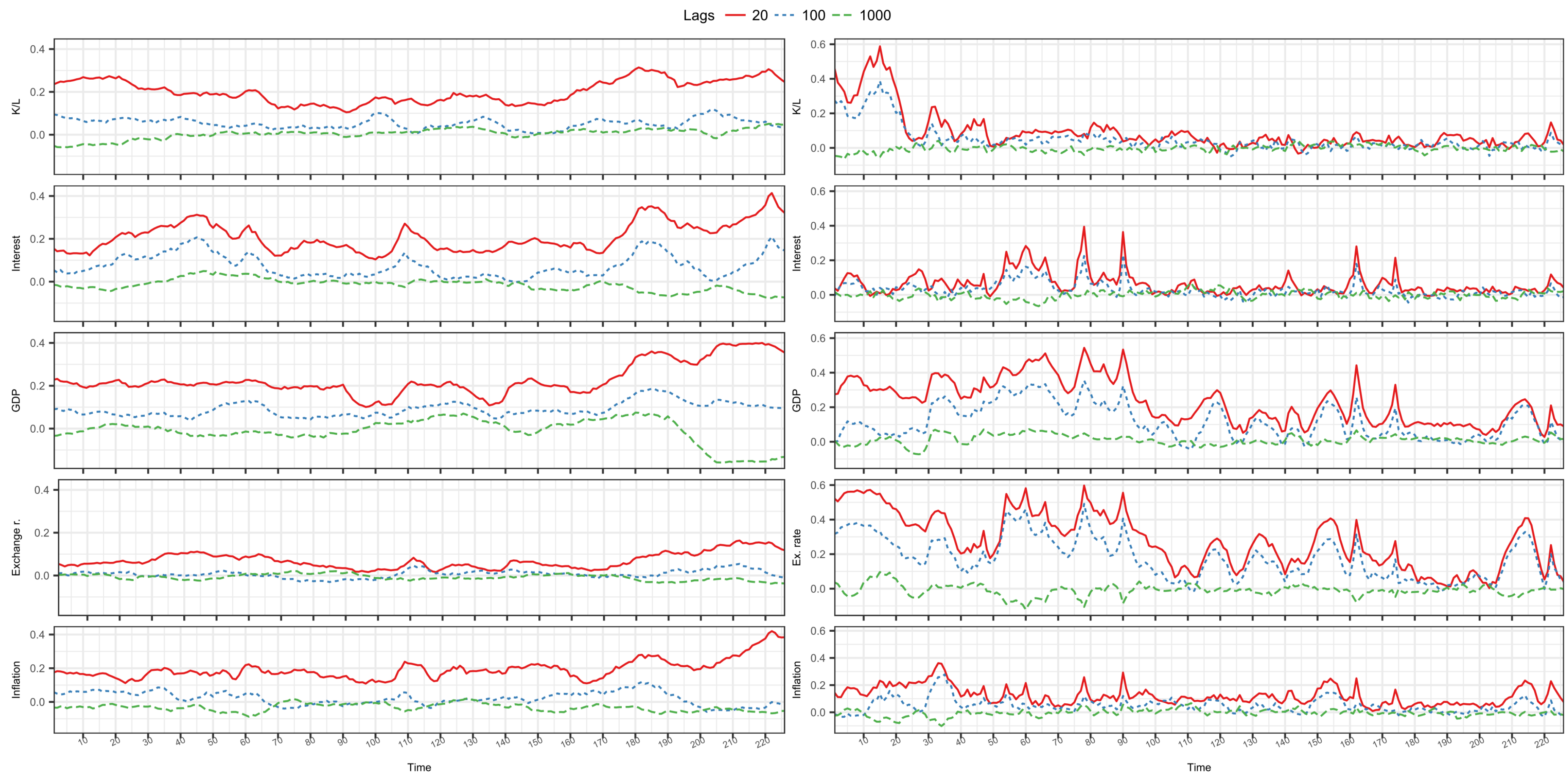
An additional convergence check is made simulating two distinct models (with different random seeds but with the same data) to calculate a potential scale reduction factor for each parameter and one multivariate factor considering the global convergence of the chain Brooks and Gelman (1998). In this stage, we replicated the same setup: 5 series, burn-in equal to 50.000 followed by 10.000 draws where one in four was kept. We calculated the Gelman factor for each first lag coefficients on the measurement equations and for the standar deviations at each time t ($t \in \{1, \ldots, 226\}$). Figure (8) contains the Gelman coefficients with their respective superior values of the 95% confidence interval. It is possible to observe that the right part of the graph, which corresponds to the standard deviations, is higher than the first part, which could suggest convergence problems for the volatilities.

Figure 8: Brooks-Gelman Diagnostic Statistics for selected coefficients and volatilities of the TVP-VAR



Computed values of the Brooks and Gelman's statistics for 2.140 selected model parameters: coefficients of the first and second lag of each variable in its own equation and volatilities of each equation, all evaluated for each one of the 226 periods considered in the posterior analysis. The Brooks and Gelman's statistics consider two independent chains and computes a positive number for each one of the parameters and values more close to 1, are considered better. The overall multivariate statistics for this two samples was equal to 3.4. Values close to one indicate that the chain converged. In the graph, the statistic is represented by the purple continuous line while the superior value of the 95% confidence interval is represented by the dashed yellow line. Roughly the first half values (in the left) are the measurement equation coefficients and the second half on the right are the volatilities. This was based on two 10k simulations using a burn-in equal to 300k iterations.

Figure 9: Autocorrelation function for selected parameters



The autocorrelation function (y axis) is based on 2500 values of each parameter. We calculated the ACF the first lag parameter of each variable in its own equation (left side) and volatilities of each variable (right side), considering the lags 20 (continuous - red line), 100 (dotted - blue line) and 1000 (dashed - green line). Each parameter was evaluated for all 226 posterior time periods, which runs along the x axis. This was based on 2.500 values taken in equally spaced intervals from 10.000 posterior draws, using a burn-in equal to 200 thousand iterations.