Identification of monetary shocks through the yield curve: Evidence for Brazil

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Abstract This paper derives a new measure of monetary shock for Brazil based on the yield curve. First, the Diebold and Li (2006) model is estimated with nominal yields. The changes of the latent variables of this model surrounding monetary policy meetings are used to analyze the effects on the Brazilian economy. Monetary policy decisions associated with steeper yield curves lead to higher future economic activity.

Keywords: Monetary policy; Yield curve.

JEL Code: E43, E52, G12.

1. Introduction

This paper derives a new measure of monetary shocks for Brazil, based on changes of the yield curve around monetary policy decisions. To obtain this new measure, first we estimate the Diebold and Li (2006) model with nominal yields. Then, we use the latent variables of this model to obtain the new shock series, which are used to assess the impact of monetary policy on the economy, through local projections.

This approach, therefore, takes into account variations of the whole yield curve around monetary policy announcements, rather than only short-term rates. Particularly after the Global Financial Crisis (GFC) of 2008, a number of countries used forward guidance and large-scale asset purchases (LASP) to try to stimulate their economies in the context of the lower bound of nominal interest rates. Forward guidance is usually associated with actions taken by central banks to influence interest rate expectations over the medium term. LASP policies, in turn, try to reduce long-term interest rates by reducing the term premium. The approach used in this paper has the advantage of capturing these dimensions of policy and can, therefore, be applied both to conventional and unconventional times. This approach follows recent research of Inoue and Rossi (2018) and Kortela and Nelimarkka (2020).
The literature on identification of monetary shocks is vast. Christiano et al. (1999) provide an early summary of identification based on the recursiveness assumption of VARs. In this approach, the main idea is that the policy interest rate reacts contemporaneously to output and inflation, but these variables react with a lag to innovations or exogenous movements in interest rates. Identification based on VAR with sign restrictions developed from Uhlig (2005). The dynamic stochastic general equilibrium (DSGE) literature, departing from Smets and Wouters (2007), identifies monetary shocks as the residuals of Taylor rules. Another approach, based on the narrative method of Romer and Romer (2004), regresses the policy rate on forecasts of GDP and inflation, and their revisions relative to previous quarters. These forecasts and revisions capture the endogenous component of monetary policy, while the residuals are taken as a shock measure, i.e., movements in the policy rate that do not reflect the state of the economy.

The idea of using financial market data, particularly fed fund futures, to identify monetary shocks can be traced back to Rudebusch (1998), Bagliano and Favero (1999), Kuttner (2001), and Faust et al. (2004). This identification scheme has the advantage of capturing the forward-looking behavior of monetary policy. This approach evolved to identification of monetary shocks based on exogenous changes in the principal components or factors extracted from a cross-section of interest rates. Gürkaynak et al. (2005) use a target and a path factor — this one closely related to the statements of the Fed — finding that long-term yields are very sensitive to the latter. Barakchian and Crowe (2013) develop a monetary shock measure extracting factors from fed fund futures. They use the first factor, interpreted as a level shock, to identify the responses of output and inflation to monetary policy. A recent example of this approach is Altavilla et al. (2019), who extract factors from changes in yields from one month to ten years around the press releases and conferences of the European Central Bank. They study the effects of monetary policy on stock prices, inflation-linked swaps, and the euro-dollar exchange rate.

Relative to the approach of extracting factors to measure monetary shocks, the approach in this paper estimates the Diebold and Li (2006) model, based on Inoue and Rossi (2018) and Kortela and Nelimarkka (2020). The advantage is that in the factor approach, the loadings are relatively unrestricted, while the Diebold and Li (2006) model imposes more discipline on the loadings (Diebold et al., 2005).

Recent papers often use high-frequency identification, based on intraday financial data around announcements (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). Ramey (2016) reviews the
literature on macroeconomic shocks, including several approaches to identify monetary shocks. For Brazil, Costa Filho (2017) reviews the empirical evidence, and derives measures based on the methods of Romer and Romer (2004) and Barakchian and Crowe (2013).

Identification of monetary shocks from the yield curve is based on the idea that the term structure contains important information on the expected path of future interest rates and changes in the perception of risk and uncertainty in the economy by financial market participants (Inoue and Rossi, 2019). This information is lost in other approaches to identify shocks. While Brazil has never experienced zero-lower-bound episodes, identifying monetary shocks through the yield curve is likely more informative about other dimensions of monetary policy announcements. For instance, shifts in the whole yield curve are associated not only to changes in short-term policy rates, but also to the expected future path of short-term interest rates conveyed through communication from the central bank.

The content of this paper is of interest to financial market participants, policymakers, and academics, having both practical and theoretical consequences.

The rest of the paper is organized as follows. Section 2 describes the Diebold and Li (2006) model. Section 3 presents the data. Section 4 shows the results of the estimation. Section 5 estimates the effects on inflation, measures of economic activity, and the real exchange rate through local projections. Section 6 estimates the effects on the economy considering the latent variables in all months, regardless of whether monetary policy meetings occurred or not. Section 7 presents a comparison with other monetary shocks in the literature. Finally, section 8 concludes.

2. Diebold and Li (2006) model

In the Diebold and Li (2006) model, the yield curve is a function of three unobservable factors (level, curvature, and slope). Given some restrictions on the factor loadings, these can be interpreted as long-, medium-, and short-term factors, respectively. The model is given by the following function:

\[
r_{\tau,t} = L_t + S_t \left(1 - \frac{e^{-\lambda \tau}}{\lambda \tau}\right) + C_t \left(1 - \frac{e^{-\lambda \tau}}{\lambda \tau} - e^{-\lambda \tau}\right)
\]  

(1)

where \(r_{\tau,t}\) is the annualized zero-coupon interest rate of maturity \(\tau\). For the sake of standardization, we express bond maturities in months \((\tau = 1, 3, 6, 12, 18, 24, 30, 36, 48, 60, 120)\), not years. This follows Diebold and Li (2006),
Diebold et al. (2006), and Caldeira et al. (2010), who express bond maturity in months.

$L_t, S_t$, and $C_t$ are the level, slope, and curvature factors, respectively, and $\lambda$ is a constant that governs the exponential rate of decay of the loadings. The greater this parameter, the faster is the decay of long-term maturities. The loading on the first factor is constant, affecting all interest rates in the same way, so it determines the level of the curve. The loading on the slope factor affects short rates more than long rates, and the loading of the curvature factor exerts more impact on medium-term rates.

The model is expressed in state space form and estimated by maximum likelihood using the Kalman Filter, following Diebold et al. (2006). Caldeira et al. (2010) defend the estimation of the Diebold-Li model using only one step and making use of the Kalman filter as opposed to the two-step method, since it leads to efficient parameter estimates, as the measurement and state equations are estimated jointly, and also due to the fact that in the one-step estimation there is no need to assume a particular value for the decay parameter $\lambda$.

Departing from Equation (1) for $\tau = 1, 3, 6, 12, 18, 24, 30, 36, 48, 60, 120$ months, the measurement equations are given by

$$r_t = \Lambda f_t + \xi_t,$$

where

$$r_t = [r_{1,t} \quad r_{3,t} \quad r_{6,t} \quad r_{12,t} \quad r_{18,t} \quad r_{24,t} \quad r_{30,t} \quad r_{36,t} \quad r_{48,t} \quad r_{60,t} \quad r_{120,t}]',$$

$\Lambda$ is the $11 \times 3$ matrix whose $\tau$th row is

$$\begin{bmatrix}
    1 \\
    \frac{1-e^{-\tau \lambda}}{\tau \lambda} \\
    \frac{1-e^{-\tau \lambda}}{\tau \lambda} - e^{-\tau \lambda}
\end{bmatrix},$$

and where $f_t = [L_t \quad S_t \quad C_t]'$ and

$$\xi_t = [\varepsilon_{1,t} \quad \varepsilon_{3,t} \quad \varepsilon_{6,t} \quad \varepsilon_{12,t} \quad \varepsilon_{18,t} \quad \varepsilon_{24,t} \quad \varepsilon_{30,t} \quad \varepsilon_{36,t} \quad \varepsilon_{48,t} \quad \varepsilon_{60,t} \quad \varepsilon_{120,t}]'.$$

The state equations form a VAR(1):

$$(f_t - \mu) = A (f_{t-1} - \mu) + \xi_t$$

where $\mu_L, \mu_S$, and $\mu_C$ denote the means of the factors and $f_t = [L_t \quad S_t \quad C_t]'$,

$$A = \begin{bmatrix}
    a_{1,1} & a_{1,2} & a_{1,3} \\
    a_{2,1} & a_{2,2} & a_{2,3} \\
    a_{3,1} & a_{3,2} & a_{3,3}
\end{bmatrix}$$
and $\mu = [\mu_L \mu_S \mu_C]'$, so that Equation (3) can be specified in more detail as

$$
\begin{bmatrix}
L_t - \mu_L \\
S_t - \mu_S \\
C_t - \mu_C
\end{bmatrix}
= 
\begin{bmatrix}
a_{1,1} & a_{1,2} & a_{1,3} \\
a_{2,1} & a_{2,2} & a_{2,3} \\
a_{3,1} & a_{3,2} & a_{3,3}
\end{bmatrix}
\begin{bmatrix}
L_{t-1} - \mu_L \\
S_{t-1} - \mu_S \\
C_{t-1} - \mu_C
\end{bmatrix} + 
\begin{bmatrix}
\xi_{1t} \\
\xi_{2t} \\
\xi_{3t}
\end{bmatrix}.
$$

(4)

For the errors, the assumption is that the terms in the measurement equations are not cross-correlated, but can be correlated in the state equations. Therefore, it is allowed that the covariance between the level, slope, and curvature factors may be different from zero. In other words, it is assumed that the $\xi_{jt}$ are mutually correlated, while the $\varepsilon(\tau,t)$ are mutually independent and uncorrelated with $\xi_{jt}$, for $j = L,S,C$.

3. Data

To estimate the Diebold-Li model, nominal yields of eleven maturities are used: 1-month, 3-month, 6-month, 1-year, 1.5-year, 2-year, 2.5-year, 3-year, 4-year, 5-year, and 10-year. The data is on a daily basis, ranging from the beginning of 2004 to the end of 2019, encompassing 4,174 observations. The series used in the estimation were downloaded from Bloomberg, with the following tickers: PREDI30, PREDI90, PREDI180, PREDI360, PREDI540, PREDI720, PREDI900, PREDI1080, PREDI1440, PREDI1800 and PREDI2520 Index. Figure 1 depicts most series used in the estimation.

4. Results

Table 1 presents the estimated coefficients of the Diebold-Li model presented in Section 2.

For the estimation, the initial values of the level ($\mu_L = 12$), slope ($\mu_S = 1$), and curvature ($\mu_C = 0.7$) are set at their empirical counterparts. The initial value of the speed of adjustment parameter ($\lambda = 0.1$) is set at a value close to that of Caldeira et al. (2010). Parameters of the matrix A are initialized with 0.5, along with all standard deviations of the measurement equations. The standard deviations of the latent factors and their covariances are initialized with 1.

Except for the averages of the slope ($\hat{\mu}_S$) and the curvature ($\hat{\mu}_C$), all other estimated coefficients are statistically significant. The mean level is estimated at $\hat{\mu}_L = 14.56$.

Considering the state equations, the level is positively affected by previous deviations from its mean ($\hat{a}_{11} = 0.433$), negatively affected by previous...
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Table 1
Estimates of the parameters of the Diebold-Li model

<table>
<thead>
<tr>
<th>parameter</th>
<th>initial value</th>
<th>estimate</th>
<th>std. error</th>
<th>z-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{11}$</td>
<td>0.5</td>
<td>0.433</td>
<td>0.038</td>
<td>11.13</td>
<td>0.000</td>
</tr>
<tr>
<td>$a_{12}$</td>
<td>0.5</td>
<td>-0.20</td>
<td>0.041</td>
<td>-4.77</td>
<td>0.000</td>
</tr>
<tr>
<td>$a_{13}$</td>
<td>0.5</td>
<td>0.779</td>
<td>0.052</td>
<td>14.94</td>
<td>0.000</td>
</tr>
<tr>
<td>$a_{21}$</td>
<td>0.5</td>
<td>-0.24</td>
<td>0.103</td>
<td>-2.37</td>
<td>0.017</td>
</tr>
<tr>
<td>$a_{22}$</td>
<td>0.5</td>
<td>0.952</td>
<td>0.046</td>
<td>20.39</td>
<td>0.000</td>
</tr>
<tr>
<td>$a_{23}$</td>
<td>0.5</td>
<td>0.302</td>
<td>0.135</td>
<td>2.226</td>
<td>0.026</td>
</tr>
<tr>
<td>$a_{31}$</td>
<td>0.5</td>
<td>0.384</td>
<td>0.119</td>
<td>3.208</td>
<td>0.001</td>
</tr>
<tr>
<td>$a_{32}$</td>
<td>0.5</td>
<td>0.280</td>
<td>0.045</td>
<td>6.168</td>
<td>0.000</td>
</tr>
<tr>
<td>$a_{33}$</td>
<td>0.5</td>
<td>0.337</td>
<td>0.150</td>
<td>2.237</td>
<td>0.025</td>
</tr>
<tr>
<td>$\mu_L$</td>
<td>12</td>
<td>14.56</td>
<td>4.193</td>
<td>3.472</td>
<td>0.000</td>
</tr>
<tr>
<td>$\mu_S$</td>
<td>1</td>
<td>-0.56</td>
<td>4.059</td>
<td>-0.13</td>
<td>0.889</td>
</tr>
<tr>
<td>$\mu_C$</td>
<td>0.7</td>
<td>0.068</td>
<td>4.078</td>
<td>0.016</td>
<td>0.986</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.1</td>
<td>0.105</td>
<td>0.005</td>
<td>20.58</td>
<td>0.000</td>
</tr>
</tbody>
</table>

std dev  | initial value | estimate | std. err. | z-statistic | p-value |
<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>sd($\varepsilon_{1,t}$)</td>
<td>0.5</td>
<td>0.494</td>
<td>0.036</td>
<td>13.49</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{3,t}$)</td>
<td>0.5</td>
<td>0.483</td>
<td>0.089</td>
<td>5.376</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{6,t}$)</td>
<td>0.5</td>
<td>0.480</td>
<td>0.065</td>
<td>7.308</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{12,t}$)</td>
<td>0.5</td>
<td>0.483</td>
<td>0.069</td>
<td>6.933</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{18,t}$)</td>
<td>0.5</td>
<td>0.488</td>
<td>0.073</td>
<td>6.676</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{24,t}$)</td>
<td>0.5</td>
<td>0.481</td>
<td>0.093</td>
<td>5.141</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{30,t}$)</td>
<td>0.5</td>
<td>0.453</td>
<td>0.098</td>
<td>4.603</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{36,t}$)</td>
<td>0.5</td>
<td>0.477</td>
<td>0.137</td>
<td>3.474</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{48,t}$)</td>
<td>0.5</td>
<td>0.469</td>
<td>0.090</td>
<td>5.199</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{60,t}$)</td>
<td>0.5</td>
<td>0.417</td>
<td>0.047</td>
<td>8.756</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($\varepsilon_{120,t}$)</td>
<td>0.5</td>
<td>0.486</td>
<td>0.020</td>
<td>23.59</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($L_t$)</td>
<td>1</td>
<td>0.990</td>
<td>0.098</td>
<td>10.02</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($S_t$)</td>
<td>1</td>
<td>0.976</td>
<td>0.233</td>
<td>4.182</td>
<td>0.000</td>
</tr>
<tr>
<td>sd($C_t$)</td>
<td>1</td>
<td>0.990</td>
<td>0.428</td>
<td>2.313</td>
<td>0.020</td>
</tr>
<tr>
<td>Cov($L_t, S_t$)</td>
<td>1</td>
<td>0.954</td>
<td>0.267</td>
<td>3.567</td>
<td>0.000</td>
</tr>
<tr>
<td>Cov($L_t, C_t$)</td>
<td>1</td>
<td>1.396</td>
<td>0.473</td>
<td>2.951</td>
<td>0.003</td>
</tr>
<tr>
<td>Cov($S_t, C_t$)</td>
<td>1</td>
<td>1.163</td>
<td>0.612</td>
<td>1.901</td>
<td>0.057</td>
</tr>
</tbody>
</table>

Log Likelihood: -24545
Akaike criterion: 11.77
Schwarz criterion: 11.82
HQ criterion: 11.79
deviations of the slope from the mean ($\hat{a}_{12} = -0.20$), and positively influenced by previous deviations of the curvature state from its mean ($\hat{a}_{13} = 0.77$). The slope state is negatively affected by previous deviations of the level from its mean ($\hat{a}_{21} = -0.24$), and positively affected by previous deviations of the slope and the curvature from their means ($\hat{a}_{22} = 0.952$) and ($\hat{a}_{23} = 0.302$). Finally, the curvature state is positively affected by previous deviations of the level, slope and curvature states from their means, with estimated coefficients $\hat{a}_{31} = 0.384$, $\hat{a}_{32} = 0.28$, and $\hat{a}_{33} = 0.337$.

The standard deviations of the measurement equations — from $sd(\varepsilon_{1,t})$ to $sd(\varepsilon_{120,t})$ — are all statistically significant at the 1% level. The standard deviations of the latent variables are estimated at $\hat{sd} (L_t) = 0.99$, $\hat{sd} (S_t) = 0.976$, and $\hat{sd} (C_t) = 0.99$ for the level, slope, and curvature, respectively. The covariance between the level and the slope is estimated at $\hat{Cov} (L_t, S_t) = 0.954$, the covariance between the level and curvature is estimated at $\hat{Cov} (L_t, C_t) = 1.396$, while the covariance between the slope and curvature is estimated at $\hat{Cov} (S_t, C_t) = 1.163$.

The decay parameter, which governs the exponential decay rate, is estimated at $\hat{\lambda} = 0.10$. This figure is very close to the one obtained by Caldeira et al. (2010) using daily data from 2006 to 2009 for Brazil in a single-step
estimation, $\lambda = 0.1047$. Diebold and Li (2006) fix $\lambda = 0.0609$ in the estimation with nominal yields and monthly data. Diebold et al. (2006) estimate $\lambda = 0.077$, also with U.S. Treasury nominal yields at the monthly frequency in a single-step estimation.

The filtered states of the estimated Diebold-Li model, along with their empirical counterparts, are presented in Figure 2 above. Filtered estimates are closer to real-time estimates, since the estimation of the latent variables uses past and current, but not future, data. Nonetheless, the full sample is used to estimate the parameters of the model. While the Diebold-Li model is estimated at the daily frequency, Figure 2 depicts the quarterly average values of the filtered states obtained from the estimation of the model. The empirical level is represented by the 10-year yield, the empirical slope is represented by the difference between the 10-year and the 1-month yield, and the empirical curvature is twice the 5-year yield minus the sum of the 1-month and the 10-year yield. The correlation between the level obtained from the model and the empirical level is 0.98, the correlation between the slope and the empirical slope is 0.99, and the correlation between the curvature and the empirical curvature is 0.48.

The level of the curve can be thought of as a measure of the nominal neutral rate of the economy in real time, since the level is considered the
long-run factor, unaffected by monetary policy.\(^1\)

Overall, the level of the nominal curve since 2004 shows a marked downward trend, although with some spikes and volatility during specific episodes. Considering monthly data, the level of the curve fell from more than 16% p.a. in June 2006 to less than 10% p.a. in May 2007. After that, it began to ascend, peaking at 18% p.a. at the height of the financial crisis in October 2008. Another downward period was from March 2012 to May 2013, when the level declined from 11% p.a. to a trough of 9.5% p.a. immediately before the Taper Tantrum in 2013. After this episode, the level of the curve climbed again, reaching a peak of more than 13% p.a in January 2014. After some stabilization at the level of 11% p.a., the level peaked again in January 2016, reaching more than 16% p.a. in the middle of the recession and political crisis of 2014-2016. From 2016 to 2018, the level of the curve stabilized between the range of 11 and 13% p.a. After September 2018, the level of the curve began another downward phase, descending from 12.5% p.a. to around 7.5% p.a. at the end of 2019. Considering an inflation target of 4% in 2020, these results are consistent with an implied neutral real rate of 3.5% at the end of 2019.

5. Effects of monetary shocks on the Brazilian economy

Having estimated the Diebold and Li (2006) model and obtained the latent variables of the nominal yield curve (level, slope, and curvature) in Section 4, this section estimates the impact of changes in these variables surrounding monetary policy decisions on economic activity and inflation. More specifically, each monetary policy meeting from 2004 to 2019 is associated with changes in the level, slope, and curvature obtained from the Diebold and Li model. The change in the latent variables is computed from the business day immediately after the meeting and the day of the meeting (usually on Wednesday).

In this estimation, data is at the monthly frequency. For inflation, the non-regulated (freely determined) Brazilian consumer price index (Índice Nacional de Preços ao Consumidor Amplo, or IPCA) is used. The measure of economic activity is the IBC-Br index of the Central Bank of Brazil. In the estimations below, the log of the seasonally-adjusted series is used, computed as \(100 \times \log(IBC-Br)\). For the real exchange rate, we also use the log of the series, computed as \(100 \times \log(REER)\). The series for inflation, IBC-

\(^1\)Considering the expression for \(r_{t}^{\tau}\) in Equation (1), taking the limit \(\lim_{\tau \to +\infty} r_{t}^{\tau} = L_t\), so the level of the curve corresponds to the longest available yield, and is usually associated with technology shocks (Wu, 2006).
Br, and real exchange rate are downloaded from the SGS\textsuperscript{2} database of the Central Bank of Brazil, with code series 11,428 for inflation, 24,364 for the seasonally-adjusted IBC-Br series, and 11,752 for the index of the real effective exchange rate deflated by the IPCA. Higher values of the real exchange rate series mean that the Brazilian Real is more devalued, relative to other currencies.

The first row in Figure 4 depicts the data. The second row shows the changes of the latent variables in months in which there were monetary policy meetings, hence the fluctuations around zero. The third row presents the latent variables, basically repeating the information in Figure 2.

Since 2006, monetary policy meetings take place eight times per year. The interest of this paper lies in the effects of monetary policy decisions on the yield curve, and then on the economy. Due to the monthly frequency of the data, for the estimations in this section, months in which no monetary policy meeting happened are assigned a value of 0 for the changes in the level, slope, and curvature latent variables. Therefore, even though for estimation we have data for inflation and economic activity for each month, only months that had monetary policy decisions are associated with their corresponding

\textsuperscript{2} Sistema Gerenciador de Séries Temporais.
changes in the level, slope, and curvature surrounding the announcements. We assign these changes around the days of the meetings to the month in which the meeting took place. In mathematical terms, in the estimations below the vector of shocks is given by

\[
\begin{bmatrix}
\text{level shock} \\
\text{slope shock} \\
\text{curvature shock}
\end{bmatrix} = \begin{bmatrix} \Delta L_t \\ \Delta S_t \\ \Delta C_t \end{bmatrix} d_t,
\]

where \(d_t\) is a dummy variable equal to 1 in months with monetary policy meetings and 0 otherwise.

We perform the estimation using local projections, based on Jordà (2005). As Ramey (2016, p. 40) explains, local projections put fewer restrictions on the impulse responses. Rather than estimating impulse responses based on nonlinear functions of the reduced-form parameters, local projections estimate regressions of the dependent variable at horizon \(t + h\) on the shock in period \(t\), and use the coefficients on the shock as impulse response estimates. Inoue and Rossi (2018) also use local projections. The general form of local projections is

\[ z_{t+h} = \alpha_h + \theta_h \text{shock}_t + \text{control variables} + \epsilon_{t+h}, \quad (5) \]
where $z$ is the variable of interest (either the shock itself, inflation, output, or the real exchange rate), and $\theta_h$ is the estimate of the impulse response of $z$ at horizon $h$ to a shock at time $t$. In the estimations, $h = \{1, 2, \ldots, 36\}$. All impulse responses displayed show 90% confidence bands.

Figure 5 depicts the response of inflation, output (log of the seasonally-adjusted IBC-Br), and the real exchange rate to a shock on the slope. The control variables in this case are $\text{level}_t$, $\text{level}_{t-1}$, $\text{level}_{t-2}$, $\text{curvature}_t$, $\text{curvature}_{t-1}$, $\text{curvature}_{t-2}$, $\text{inflation}_t$, $\text{inflation}_{t-1}$, $\text{inflation}_{t-2}$, $(\log \text{ibcbr})_t$, $(\log \text{ibcbr})_{t-1}$, $(\log \text{ibcbr})_{t-2}$, $\text{rer}_t$, $\text{rer}_{t-1}$, and $\text{rer}_{t-2}$, where rer stands for the real exchange rate. Equation (4) also includes two lags of the shock variable, so in case of the slope shock, shock includes $\text{slope shock}_t$, $\text{slope shock}_{t-1}$, and $\text{slope shock}_{t-2}$.

In response to a slope shock (steeper yield curve) of 1%, economic activity increases by almost 5% in the medium run and is statistically significant. The response of the real exchange rate is muted in the short run, but there is a depreciation of the Real after around 20 months.3

3This could reflect some noise in the estimation. Plagborg-Møller and Wolf (2020, p. 25) show that local projections impulse responses display more erratic behavior relative to VAR on longer horizons. In their words: “At long horizons, the iterated VAR structure enforces a smooth return to 0, while direct local projections give more erratic impulse responses.” They simulate the
The response of inflation is quite volatile. The maximum impact occurs 10 months after the shock, with inflation increasing by around 0.5%. The overall behavior of the impulse responses is consistent with monetary policy decisions associated with steeper yield curves corresponding to stimulative monetary policy. Conventional monetary policy is related to changes in the slope, since management of short-term interest rates and lack of power over long-term rates reflect on the slope of the yield curve. This is consistent with researchers who relate the slope with cyclical features of the economic cycle (Dewachter and Lyrio, 2006; Rudebusch and Wu, 2008; Wu, 2006). There is an almost-perfect correlation between the slope and the empirical slope, as depicted in Figure 2, which gives us confidence that the shock is well-identified.

Figure 6 depicts the response of inflation, output (log of the seasonally-adjusted IBC-Br), and the real exchange rate to a shock on the curvature. The control variables in this case are $\text{slope}_t$, $\text{slope}_{t-1}$, $\text{slope}_{t-2}$, $\text{level}_t$, $\text{level}_{t-1}$, $\text{level}_{t-2}$, $\text{inflation}_t$, $\text{inflation}_{t-1}$, $\text{inflation}_{t-2}$, $(\log\text{ibcbr})_t$, $(\log\text{ibcbr})_{t-1}$, $(\log\text{ibcbr})_{t-2}$, $\text{rer}_t$, $\text{rer}_{t-1}$, and $\text{rer}_{t-2}$, where $\text{rer}$ stands for the real exchange rate. Equation (4) also includes two lags of the shock variable, so in case of the curvature shock, $\text{shock}$ includes $\text{curvature shock}_t$, $\text{curvature shock}_{t-1}$, and $\text{curvature shock}_{t-2}$.

In response to a curvature shock, economic activity responds negatively, with the IBC-Br dropping by 1%, but the confidence bands are wide. The behavior of inflation is again very volatile and economically small, varying between $-0.2\%$ and $0.2\%$, and most of the time lacks statistical significance. The effect of the shock on the real exchange rate also lacks statistical significance most of the time.

The curvature is often associated with medium-term effects of monetary policy, through expectations and interest rates, such as forward guidance (Inoue and Rossi, 2019; Kortela and Nelimarkka, 2020). Earlier studies either find no significant link between the curvature factor and macroeconomic variables (Diebold et al., 2006), or link the curvature factor to movements in real interest rates unrelated to macroeconomic conditions, associated to the stance held by the central bank (Dewachter and Lyrio, 2006).

One possible reason for the lack of significance of the curvature shock for Brazil is that the country has not experienced unconventional monetary policy in the same way as in advanced countries, so monetary policy would
be reflected mainly on the slope.

Figure 7 depicts the response of inflation, output (log of the seasonally-adjusted IBC-Br), and the real exchange rate to a shock on the level. The control variables in this case are $\text{slope}_t$, $\text{slope}_{t-1}$, $\text{slope}_{t-2}$, $\text{curvature}_t$, $\text{curvature}_{t-1}$, $\text{curvature}_{t-2}$, $\text{inflation}_t$, $\text{inflation}_{t-1}$, $\text{inflation}_{t-2}$, $(\log \text{ibcbr})_t$, $(\log \text{ibcbr})_{t-1}$, $(\log \text{ibcbr})_{t-2}$, $\text{rer}_t$, $\text{rer}_{t-1}$, and $\text{rer}_{t-2}$, where $\text{rer}$ stands for the real exchange rate. Equation (4) also includes two lags of the shock variable, so in case of the level shock, $\text{shock}$ includes $\text{levelshock}_t$, $\text{levelshock}_{t-1}$, and $\text{levelshock}_{t-2}$.

In response to a shock of 1% on the level of the curve, which corresponds to an increase in the long-term rate, there is an initial positive effect on the IBC-Br, but the impact soon turns negative in the medium run. Inflation responds with high volatility, ranging between $-0.5\%$ and $0.5\%$. The impact is first positive until 10 months, and then turns negative. The shock initially leads to an appreciation of the real exchange rate, but before 10 months the shock fades. One possible interpretation is that higher long-term interest rates due to the shock attract capital inflows, appreciating the exchange rate.

These results of appreciated real exchange rate in response to higher interest rates is consistent with the theory of uncovered interest parity (UIP),
which states that the exchange rate appreciates following higher interest rates, but this is matched by expectations of a depreciated exchange rate over time.

6. Robustness to non-meeting months

In the previous section, we restricted our analysis to months with monetary policy meetings. In months without monetary policy meetings, the monetary shock was assigned a zero value. This section presents the impulse response considering shocks on the slope and level, regardless of whether there was a monetary policy meeting in a given month. The motivation for this exercise is that the central bank can influence the yield curve even in non-policy-meeting months, through communications, speeches, and hearings in Congress, for example. The curve might react to the release of macroeconomic indicators, external developments, and several other factors, in addition to monetary policy actions. The intention of this section, then, is to see how these movements feed back into the economy. The controls correspond to those used to obtain Figures 5 and 7, respectively.

The first feature is that now the shock is more persistent than the one in Figure 5. In response to a 1% steeper curve, economic activity gradually rises, with a peak effect of 2% between 10 and 20 months. The real exchange
rate appreciates along with the rise in economic activity. Both effects are statistically significant. The dynamics of inflation after the shock are very volatile, and most of the time not statistically significant.

In response to a rise of 1% in the level of the yield curve, economic activity drops by almost 4% after around 10 months. The real exchange rate depreciates by almost 5%. A possible reason is that the rise of long-term yields represented by the increase in the level of the curve is accompanied by capital outflows, weakening the currency. In this case, the impulse responses to a level shock encompass all months, regardless of whether they had a monetary meeting or not, so it likely captures all factors that affect the level of the curve. Examples of these factors include news about fiscal policy, monetary policy in advanced economies, macroeconomic announcements, inflation risk premium, etc. In contrast, Figure 7 presents the impulse responses to a level shock on days when monetary policy meetings were held. These likely reflect more purely the effects of monetary announcements.

Inflation increases by around 0.2% after the shock. All responses are statistically significant.
7. Comparison with other measures of monetary shocks

This section compares the changes in the latent variables obtained from the Diebold-Li model around monetary announcements — taken as a measure of shock — with other shocks in the literature. This is motivated by a similar exercise performed by Inoue and Rossi (2018). Table 2 shows the derivation by Romer and Romer (2004) of monetary shocks for Brazil. These shocks are derived from a regression of the policy rate on forecasts and changes of forecasts of inflation and GDP growth. The goal is to capture exogenous movements in the policy rate, using private forecasts to capture the endogenous component, related to the state of the economy. Romer and Romer (2004) run the following regression:

\[
\Delta f_{f,m} = \alpha + \beta f_b f_{b,m} + \sum_{i=-1}^{2} \gamma_i \Delta y_{m_i} \\
+ \sum_{i=-1}^{2} \lambda_i (\Delta y_{m_i} - \Delta y_{m_i-1,i}) + \sum_{i=-1}^{2} \varphi_i \pi_{m_i} \\
+ \sum_{i=-1}^{2} \theta_i (\pi_{m_i} - \pi_{m_i-1,i}) + \varepsilon_m, \tag{6}
\]

Figure 9
Level shock

- Level shock
- IBC-BR
- IPCA
- REAL FX
where $\Delta f_{f m}$ is the change in the policy rate (the fed funds rate in the US) at meeting $m$, $f_{b m}$ is the level of the policy rate before any changes associated with meeting $m$, included to capture any mean reversion behavior from the central bank, and $\pi$ and $\Delta y$ refer to the forecasts of inflation and real output growth. Finally, the $i$ transcript refers to the horizon of the forecast: $-1$ is the previous quarter; 0 is the current quarter; and 1 and 2 are one and two quarters ahead. For Brazil, we first construct constant maturity expectations for inflation and GDP growth from the survey of the Central Bank of Brazil and use these series in the regression above.\footnote{Using Central Bank of Brazil survey data for subsequent years, we construct constant maturity GDP growth and inflation expectations with the following equation: $\text{exp}_{t,j} = 12^{-1}((13-j)\text{exp}_t + (j-1)\text{exp}_{t+1})$, where $j$ refers to the month for which the expectations were collected, $t = 1,2,3$ refers to the year ahead considered, and $\text{exp}$ denotes expectations for inflation or GDP growth.}

The shocks are the residuals from the regression, i.e., policy rate movements unrelated to the state of the economy, captured by the forecasts. Table 2 presents the estimated model to obtain the shocks. In Table 2, selic\_ant refers to the level of the policy interest rate (Sistema Especial de Liquidação e Custodia, or SELIC) decided in the previous meeting, inf\_1y, inf\_2y, and inf\_3y stand for the expected inflation 1, 2, and 3 years ahead, while growth\_1y is the GDP growth expectation 1 year ahead.

Unlike Section 5, in which estimations of local projection models were based on monthly frequency between January 2003 to December 2019, encompassing 192 observations, in this section the models are estimated at the frequency of monetary policy meetings, comprising 136 observations from 2004 to 2019.

Table 3 presents regressions of the Romer and Romer (2004) shocks (henceforth RR shocks) as the dependent variable using changes of (filtered) latent variables from the Diebold and Li (2006) model as explanatory variables:

$$rr \text{ shocks}_t = \alpha + \beta \Delta \text{latent}_t + \epsilon_t,$$

where $\Delta \text{latent}_t$ is either the change in the level, slope, or curvature. These changes are obtained from the estimation of the Diebold and Li (2006) model in Section 4 around monetary policy meetings.

The results show that RR shocks are negatively related with changes in the slope, with estimated coefficient $\hat{\beta} = -0.76$ in column 2.

Table 4 presents regressions of the RR shocks as the dependent variable using filtered latent variables from the Diebold and Li (2006) model as explanatory variables, along with a measure of the surprise component of mon-
Table 2
Derivation of Romer and Romer (2004) shocks

<table>
<thead>
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<tr>
<td></td>
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<tr>
<td>inf1y</td>
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<td>inf2y</td>
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<td>(0.25)</td>
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<td>(0.22)</td>
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<tr>
<td>R-squared</td>
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Robust standard errors in parentheses. ***: p<0.01, **: p<0.05, *: p<0.1

Table 3
Romer and Romer shocks and latent variables

<table>
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<tr>
<td>R-squared</td>
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<td>0.092</td>
<td>0.016</td>
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</table>

Robust standard errors in parentheses. ***: p<0.01, **: p<0.05, *: p<0.1
etary policy announcements. The general specification of column 3 is therefore

\[ rr \text{ shocks}_t = \alpha + \beta_1 \Delta \text{level}_t + \beta_2 \Delta \text{slope}_t \]
\[ + \beta_3 \Delta \text{curvature}_t + \beta_4 \text{surprise}_t + \varepsilon_t, \]  

where \( rr \text{ shocks}_t \) stands for the RR shocks, \( \Delta \text{level}_t, \Delta \text{slope}_t, \) and \( \Delta \text{curvature}_t \) are, respectively, the changes of the level, slope, and curvature around monetary policy announcements. The surprise component is computed as the difference from the SELIC rate announced in each monetary policy meeting and the expectations from the Central Bank survey in the neighborhood of the meeting. More specifically,

\[ \text{surprise} = \text{selic}_t - E_{t-1}(\text{selic}_t). \]

Through the SGS, the Central Bank of Brazil discloses daily information about the expected SELIC rate at the end of each month. Expectations were collected for the months in which monetary policy meetings took place, on the business day immediately before each meeting. Surprises were then computed as the difference between the actual SELIC rate decided in each meeting and the expected rate.

The results in column 3 show that once all the latent variables are controlled for, a negative and statistically-significant relationship exists between \( rr \text{ shocks} \) and changes in the slope (with estimated coefficient \( \hat{\beta}_2 = -0.81 \)). The simple regression of \( rr \text{ shocks} \) against surprises in column 1 shows a positive and statistically significant relationship (\( \hat{\beta} = 0.96 \)). This variable retains its statistical significance in the multiple regression in column 3 (\( \hat{\beta}_4 = 0.67 \)).

The intuition for the positive coefficient of the surprise variable on RR shocks is that when the central bank raises (or cuts) rates more than would be dictated by the changes in output and inflation, this tends to be associated with higher (or lower) rates than what economists were expecting for each meeting. In turn, RR shocks tend to be negatively associated with the slope of the curve. When the central bank raises (or cuts) rates more than the changes in output and inflation, leading to a positive (negative) RR shock, this tends to be associated with a flatter (steeper) yield curve.

Figure 10 depicts the RR shocks, changes in the slope, and surprises from 2005 onwards. Overall, RR shocks move along with surprises, while there is a negative relationship between these variables and changes in the slope, consistent with results presented in column 3 of Table 4.

This negative relationship is also consistent with Bu et al. (2020), who regress several measures of the slope on different measures of monetary shocks
for the United States. They find that positive monetary shocks lead to higher 5-year interest rates, and mostly negative coefficients of the monetary shocks on the spreads, meaning a flatter slope. They find that their shock measure affects 2- and 5-year rates, which they associate to the notion that the Fed aims to affect rates around this horizon, an assumption that became more appropriate during the zero-lower-bound period.

Considering the period 2005-2019, there were positive RR shocks in 2005. Authorities at the time were resolute to break the backbone of inflation, and positive RR shocks are consistent with policy interest rates higher than would be dictated by forecasts of inflation and GDP growth. The tightening cycle began in December 2004, with the Central Bank of Brazil raising the SELIC to 17.75% p.a. In May 2005 the SELIC rate was raised to 19.75% and was kept at that level until September 2005.

RR shocks show some volatility around zero during 2006-2007. The Central Bank began cutting rates in September 2005, first to 19.50 from 19.75% p.a. The easing cycle was very long, with the SELIC rate reaching 11.25% p.a. in September 2007. This was followed by very low inflation expectations and current inflation at the time. Accordingly, the inflation rate measured by the IPCA finished 2006 at 3.14%, against an inflation target of 4.5%.

There were positive RR shocks ahead of the financial crisis of 2008. In-
flation was under pressure at the time, due to skyrocketing commodity prices. The Central Bank began to raise the SELIC rate in April 2008, lifting rates to 11.75% p.a. The hiking cycle lasted for the remainder of 2008, reaching 13.75% in September 2008. Even with some signs of an upcoming financial crisis, monetary policy followed very closely the prescriptions of the inflation-targeting regime, namely the emphasis on inflation expectations.

In January 2009 the Central Bank began cutting rates, from 13.75% to 12.75%, reaching a trough in April 2010, at 8.75% p.a. This easing cycle after the financial crisis is represented by mostly negative RR shocks observed in 2009-2010. The negative RR shocks during 2011-2012 correspond to the easing cycle which began with the unexpected cut in the SELIC rate in August 2011, from 12.50% to 12% p.a., and lasted until October 2012, when the SELIC rate was cut to 7.25% p.a. Authorities at the time were concerned about potential spillovers of the European sovereign debt crisis on the Brazilian economy, which in their view would help to control inflation.

There were mostly positive RR shocks from 2013 to the end of 2016. In May 2013 the Central Bank embarked on a tightening cycle, in a context of expansionary fiscal policy and the Taper Tantrum shock. The SELIC rate was then raised from 7.25% p.a. in April 2013 to a peak of 14.25% in July 2015 in the turmoil of a severe recession, a shock on regulated prices, and falling commodity prices. In October 2016 the Central Bank began cutting rates, and the negative RR shocks in 2016-2017 correspond to this easing cycle. There were positive shocks from March 2018 to June 2019, amidst the truck drivers’ strike and volatility in financial markets stemming from Turkey and Argentina. These positive shocks mean that the SELIC rate was higher than would be dictated by forecasts of inflation and GDP growth at the time. After the SELIC rate was lowered from 6.75% to 6.50% in March 2018, it was held at that level until September 2019, when the easing cycle resumed. This movement corresponds to the negative RR observed in the final months in Figure 10.

8. Conclusion

This paper sought to contribute to the literature on identification of monetary shocks for Brazil. It was motivated by recent research by Inoue and Rossi (2018) and Kortela and Nelimarkka (2020). Although these authors focus on unconventional monetary policies, their approach can be extended to countries that did not experience zero-lower-bound episodes, since it captures different dimensions of monetary policy, often neglected when only short-term rates are used.
First, the Diebold and Li (2006) model was estimated with nominal yields. A first result is that the level of the nominal yield curve, which can be taken as a real-time measure of the long-term, short-run neutral rate, declined markedly from 2018 onwards, descending from more than 12% p.a. in September 2018 to around 7.5% p.a. at the end of 2019. Considering the inflation target of 4% for 2020, this would be consistent with a long-term, short-run neutral real rate of around 3.5% at the end of 2019.

The changes of the latent variables of this model around monetary policy meetings were used to identify monetary shocks. Using local projections, shocks on the slope were found to be consistent with expansionary monetary policy, leading to higher economic activity. Shocks on the level, which corresponds to the long-term rate, were found to induce a significant decline in economic activity and a weaker real exchange rate. The implication of these results seems to be that the combination of a steep yield curve with a low level (long-term) rate seems to be the best combination, in terms of economic activity.

Adrian et al. (2010) present a theoretical justification for the argument of why steep yield curves are good for the economy in terms of economic activity. The mechanism is through the balance management of financial intermediaries. Steep yield curves tend to increase net interest margins, since
intermediaries borrow short-term and lend long-term. This makes lending more profitable and expands the supply of credit, positively affecting economic activity. The opposite happens when yield curves flatten or invert. This causal mechanism emphasizes the slope of the yield curve as a measure of the stance of monetary policy, rather than interpretations of the behavior of long-term rates based on the expectations theory of the term structure, in which short-term rates are transmitted to long-term rates through expectations.

In a recent paper, Paul (2020) shows that banks’ net interest margins move in a strongly correlated fashion with measures of term premia. Decomposing yields in expected short-term rates and term premia, there is evidence that banks’ stock returns and net interest margins are impacted positively by higher term premia, and negatively by expectations of higher short-term rates in the future. Therefore, steeper yield curves are positive for maturity transformation, as long as they are driven by higher term premia. The policy implication of this finding is that unconventional monetary policies, such as quantitative easing or Operation Twist, that try to lower term premium or flatten the yield curve may have some negative effects on the economy by lowering bank profitability and bank lending.

Earlier literature based on reduced-form estimations, reviewed by Rudebusch et al. (2006), showed that lower (higher) term premium was associated with slower (higher) future growth, consistent with the “banking view” evidence of Paul (2020). In turn, Rudebusch et al. (2006) present evidence that declines in term premium are associated with higher future GDP growth, in line with what they label “the Bernanke/practitioner view,” in which lower term premium is related to stimulus to the economy by making financial market conditions more accommodative for some classes of borrowers. This latter interpretation is also consistent with the evidence that the term premium is countercyclical and correlated with measures of uncertainty in the economy, and therefore harmful for the economy.

References


URL: https://ideas.repec.org/p/fip/fednsr/421.html

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Identification of monetary shocks through the yield curve


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URL: http://www.nber.org/papers/w21978.pdf

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**URL:** https://academic.oup.com/ej/article/118/530/906-926/5089507

**URL:** https://pubs.aeaweb.org/doi/10.1257/aer.97.3.586

**URL:** https://linkinghub.elsevier.com/retrieve/pii/S0304393205000073

**URL:** http://www.jstor.org/stable/3838968