The effects of Brazilian Central Bank Communication on the Yield Curve

Cássio R. A. Alves* Márcio P. Laurini**

Abstract

This paper investigates the bidirectional relation between the Brazilian Central Bank Communication and the yield curve. Using latent factors, observable macroeconomic variables, and observable variables representing central bank communication, we estimate a model that summarizes the yield curve. We find evidence of the effects of Brazilian Central Bank Communication on the movements of the yield curve and the impact of the yield curve components in Brazilian central bank communication. In particular, Central Bank Communication can shape yield curve curvature and slope. Additionally, we find a strong relation between Central Bank Communication and the curvature of the yield curve. These results show that Central Bank Communication impacts market players, making it a valuable instrument for monetary policy.

Keywords: Yield Curve, Sentiment Analysis, Bayesian Estimation, Central Bank Communication.

JEL: E43, E52, D83

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1 Introduction

Researchers and practitioners have increasingly recognized the importance of central bank communication on macroeconomic variables, such as inflation and interest rates. It is still unclear, however, how the Central Bank Communication impacts the term structure of interest rates and how it is affected by changes in those interest rates. Some authors argue that central bank communication affects the long maturity of the yield curve (Leombroni et al., 2021, for instance), and others advocate that it affects only the short maturity of the yield curve (Máté et al., 2021, for instance). Also, the effects of yield curve shape on Central Bank Communication, if any, are unclear. This paper investigates the bi-direction effects between the Central Bank Communication and the term structure of the interest rate.

The most common monetary policy instrument is the short-term interest rate, which policymakers can control directly. Nevertheless, policymakers cannot directly affect longer maturities of interest rates. Since the entire term structure of interest rates affects investment and consumption decisions, all maturities are relevant to policymakers. The change in the short-term interest rate by the central bank may cause an indirect impact on the yield curve because investors will respond to the new short-term interest rate by trading their assets. How the investor will relocate their portfolio, however, will depend on their expectation about the future path of monetary policy and other economic fundamentals, and it is out of the control of the interest rate policy instrument.

The recent literature on central banking recognized that Central Bank Communication may also serve as a monetary policy instrument. This sort of policy instrument, in turn, may affect medium- and long-term interest by shaping the agent's expectations. By telling their vision about future interest rate decisions, inflation, and economic activity, the central bank may update the agent's beliefs about the economic fundamentals, affecting their trading and, ultimately, the price and the assets' returns. This mechanism is known as the *information effect*: Central Bank announcements lead the private sector to update its belief about the monetary policy path and future time path economic fundamentals (Romer and Romer, 2000; Nakamura and Steinsson, 2018).

The empirical evidence of how central bank communication affects the term structure of interest rates is conflicting. Part of the literature argues that Central Bank communication impacts only short-term yield curve maturities (Lucca and Trebbi, 2009; Máté et al., 2021) and the other part says that, instead, it affects long-term yield curve maturities (Lamla and Lein, 2011; Chague et al., 2015; Leombroni et al., 2021). This conflicting evidence may be related to different data and hypotheses used to model and estimate yield curves and central bank communication. For instance, an assumption in the literature is that the equation drove the economy and the central bank communication have no contemporaneous or lagged interest rate for any maturity[1]. Also, in some works, the effect of central bank communication on the interest rate is modeled for a given maturity (Lucca and Trebbi, 2009; Lamla and Lein, 2011; Máté et al., 2021), requiring estimating a different model for each maturity. Likewise, a branch of literature assumes that Central Bank Communication is determined independently of the shape of the yield curve. This hypothesis implies a unidirectional effect from CBC to yield curve (CBC-yield assumption). The Central bank may, however, react to changes in the shape of the yield curve since it is related to several macroeconomic variables.

This paper aims to investigate the bidirectional relationship between central bank communication and the yield curve. In doing so, we allow for both the yield curve affecting the CBC and CBC affecting the yield curve. Specifically, we extend the DNS of Diebold and Li (2006) to also include the central bank communication in addition to the latent factors (level, slope, and curvature) and macroeconomic factors (inflation, capacity of utilization, and interest rate). This model allows us to study the bidirectional effect between CBC and the yield curve and also to consider the lagged effects of the yield curve due to the autoregressive structure of latent factors.

Our results showed that central bank communication indeed impacts the shape of the yield curve. Specifically, if the central bank talks in a more positive way the curvature of the yield curve response is positive. If instead, the central bank has a negative discourse, then the slope and curvature response is negative. Since changes in curvature are related to intermediate maturity changes, our results indicate that the central bank can affect more than just the short-term interest rate by using central bank communication as a policy instrument. We also find that, conversely, changes in the shape of the yield curve affect central bank

[1] See, for example, Lucca and Trebbi (2009), p. 30.

communication. Finally, we find a relation between the central bank communication to the curvature factor of the yield curve.

Our findings complement and connect to the following works of literature. While Diebold et al. (2006) relates the level and slope factors to macroeconomic variables, we relate the curvature factor with central bank communication. Chun (2011) relates the fluctuations in bonds with the expected path of monetary policy and macroeconomy using analyst forecasts. Our approach can be seen as an alternative that uses Central Bank Communication as an agent expectation. Han et al. (2021) relate the shape of the yield curve, associated with a time-varying factor loading, with real macroeconomic variables and argue that this time-varying factor loading contains information about the market perception of the economic risk and uncertainty. In our approach, we use central bank communication to include the perception of economic risk in the model. We believe that our results shed new light on the effects of central bank communication on the yield curve.

2 Quantifying the Central Bank Communication

The most usual form Central Bank Communicates with the private sector is by issuing press releases. This sort of communication often occurs after a council meeting, which defines the short-term interest rate considering the council members' vision of the economic outlook. The content is documented in the textual press release and made available for private agents in the economy. In the case of the Brazilian Central Bank, this communication takes place every forty-five days using two press releases: the COPOM Minutes and the COPOM Statements. While the Statement is a short document that briefly explains the decision on a short-term interest rate, the Minutes are a longer document detailing the macroeconomic outlook and discussing the decision made by the committee.

A natural way to quantify the Central Bank Communication is to analyze the press release issued by the Central Bank, and researchers widely use this practice (Boukus and Rosenberg, 2006; Lucca and Trebbi, 2009; Rosa, 2011; Chague et al., 2015). To transform the textual information into numerical variables, we used sentiment analysis to extract information from the COPOM minutes made available for the Central Bank. We start by acquiring unprocessed text data and appropriately handling it. After collecting the raw data at each meeting, we remove punctuation, blank lines, stop words, and the names of the members of the monetary policy committee in order to remove words that should not impact the tone of the text. It is important to note that the COPOM announcements and minutes were only regularly published by the Brazilian central bank starting in 2006, which serves as the starting year for our sample in this article. By categorizing the content of these papers into semantic categories, we utilize this processed text data to measure the Central Bank of Brazil's attitude.

We use a dictionary-oriented technique to analyze the sentiment of the Copom minutes. The vocabulary of these documents is highly specialized, and the phrases employed have specific connotations, usually with financial meanings. As a result, we classified the words in the papers using the financial dictionary offered by Loughran and McDonald (2011). This dictionary helps us to identify each word's semantic content, categorizing it as positive, negative, or uncertain. We create the sentiment variables representing central bank communication using these three semantic categorizations. We regard the proportion of each category to the total amount of words in each document as sentiment variables for Copom minutes. For every period t that the Copom meetings take place, we denote the proportion of positive, negative, and uncertainty words by $s_{p,t}$, $s_{n,t}$ and $s_{u,t}$. We also follow Cannon (2015) to define the tone of the central bank by:

$$\tau_t \equiv \frac{s_{p,t} - s_{n,t}}{s_{p,t} + s_{n,t}}. \tag{1}$$

The tone summarizes the sentiment of the central bank in one variable, and it is helpful to analyze the central bank communication and yield curve relationship. We used these four variables to analyze how central bank communication affects the term structure of interest rates.

3 The Yield Curve and the Central Bank Communication

To analyze the interconnection between the yield curve and central bank communication, we augmented the Dynamic Nelson and Siegel (DNS) proposed by Diebold and Li (2006) to include Central Bank Communication as a new factor. Considering observables and latent factors, the DNS has proved to perform well in fitting and forecasting the yield curve. The original DNS of Diebold and Li (2006) decomposes the yield curve using only the unobserved factors known as level (L_t), slope (S_t), and curvature (C_t). Then, Diebold et al. (2006) extend the original model to include a bi-direction relation between the unobserved factors and observed macroeconomic factors, specifically inflation, capacity of utilization, and interest rate. Our model extends this macro-yield model to include central bank communication.

To include the central bank communication in the DNS model, let us define the vector of factors as $X_t \equiv (L_t, S_t, C_t, s_{p,t}, s_{n,t}, s_{u,t}, CU_t, R_t, \pi_t)'$. We assume that the factors follow a Vector Auto-Regression (VAR) representation:

$$X_t = c + \Phi X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(\mathbf{0}, Q), \tag{2}$$

where c is a vector of constant, Φ is a 9×9 matrix of VAR coefficients and Q is assumed to be diagonal. In line with the DNS model, we use the unobserved factors to build the entire term structure of interest rate:

$$y_t(m) = L_t + S_t \left(\frac{1 - e^{-\lambda m}}{\lambda m} \right) + C_t \left(\frac{1 - e^{-\lambda m}}{\lambda m} - e^{-\lambda m} \right) + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2), \tag{3}$$

where $y_t(m)$ is the interest rate in period t of a bond with maturity m and λ is a factor decay.

The model formed by Equations (2) and (3) describes the dynamics of the yield curve considering macroeconomic variables and central bank communication. The parameters of the model can be summarized in a vector $\theta = (c, \phi_{ij}, q_i, \lambda, \sigma_\eta^2)$, where ϕ_{ij} is the elements of the matrix Φ, q_i is the diagonal elements of the matrix Q and $i, j \in \{1, \cdots, 9\}$. For a given set of parameters θ, we can assess how the central bank communication (and macroeconomic variables) affects the latent factor L_t, S_t, and C_t. Depending on the size of the factor decay λ, the latent factors will build the entire term structure of interest rate, so we can indirectly assess the effect of communication and macroeconomic shocks in the yield curve. The level, slope, and curvature are unobservable, and we need to estimate them.

We can estimate the vector of parameter θ and latent components in a Frequentist or Bayesian approach. In the Frequentist case, we can construct the likelihood function by the prediction error decomposition produced from the Kalman Filter and then maximize this function (Diebold et al., 2006). The maximum likelihood estimation, however, may present numerical problems, particularly when the number of factors increases. We use a Bayesian technique estimation (Laurini and Hotta, 2010) to prevent this kind of issue. In the Bayesian case, we elicit prior distribution to mix with likelihood function information. Then, we use Markov Chain Monte Carlo (MCMC) methods to sample from the posterior distribution. In Appendix A, we present prior distribution and MCMC details.

4 Results

4.1 Yield curve fit

We estimate the model for yields of eight different maturities, presented in the first column of Table 1. The DNS model augmented with central bank communication fits the yield curve well since the difference between the fitted yield curve and the observed yield curve, using the estimated latent factors, is negligible. Table 1 shows some statistics of this difference.

Figure 1 shows the estimated latent factors used to build the fitted yield curve. The level factor presents high persistence behavior and displays a decreasing tendency overall. In contrast, the estimated slope and curvature are less persistent and assume both positive and negative values. Also, there is a correlation of 0.5 between the slope and curvature movements.

Since these three unobservable factors form the entire yield curve in the DNS model, analyzing their dynamic behavior and relation to other observed factors helps us to understand the yield curve behavior.

Table 1: Summary statistics for the difference between the fitted yield curve and the observed yield curve.

Maturities (in months)	Mean	Std. dev.	Min	25%	50%	75%	Max
1	-0.0002	0.0001	-0.0004	-0.0002	-0.0002	-0.0001	0.0001
2	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0001	0.0002
3	0.0001	0.0000	-0.0001	0.0000	0.0001	0.0001	0.0002
6	0.0001	0.0001	-0.0001	0.0001	0.0001	0.0002	0.0003
9	0.0001	0.0001	-0.0003	0.0000	0.0001	0.0002	0.0004
12	-0.0000	0.0001	-0.0005	-0.0001	-0.0000	0.0001	0.0004
24	0.0000	0.0003	-0.0011	-0.0002	0.0000	0.0002	0.0009
36	0.0003	0.0004	-0.0015	-0.0000	0.0003	0.0006	0.0015

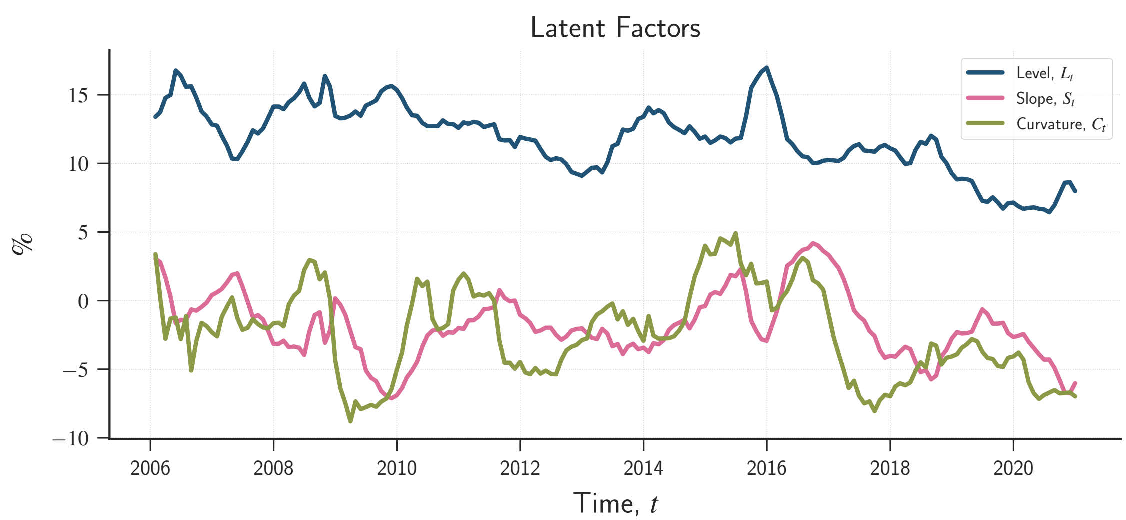

Figure 1: Latent factors: level, slope and curvature

4.2 Unobservable factors and related variables

We begin by analyzing the correlation between the latent factors and the extracted sentiment of central bank communication, described in the proportion of positive, negative, and uncertain words. Figure 2 displays the correlation matrix of latent factors and sentiment variables. In general, the correlation between latent factors and the sentiment of the central bank is high. Specifically, the curvature of the yield curve is related to all sentiment variables. The slope, in turn, is only weakly correlated to the proportion of positive and uncertain words, but it is highly associated with proportion of negative words. The level is also weak correlated to the positive words. This fact leads us to investigate further the relationship between the curvature factor and central bank communication.

Figure 2: Heat-map of correlation matrix: Yield curve latent factors and central bank communication

A large body of literature links the level factor with inflation and the slope factor with the economic activity cycle. Links between observable variables and the curvature of the yield curve are less frequent. Here, we summarize the central bank communication in the tone variable, as defined in Equation (1), and link the curvature of the yield curve with this variable. Figure 3 displays the estimated latent factors and the linked comparison series.

In panel (a) of Figure 3, we can observe that the level of the yield curve is correlated with inflation, as highlighted in the literature (see, e. g., Diebold et al. (2006)). The literature also usually connects the slope factor with the economic cycle. We use the year-on-year economic growth to represent the cycle. In contrast to the finds in the literature, the correlation between the cycle and the slope factor is low (see panel (b) of Figure 3). Surprisingly, the curvature factor and the central bank communication (represented by the tone variable) move in the same direction overall, presenting a Pearson correlation of 0.50, as shown by panel (c) of Figure 3.

The linkage between the curvature factor and central bank communication sheds new

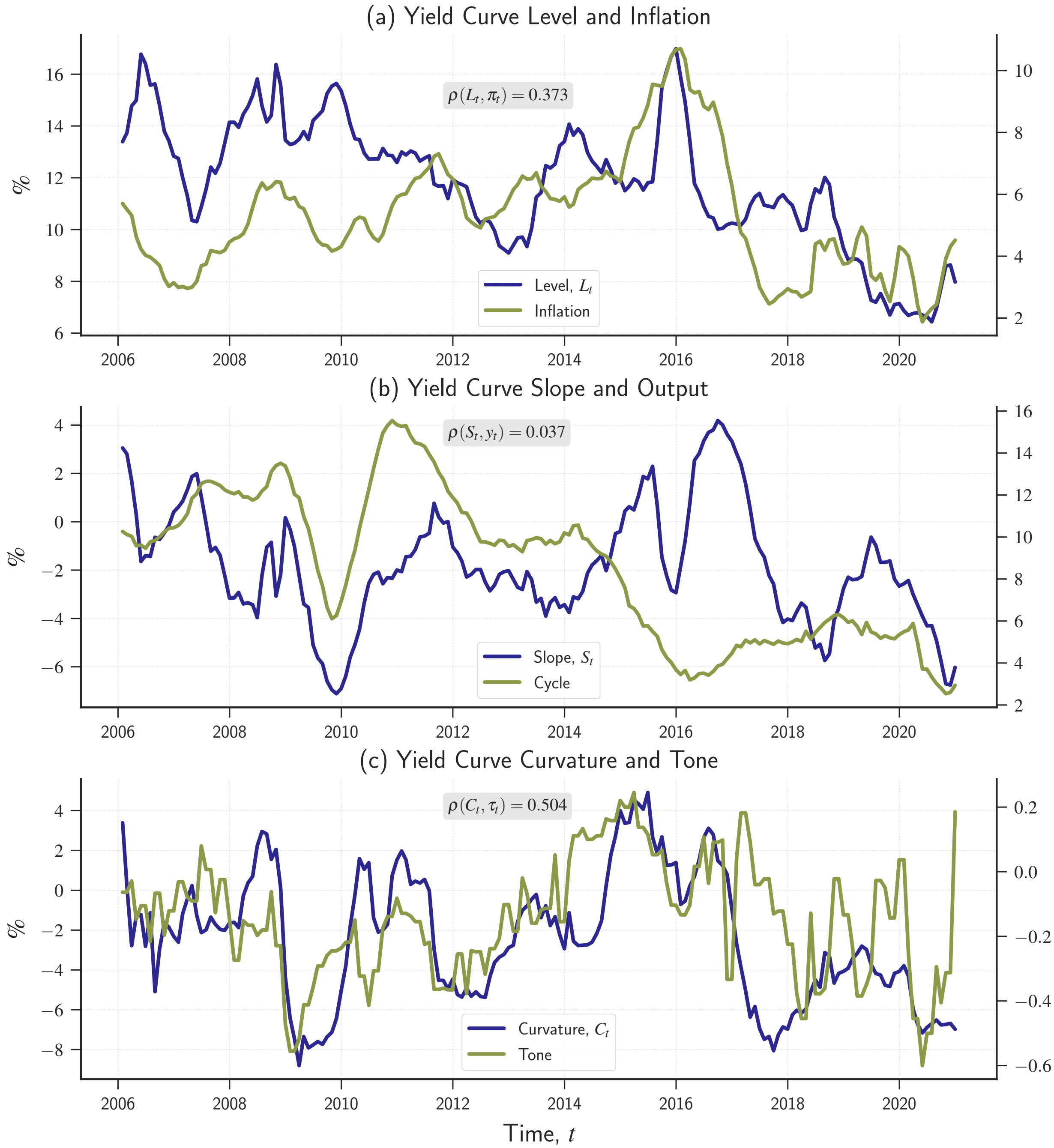

Figure 3: Level, Slope and curvature factors and its empirical counterparts.

light on how Central bank communication can serve as a tool to affect the term structure of interest rates. Increasing the curvature of the yield curve means that medium-term maturities will have higher interest rates (Litterman and Scheinkman, 1991; Diebold and Li, 2006). Accordingly, our find implies that central bank communication is related to the movements in medium-term maturities, which is in line with the literature that argues that the impact of the CBC is beyond the short-term but can affect other maturities too (Lamla and Lein, 2011; Chague et al., 2015; Leombroni et al., 2021).

For the Brazilian yield curve, the slope and curvature are positively correlated. Thus, the tone of central bank communication is also associated with the yield curve slope, presenting a correlation of 0.42. The literature argues that the yield curve slope can predict recessions (Fama, 1986; Estrella and Mishkin, 1998; Rudebusch and Williams, 2009; Benzoni et al., 2018). Financial economists claim that the yield curve slope "contains information about current and expected future monetary actions" (Benzoni et al., 2018, p. 1).

We claim that the central bank informs the private sector about the current and expected future monetary policy in their communications and also their point of view about the economic scenario. Therefore, CBC also contains information about the cycle, which is in line with previous results of Gardner et al. (2022), who argue that their sentiment index of FOMC describes good and bad times. Indeed, for the Brazilian case, the tone of the Brazilian central bank presents a decreasing tendency during recessions, as shown in Figure 6, in Appendix B. Han et al. (2021) also argues that, before recessions, the role of curvature and slope is smaller, and during recessions, it tends to play a more relevant role. The tone of the Brazilian central bank, which is correlated with the slope and curvature in the data, captures this movement and informs the market. This knowledge changes the investors' beliefs, possibly implying a change in their portfolios, affecting prices and interest rates of different maturities.

4.3 The yield curve and central bank communication dynamics

We now carry out an impulse response analysis to verify how the effects of the different types of discourse (more positive, negative, or uncertain) impact the yield curve. We divide the impulse response function analysis into two groups. The first analyzes how central bank communication shocks affect the latent factors of the yield curve and how long these shocks last to dissipate. The second group examines how the latent factors shocks affect central bank communication. In Appendix B, we present the complete impulse response function in

Figure 7[2].

Let us now describe the first group of impulse responses. Figure 4 displays the response of level, slope, and curvature to shocks in negative, positive, and uncertainty words, all in the proportion of total words. The response of the level factor to shocks in negative words is negligible, but it is non-negligible for shocks in the proportion of positive and negative words. In reaction to the proportion of positive word shocks, the level rises and then dissipates slowly. The level response to uncertain word shocks is negative and more persistent.

The intriguing reactions to analyze are the response of slope and curvature since the results of section 4.2 indicate a relation of these two factors with central bank communication. An increase in the proportion of negative words (which decreases the tone) reduces both the slope and the curvature factor. Around five months ahead, the curvature achieves a negative one-to-one response. Similarly, the response of the curvature to an increase in the proportion of positive words (which increases the tone) reaches a positive one-to-one around five months. The reaction of slope to shocks in the proportion of positive words is almost negligible, considering the 50% credible interval.

We can interpret these responses of curvature and slope to the shocks in positive and negative words as an effect of the central bank communication in the short and medium term of interest rate. When the Central bank surprisingly informs the market of its vision about the economic outlook, increasing the proportion of positive (negative) words in its communications, private agents will change their portfolios in such a way that the curvature of the yield curve will increase (decrease). This increase (decreasing) means that medium-term yield bonds are also increasing (decreasing). Since the slope also declines with a positive shock in the proportion of negative words, the short-term yield bonds will also reduce. Thus, central bank communication can serve as a tool to affect not only short-term interest rates but also medium-term yields. Again, this result is in line with the literature that argues that the impact of the CBC is beyond the short-term but can affect other maturities too (Lamla and Lein, 2011; Chague et al., 2015; Leombroni et al., 2021).

Finally, let us describe the second group of impulse responses, which analyzes how central

[2]The impulse response function in Figure 7 of appendix B also shows the 90% credible interval. In the main text, however, we only present the 50% credible interval to take a closer look at the behavior of point estimation of the responses, represented by the median of the posterior.

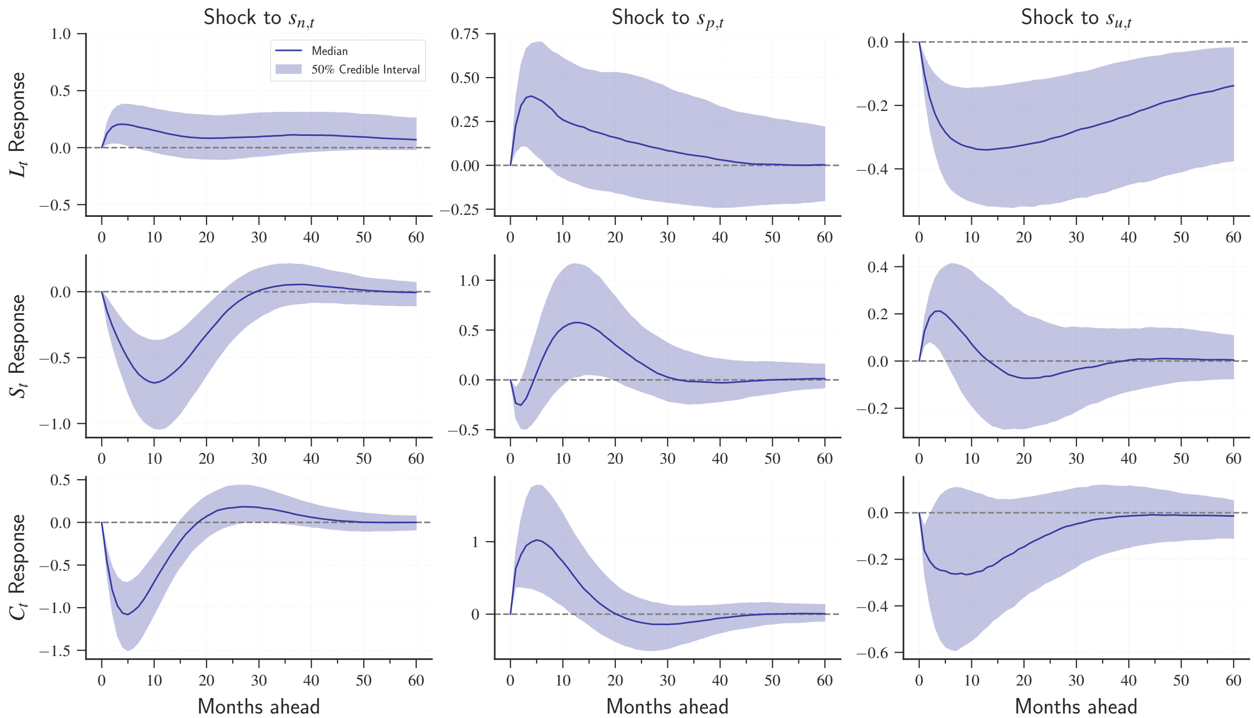

Figure 4: Impulse response function: level, slope, and curvature response to shocks in sentiment variables. The solid blue line represents the median and the shaded blue area represents the 50% credible interval.

bank communication reacts in response to changes in the shape of the yield curve. To do so, we analyze the impulse response function presented in Figure 5. In general, the proportion of negative, positive, and uncertain words increases – some months ahead – considering the credible interval 50%. An increase in the level factor does not affect the proportion of negative words in the first months, considering the credible interval. Around ten months ahead, however, the increase in the level also raises the proportion of the negative words publicized by the central bank. We find a similar pattern for slope and curvature shocks. This result means that the central bank does not react immediately to the proportion of negative words, although it will increase at some point.

The proportion of positive and uncertain words increases immediately for shocks in any of the latent factors[3] and the response dissipates around thirty months ahead. The reaction of the proportion of uncertain words is also positive and immediate for all three shocks. Thus,

[3] An exception is the reaction of the proportion of positive words to the curvature shock, which decreases in the first month but then starts to increase. Considering the credible interval, however, we can view the pattern as equal to the other shocks

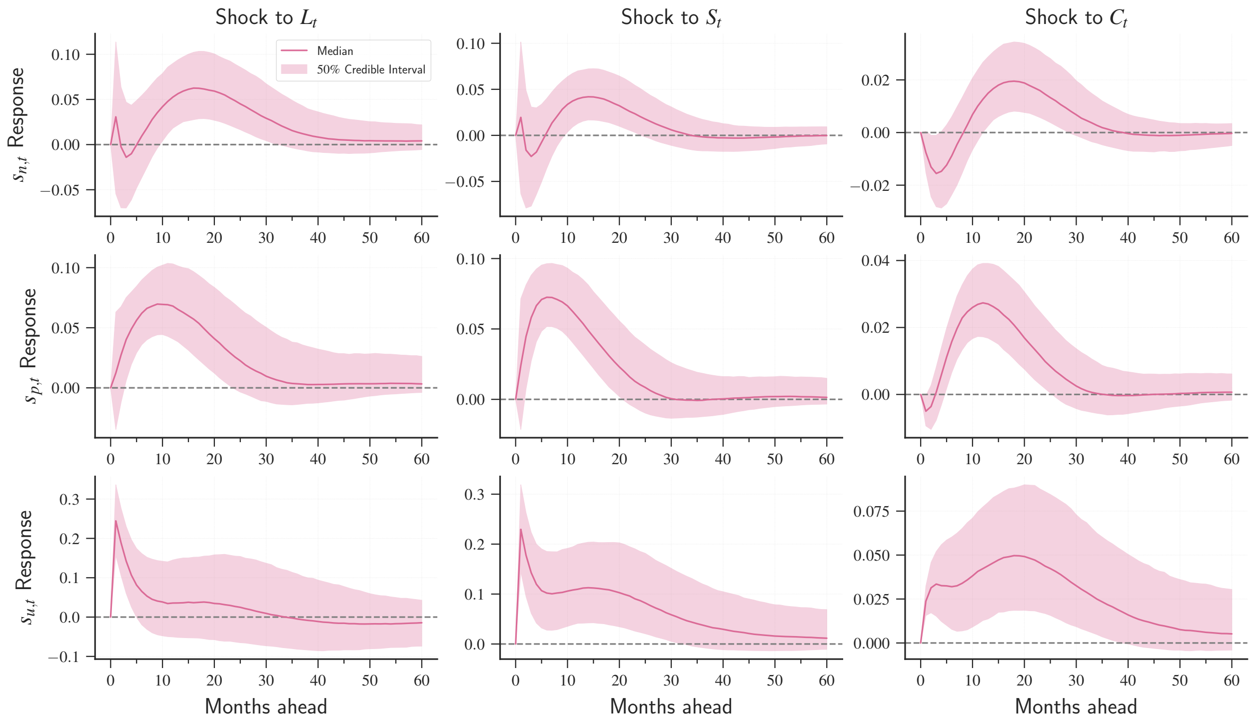

Figure 5: Impulse response function: Proportion of negative, positive, and uncertainty response to shocks in latent factors of the yield curve. The solid red line represents the median and the shaded red area represents the 50% credible interval.

we can conclude that the central bank communication also reacts to the changes in the yield curve shape, represented by the latent factors.

5 Conclusion

In this paper, we study the effect of central bank communication on the yield curve. To do so, we used an augmented dynamic Nelson and Siegel model that makes the shape of the yield curve depend on central bank communication. We find that the yield curve, represented by its latent factors, affects and is affected by the Central bank communication. Specifically, we find that the curvature of the yield curve is closely related to Central bank communication. A central bank with a more positive discourse is associated with a greater curvature of the yield curve. Central bank communication is also related to the slope factor, showing that short and medium maturities of interest rates are affected by Central bank communication. Therefore, Central bank communication may serve as a monetary policy tool cable to impact medium-term interest rates in addition to the traditional short-term interest rate instrument.

References

Benzoni, L., O. Chyruk, and D. Kelley (2018). Why does the yield-curve slope predict recessions? *Available at SSRN 3271363*.

Betancourt, M. (2017). A conceptual introduction to hamiltonian monte carlo. *arXiv preprint arXiv:1701.02434*.

Boukus, E. and J. V. Rosenberg (2006). The information content of FOMC minutes. *Available at SSRN 922312*.

Cannon, S. (2015). Sentiment of the FOMC: Unscripted. *Economic Review-Federal Reserve Bank of Kansas City 5*.

Chague, F., R. De-Losso, B. Giovannetti, and P. Manoel (2015). Central bank communication affects the term-structure of interest rates. *Revista Brasileira de Economia 69*, 147–162.

Chun, A. L. (2011). Expectations, bond yields, and monetary policy. *The Review of Financial Studies 24*(1), 208–247.

Diebold, F. X. and C. Li (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics 130*(2), 337–364.

Diebold, F. X., G. D. Rudebusch, and S. B. Aruoba (2006). The macroeconomy and the yield curve: A dynamic latent factor approach. *Journal of Econometrics 131*(1-2), 309–338.

Estrella, A. and F. S. Mishkin (1998). Predicting us recessions: Financial variables as leading indicators. *Review of Economics and Statistics 80*(1), 45–61.

Fama, E. F. (1986). Term premiums and default premiums in money markets. *Journal of Financial Economics 17*(1), 175–196.

Gardner, B., C. Scotti, and C. Vega (2022). Words speak as loudly as actions: Central bank communication and the response of equity prices to macroeconomic announcements. *Journal of Econometrics 231*(2), 387–409.

Gelman, A. and D. B. Rubin (1992). Inference from iterative simulation using multiple sequences. *Statistical science 7*(4), 457–472.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculations of posterior moments. *Bayesian statistics 4*, 641–649.

Han, Y., A. Jiao, and J. Ma (2021). The predictive power of Nelson–Siegel factor loadings for the real economy. *Journal of Empirical Finance 64*, 95–127.

Hoffman, M. D., A. Gelman, et al. (2014). The no-u-turn sampler: adaptively setting path lengths in hamiltonian monte carlo. *J. Mach. Learn. Res. 15*(1), 1593–1623.

Lamla, M. J. and S. M. Lein (2011). What matters when? the impact of ECB communication on financial market expectations. *Applied Economics 43*(28), 4289–4309.

Laurini, M. P. and L. K. Hotta (2010). Bayesian extensions to diebold-li term structure model. *International Review of Financial Analysis 19*(5), 342–350.

Leombroni, M., A. Vedolin, G. Venter, and P. Whelan (2021). Central bank communication and the yield curve. *Journal of Financial Economics 141*(3), 860–880.

Litterman, R. and J. Scheinkman (1991). Common factors affecting bond returns. *Journal of Fixed Income 1*(1), 54–61.

Loughran, T. and B. McDonald (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance 66*(1), 35–65.

Lucca, D. O. and F. Trebbi (2009). Measuring central bank communication: an automated approach with application to FOMC statements. Technical report, National Bureau of Economic Research.

Máté, Á., M. Sebők, and T. Barczikay (2021). The effect of central bank communication on sovereign bond yields: The case of Hungary. *Plos One 16*(2), e0245515.

Nakamura, E. and J. Steinsson (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics 133*(3), 1283–1330.

Romer, C. D. and D. H. Romer (2000). Federal reserve information and the behavior of interest rates. *American Economic Review 90*(3), 429–457.

Rosa, C. (2011). Talking less and moving the market more: Evidence from the ECB and the FED. *Scottish Journal of Political Economy 58*(1), 51–81.

Rudebusch, G. D. and J. C. Williams (2009). Forecasting recessions: the puzzle of the enduring power of the yield curve. *Journal of Business & Economic Statistics 27*(4), 492–503.

A Bayesian estimation details

The prior distribution can be briefly summarized as follows. For the variance parameters, σ_i^2 and σ_η, we specify gamma distributions to ensure the positiveness of these parameters. The decay parameter λ also needs to be positive. Therefore, we use a log-normal distribution for this parameter. For the persistence parameters, ϕ_{ii}, we use a normal distribution truncated in the range $(0, 1)$, since we are interested in a stationary system. For the parameters ϕ_{ij}, with $j \neq i$ we assume a prior normal distribution. The prior distribution for the rest of the parameters, c_i, γ_i, and α_i, are standard normal distributions. More details about the prior distributions are available upon request.

We run three chains with a total of $20,000$ iterations to estimate the posterior distribution of the model and exclude the first $10,000$ as a burn-in period. For this number of iterations, the MCMC algorithms converge, following usual diagnostics (Gelman and Rubin (1992), Geweke (1992), and visual inspection of trace plots.).

The method used to sample from the posterior of the augmented DNS model was the Hamiltonian Monte Carlo. The Hamiltonian Monte Carlo (HMC) is a Markov Chain Monte Carlo (MCMC) algorithm that uses gradient information to sample from the posterior distribution efficiently. The samples are generated by simulating Hamiltonian dynamics in the posterior distribution. By using gradient information, the HMC can explore the parameter space more efficiently than traditional methods, such as Random Walk Metropolis-Hastings. In short, the algorithm consists in proposing a new draw by combining gradient information and the simulated Hamiltonian dynamics and, then, accepts this proposal using a metropolis step. See Laurini and Hotta (2010) for a detailed explanation of the DNS model Bayesian estimation using HMC, and see Hoffman et al. (2014) and Betancourt (2017) for a detailed explanation of the HMC algorithm.

B Additional Figures

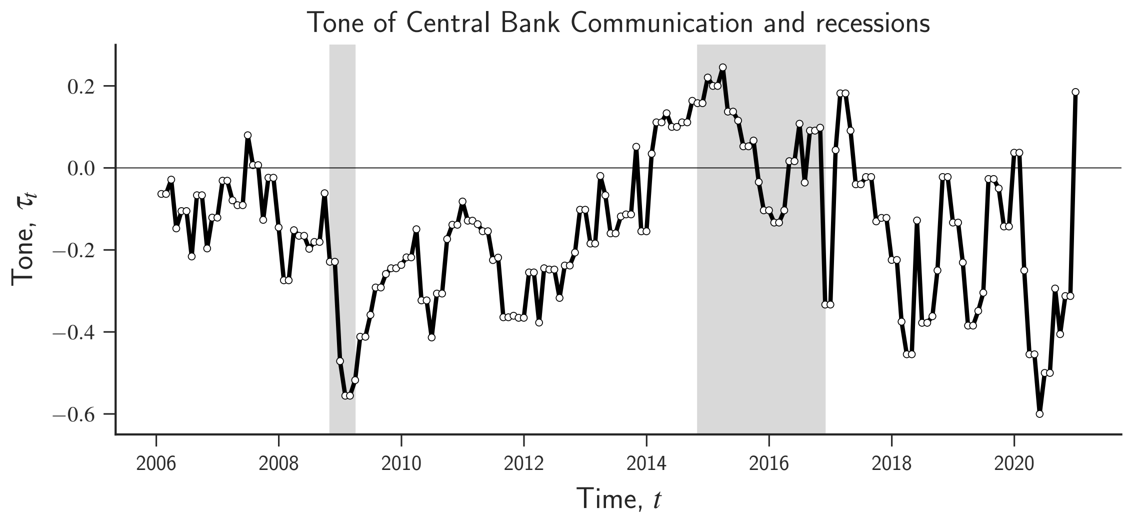

Figure 6: Tone and Recessions

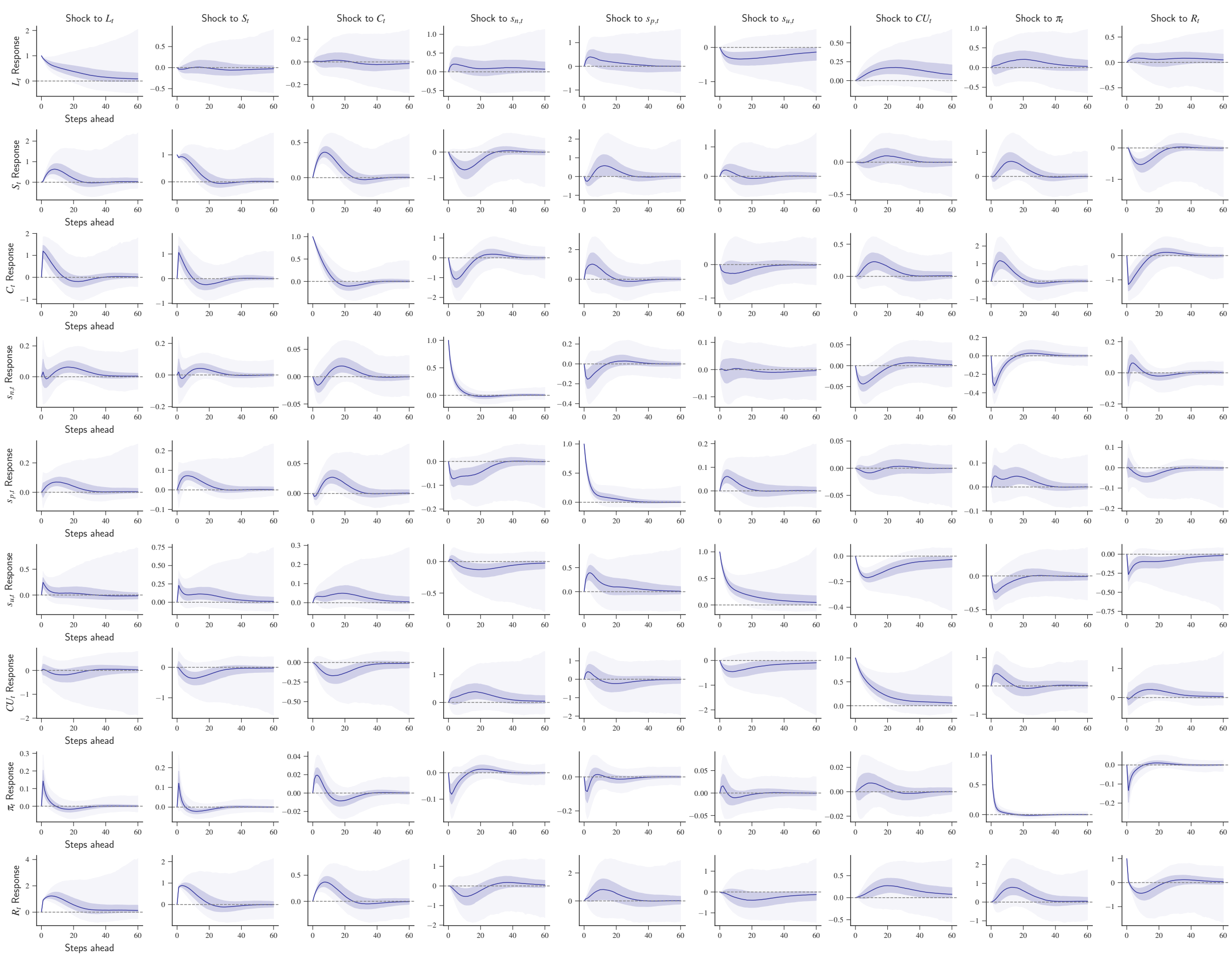

Figure 7: Complete impulse response functions