The Predictive Power of Central Bank Communication: Evidence from Mexico

Christian Admin De la Huerta Avila*

Abstract

Understanding the impact of central bank communication on the effective transmission and predictability of monetary policy is paramount. In this paper, we analyze the predictive power of Banco de México’s communication by implementing Natural Language Processing. Using a Latent Dirichlet Allocation model and dictionary-based sentiment analysis, we develop a Hawkish-Dovish Tone index to measure the bias of Banco de México’s monetary policy statements. We show that, through its communication strategy, the central bank can effectively telegraph the expected moves for the next monetary policy meeting. Overall, the results are consistent with the estimated effects of central bank communication as a predictor of upcoming short-term interest rate decisions.

**Keywords**: central bank communication, monetary policy, natural language processing, ordinal logit, predictability.

**JEL Classification**: C25, C45, E52, E58.

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1. Introduction

Over the years, central banks (CB) have acquired considerable power in managing monetary policy. These institutions historically grew up with certain amount of mystery and opacity in the public perception, due to the technical nature of their functions, their ambiguous method of action, and their cautious communication.

However, in recent decades, many CBs have made efforts to increase transparency and accountability, recognizing the importance of greater clarity in their actions and communications. This evolution has led to a shift from the secretive, enigmatic, and ambiguous prototype of the old CB to a design that encourages openness, intelligibility, and honesty. Nowadays, in most CBs around the globe, communication, which includes policy statements, bulletins, minutes, press conferences, reports, forecasts, public speeches, among other channels, has become increasingly important in the central banker’s toolkit (Blinder et al., 2017). Therefore, communication and, more specifically, the language of central bankers has become an integral part of CB’s day-to-day policymaking.

The importance of communication for CBs lies in its dual role. Firstly, effective communication may shape public expectations of future macroeconomic outcomes, influencing financial market behavior and, consequently, the broader economy. By providing guidance on future policy actions, CBs can anchor expectations and reduce noise in financial markets, thereby improving the transmission of monetary policy. Secondly, as independent institutions, central bankers operate beyond direct democratic control. Transparency through communication is essential for ensuring accountability to the public they serve. By sharing information about policy decisions, the rationale behind them, and the economic conditions influencing them, CB communication fosters transparency. While the literature has extensively examined transparency (see Fry et al., 2000; Blinder et al., 2001; Geraats, 2002, 2007; Eijffinger & Geraats, 2006; Cihák, 2007; Dincer & Eichengreen, 2008, 2010, 2014; and Dincer et al., 2019, 2022) leading to the creation of various indicators associated with these issues, and a consensus on information sharing, there is growing research exploring the potential power of CB communication as a monetary policy tool.

In this regard, studying the predictive effects of CB communication on upcoming policy rate decisions holds crucial significance in the field of monetary policy. Communication serves as a vital channel through which policymakers convey their intentions, insights, and assessments to financial markets, economic agents, and the public at large. Understanding how this communication can be leveraged as a tool offers valuable insights into the dynamics of policy transmission and its impact on macroeconomic variables. By delving into the
relationship between central bank statements, market responses, and subsequent policy rate outcomes, researchers and policymakers gain a deeper understanding of the effectiveness of communication strategies, the accuracy of market interpretations, and the potential scope for forward guidance. This knowledge can be used to make more informed decisions, enhance the credibility of CB communication and contribute to the overall effectiveness of monetary policy in promoting economic stability and growth.

The purpose of this paper is to analyze how CB communication can be used as a tool in the Mexican economy. We are interested in answering the question of whether Banco de México (Banxico) can use its communication strategy as a potential source of guidance for upcoming interest rate decisions. Specifically, we examine the language used in Banxico’s monetary policy statements (MPS) during the period in which it has implemented its monetary policy through an operational target for the overnight interbank interest rate. Since MPS are often accompanied by changes in the monetary stance (whether hikes, cuts, or no changes), they are perceived as a potential tool for generating “monetary policy news” (Bomfim, 2003). Consequently, in these publications, CBs can share relevant information and potentially influence financial adjustments and market expectations about the future path of short-term interest rates (Blattner et al., 2008; Milani & Treadwell, 2012).

To assess the potential power of Banxico’s communication as a policy tool, we first focused on extracting qualitative information from the MPS. We implemented Natural Language Processing (NLP) techniques over a set of 131 documents, starting on Banxico’s February 2008 decision and ending in December 2022. To do so, we used a Latent Dirichlet Allocation (LDA) model, first proposed by Blei et al. (2003), to analyze latent topics contained in the set of Banxico’s publications. We identified the semantic structure of the MPS and labeled subjects on which Banxico has focused its communication, such as monetary policy, economic activity, international affairs, among others. Subsequently, we opted to leverage the insights gained from the LDA model to develop our Hawkish-Dovish Tone (HDT) weighted index, by applying a dictionary-based sentiment analysis method.

With the information gathered, we focused on determining whether the tone of the documents may help to predict upcoming policy decisions. In particular, we tested if the qualitative information provided by Banxico contains relevant “monetary policy news” by including the HDT weighted index on an ordinal logit regression using discrete changes in Banxico policy rate as the dependent variable. Likewise, we incorporated other relevant explanatory variables in the regression, such as inflation and output gaps and short-term private sector expectations. Throughout the paper, it is argued that the central bank uses its MPS to communicate important signals that are crucial for determining the short-
term monetary policy. Additionally, these signals cannot be captured by conventional macroeconomic indicators. The results hold across different econometric specifications, suggesting that Banxico’s communication is effective in anticipating 7 out of 10 interest rate decisions in the short run.

These findings are in line with other relevant papers (see Bennani & Neuenkirch, 2017; Picault & Renault, 2017; Baranowski et al., 2021; Priola et al., 2022; and Astuti et al., 2022) that evaluate the predictive power of CB speech and its effectiveness as a monetary policy tool. In our case, the results are especially relevant because Banxico has made many efforts to improve its communication strategy in recent years, so it is worth mentioning that the modifications in the CB’s main publication have been effective so that it can be read as a tool that provides relevant news about the institution’s outlook.

The rest of the paper is divided as follows. Firstly, a brief review of related literature is provided in Section 2. In Section 3, the evolution of Banco de México’s monetary and communication strategy over the last few decades is described, along with an overview of the structure of monetary policy statements. Section 4 presents the main analysis of this paper, including LDA modeling, sentiment analysis, and econometric estimations. Finally, Section 5 concludes with a summary of the results and implications for central bank communication.

2. Literature review

Central banking has undergone significant changes over the past few decades. Today, the era of “mumbling with great incoherence” is over\(^1\), and CBs around the world are more independent and transparent than ever before. This wasn’t always the case. In the past, the consensus was that central bankers should be secretive and mysterious authorities with a high degree of opacity. It was believed that CBs should maintain little or no communication with the public and markets, or if so, convey coded messages extremely difficult to read and understand.\(^2\)

\(^1\)The words “mumbling with great incoherence” were uttered by Alan Greenspan during his appearance before the Senate in 1987, referring to the ambiguous central banking practices of the time. As Gabriel Makhlouf, Governor of the Central Bank of Ireland, said, those days are long gone (see Makhlouf, 2020).

\(^2\)For example, during the 1960s, economist Milton Friedman underscored the pivotal elements of a central bank’s function, emphasizing the avoidance of accountability and the attainment of public prestige (see Faust & Svensson, 2001). The principle of “never excuse, never explain” is attributed to Montagu Norman, former Bank of England chairman, who steadfastly refrained from parliamentary testimonies (see Boyle, 1967). Mervyn King encapsulates the late 20th-century perspective on central bank communication, recalling a dinner with Paul Volcker where the advice “mystique” was bestowed, epitomizing the enigmatic tradition and wisdom of central banking during that era (Lindsey et al, 2005).
Even though this view of central banking as full of mysticism, secrecy, and opacity has remained at the heart of some scholars and central bankers, the experience of the "Great Inflation" and developments in Time Inconsistency and Institutional Design Theory highlighted the need for central bankers with a high degree of independence and credibility (see Kydland & Prescott, 1977; Calvo, 1978; Barro & Gordon, 1983; and Rogoff, 1985). The changes that originated in the last decades of the twentieth century, both in theory and practice, were a significant departure from the past, fostering greater CB independence, promoting inflation targeting schemes, rethinking monetary policy methods, and prioritizing transparency and communication. On the other hand, these changes also led to the CBs being in the spotlight and monetary policy gradually evolving into the main tool of macroeconomic stability (see Bernanke, 2022). Alan Blinder, former Vice Chairman of the Federal Reserve, termed the shift towards greater openness and transparency in central banking as the “Quiet Revolution” (see Blinder, 2004).

The study of CB communication dates to the research conducted by Christina and David Romer (1989), which is a significant contribution to this field. Using the narrative approach, they analyzed a series of time periods during which the Federal Reserve’s language was restrictive. Their findings indicate that narratives, which include historical records, explanations of the decision-making process, and accounts of the sources of monetary disruptions, are linked to various macroeconomic consequences, such as the real impacts of monetary shocks. A large number of theoretical and empirical papers have focused on communication in the past two decades. For example, some studies stress that CB communication could shape market expectations, making central bank behavior more predictable and market reactions more consistent with macroeconomic goals (for instance, see Blinder, 1999; Blinder et al., 2001; Woodford, 2001; Kohn & Sack, 2004; Bernanke et al., 2004; Blinder et al., 2008; Bernanke et al., 2019).

Initially perceived as a credibility enhancer or support for limited transmission channels, CB communication has evolved into a consensus-driven tool integral to monetary policy, particularly in influencing long-term interest rates, bolstered by a deeper understanding of market effects on financial stability and prices (see Ehrmann & Fratzscher, 2007). This transformation has reshaped monetary policy strategy and the central banker’s toolkit in the context of growing authority and market expectations influence. With the development of communication tools such as policy statements, bulletins, minutes, press conferences, reports, forecasts, public speeches, among others, a lot of literature has emerged trying to understand the impact of communication, both theoretical and empirically, on market expectations, signals on the yield curve and the effective transmission of monetary policy (see Blattner et
The findings of these studies suggest that, in general, communication is seen as a tool to prepare markets for upcoming decisions, and can be used as a potential source of “monetary policy news”, as it provides relevant information to financial markets and the public at large so that they become increasingly familiar with the way CBs think and act. This, in turn, contributes to making actions more predictable and enhancing credibility.

Interest in CB’s language has increased especially after the episodes of the Global Financial Crisis and the COVID-19 pandemic. Some empirical work has used the “narrative approach” to construct indicators by identifying certain relevant words in CB communications, and then investigating how the tone bias impacts the predictability of monetary policy, and other set of macroeconomic and financial variables (for example, see Rosa & Verga 2008; Heinemann & Ullrich, 2007; and Hayo & Neuenkirch, 2010). However, there are three fundamental problems with these indicators: they are based on idiosyncratic identification of the communication, i.e., the researcher prints bias by focusing exclusively on the words and phrases she considers relevant in the tone of the CB; their construction becomes particularly complicated when large numbers of documents are analyzed; and they are inconsistent when there are major changes in narratives.

In this regard, a second generation of empirical studies has emerged that address this problem and make use of Natural Language Processing (NLP) techniques. This body of research aims to decipher the semantic content of CB communication and to interpret both the quantity and quality of messages conveyed through official documents and other central banking-related texts. This body of research mainly exploded two data analysis methodologies: Latent Dirichlet Allocation (LDA) and sentiment analysis. The key idea behind this is to uncover the semantic structure of CB publications and extract signals (or sentiment) from large amounts of unstructured data, such as the words contained in the documents.

In the context of central banking, the LDA algorithm in combination with sentiment analysis has been used since the work of Hansen & McMahon (2016). They explore how Blattner et al. (2008) distinguish between two types of predictability of monetary policy: short-term and long-term predictability. While short-term predictability is narrowly defined as the ability of the public to anticipate monetary policy decisions correctly over short horizons, the broader, ultimately more meaningful concept of longer-term predictability also encompasses the ability of the private sector to understand the monetary policy framework of a central bank, i.e. its objectives and systematic behavior in reacting to different circumstances and contingencies. This paper focuses on the short-term definition of predictability.

Section 4 briefly describes both methodologies.
multidimensional aspects of Fed communication have effects on both the market and real economic variables. Similarly, this method has been previously applied to study different aspects of CB communication. For example, the consequences of transparency in monetary policymakers’ deliberations reflected in monetary policy meeting transcripts (Hansen et al. 2018); the role of information from inflation reports on market interest rates (Hansen et al. 2019); the power of CB talk as a predictor of future financial market behavior (Petropoulos & Siakoulis, 2021); the impact of communications on the returns of financial variables (Gu et al., 2022; Möller & Reichmann, 2021); the effects of communication on consumer inflation expectations (Szyszko et al., 2022); the influence on macroeconomic, monetary and financial variables, and the idiosyncratic effects of central bankers’ discourse or persistence of sentiment in communication (Hayo & Zahner, 2023); and the impact of press conference speech on financial markets (Gorodnichenko et al., 2023).

In parallel, using tone indicators derived from different validated dictionaries for CB sentiment analysis (see Loughran & McDonald, 2011, 2014; Apel & Blix-Grimaldi, 2012, 2014; Apel et al., 2019; Bennani & Neuenkirch, 2017; and Gonzalez & Tadle, 2021), several studies have constructed tone indicators to capture bias in CB communications. The dictionaries categorize the words used by the CBs as either hawkish or dovish with the goal of capturing the policy bias of central bankers, thus, they allow to assign a numerical value and create a measurement that accurately reflects this bias. Using this type of indicators, there is growing evidence for different CBs that support the idea that communication is a powerful and efficient tool to anticipate future interest rate decisions (Tobback et al., 2017; Baranowski et al., 2021; Astuti et al., 2022; and Priola et al., 2022).

In the particular case of Banco de México, not much research has focused on communication. To the best of our knowledge, only Cermeño & Navarrete (2011) and López Marmolejo (2013) have previously addressed this topic. The former constructs a bias index for Banxico’s monetary policy statement and integrates it into an ordinal regression using changes in the next period’s monetary stance as the dependent variable, revealing the short-term predictive effectiveness. López Marmolejo develops a communication index based on relevant sentences from the statements and incorporates it to a Taylor rule OLS estimation, suggesting that Banxico’s communication signals help to predict short-term interest rates and align market expectations. This research highlights the potential influence of Banxico’s communication strategy in shaping expectations about future macroeconomic outcomes, helping to reduce uncertainty, noise, and volatility in financial markets linked to central bank operations.

This paper contributes to this growing literature. The main difference with the aforementioned studies is the type of identification of central bank language. Cermeño & Navarrete
(2011) and López Marmolejo (2013) use a narrative approach with a subjective method, i.e.,
they assign values to Banxico’s communication depending on their idiosyncratic evaluation
of the phrases and words they consider relevant. In contrast, the methodology presented in
this paper focuses on analyzing the predictive power of Banxico’s communication through
the lens of LDA models and sentiment analysis, therefore, the identification relies on statis-
tical processing of the information, subtracting subjectivity from the interpretation of CB
communication.

3. Banco de Mexico’s Communication Strategy

Like in many other CBs around the world, Banxico’s communication strategy has evolved.
Since the early 2000s, the CB began publishing the monetary policy statement (MPS)
reporting its monetary policy decisions, as well as a quarterly inflation report (QIR) aimed
at analyzing economic developments and its consistent monetary policy to meet the objective
of maintaining low and stable inflation. This was followed in 2001 by the formal adoption of
an Inflation Targeting Regime (ITR). Since then, the strategy and communication design
have undergone some changes. The first one culminated in 2011, when, after adopting an
operational target for the overnight interbank interest rate in 2008 and gradually decreasing
the number of monetary policy meetings (MPM) per year, the central bank determined a
calendar with 8 pre-set dates for its monetary policy decisions.

At the MPM the Governing Board can raise, leave unchanged, or cut the policy rate to
influence monetary and financial conditions in line with its mandate to maintain low and
stable inflation. In addition, in the event of extreme economic and financial developments
that require Banxico’s intervention, the Governing Board may adjust the monetary policy
stance at dates other than those established in advance. After each meeting, Banxico releases
the MPS, informing the modifications on the monetary stance.

In addition, Banxico has made other major developments toward greater transparency
and effective communication. For example, since 2011 the institution publishes Minutes of
the MPM, and in 2018 announced that transcripts will be issued three years after the date of
each meeting, making available to the public transcripts of 2018, 2019, and part of 2020 so far.
In 2018, Banxico updated its communication strategy and shifted to an Inflation Forecast
Targeting (IFT) scheme. In 2020, the General Communication Criteria of the Governing
Board and Banxico’s staff were updated and made public for the first time. Since August
2021, the bank conveyed to publish and update the inflation forecast in every monetary policy
statement and identify the direction of the vote of each of the members who participated
in said meeting, indicating the members who adopted the decision taken and, if applicable, those who voted for an alternative decision and what it consisted of. Finally, in May 2022 Banxico took a major step by formally delivering verbal forward guidance in the monetary policy statements. Table 1 summarizes the evolution of Banxico’s communication strategy.

3.1. Monetary Policy Statements

Given the major changes in Banxico’s communication strategy, the QIR, MPS and Minutes have positioned as the main publications in which the CB conveys information about its view on the macroeconomic outlook and explains the rationale behind the monetary policy decisions. MPS are scrutinized by CB watchers because these documents are recognized as potential source of “monetary policy news” since they are published right after the MPM (Bomfim, 2003). Therefore, this publication may contain relevant information and potentially influence financial adjustments and market expectations about the future path of short-term interest rates (Blattner et al., 2008; Milani & Treadwell, 2012).

Our focus in this paper is on the MPS as a way of facilitating CB communication. Particularly, we decided to study the publications between 2008 and 2022 to have a full sample in the period in which Banxico has been conducting its monetary policy strategy through an operational target for the overnight interbank interest rate. The documents consist of a few pages (no more than 3 at their longest over the period under study) containing mainly the following information: i) international developments since the last meeting; ii) a review of economic and financial outlooks for the domestic economy; iii) Banxico’s view on both observed and expected inflation; iv) the balance of risks to the inflation forecast; v) a brief explanation of the rationale behind the monetary policy decision; vi) since May 2021 an update of the inflation forecast.

As highlighted by Hansen et al. (2019), the CB qualitative communication contains information that most of the time is challenging to summarize into quantitative data, so it represents an additional source to traditional macroeconomic time series. In that sense, our database is constructed with the text of the documents leaving aside the forecast tables. In the period under study occurred a total of 131 policy decisions. We collected the statements from Banxico’s official website and stored the information into plain text documents. Before applying any text analysis technique, it is necessary to pre-process the plain text documents and perform a text mining methodology to remove all unnecessary information and obtain a Communication Corpus and a Document-Term Matrix (DTM). All these steps can be consulted in the Appendix.
<table>
<thead>
<tr>
<th>Year</th>
<th>Advances in the communication strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Start of the publication of monetary policy decision bulletins. The publication of Quarterly reports is established, accompanied by a presentation and a press conference.</td>
</tr>
<tr>
<td>2001</td>
<td>Formal adoption of an Inflation Targeting Regime.</td>
</tr>
<tr>
<td>2003</td>
<td>The bank sets specific dates for monetary policy decisions. At least one bulletin is published at the end of the month and another if the policy changes from one month to the next.</td>
</tr>
<tr>
<td>2006</td>
<td>Monetary policy decisions decrease from 23 to 12 a year.</td>
</tr>
<tr>
<td>2008</td>
<td>Monetary policy decisions decrease from 12 to 11 a year. The central bank begins to implement its monetary policy through an operational target for the overnight interbank interest rate.</td>
</tr>
<tr>
<td>2010</td>
<td>Inflation reports include fan charts for inflation and growth forecasts. Start of the publication of the minutes of Governing Board’s meetings.</td>
</tr>
<tr>
<td>2011</td>
<td>Monetary policy decisions decrease from 11 to 8 a year. Video broadcast of the presentation of the Quarterly Inflation Report.</td>
</tr>
<tr>
<td>2016</td>
<td>Former Governor Agustín Carstens announces the launch of the ‘Banxico Educa’ website. This site aims to inform and educate the general public about the objectives, goals and duties of Banco de México. It is also intended to be a means of dissemination and education on economic and financial culture for the country.</td>
</tr>
<tr>
<td>2017</td>
<td>The central projection path for inflation and economic activity is included in the fan charts.</td>
</tr>
<tr>
<td>2018</td>
<td>The central bank shifts its monetary policy strategy to Inflation Forecast Targeting. Inflation reports include for the first time point forecasts of annual quarterly inflation. The minutes begin to disclose the identity of the voters and, in case of dissent, also incorporate a section explaining the reasons behind the dissenters’ vote. The minutes and monetary policy statements are published simultaneously in Spanish and English on the corresponding date. Announcement that transcripts of the meetings will be made available to the public three years after the meeting. The Governing Board adopts a Banxico Speakers approach, making available transcripts of speeches and public presentations by the members.</td>
</tr>
<tr>
<td>2020</td>
<td>The General Communication Criteria for the Governing Board and Banxico’s staff are updated and made public for the first time. It is established that the press releases, monetary policy statements and minutes would be made clearer and more concise in its extension.</td>
</tr>
<tr>
<td>2021</td>
<td>First disclosure of transcripts. An update of headline and core inflation forecasts for the following eight quarters is published after each monetary policy decision. The monetary policy statements identify the direction of the vote of each of the members of the Governing Board who participated in said meeting, indicating the members who adopted the decision taken and, if applicable, those who voted for an alternative decision and what it consisted of.</td>
</tr>
<tr>
<td>2022</td>
<td>Forward guidance is included in monetary policy statements.</td>
</tr>
</tbody>
</table>

Source: Banxico’s official documents and press releases from the Governing Board.
4. The Predictive Power of Central Bank Communication

We estimated the predictive power of CB communication following a similar methodology as in Tobback et al. (2017), Baranowski et al. (2021), Astuti et al. (2022) and Priola et al. (2022). First, using a Latent Dirichlet Allocation (LDA) model, we derived a series of latent topics that were the focus of Banxico’s language between 2008 and 2022. Then, since topics alone do not provide relevant measurable information, we decided to apply dictionary-based sentiment analysis to obtain our Hawkish-Dovish Tone (HDT) index of Banxico’s monetary policy statements.

With the information gathered, we focused on determining whether the tone of the documents can help to predict upcoming monetary policy decisions. Specifically, we examined whether the qualitative information provided by Banxico contains relevant “monetary policy news” by including the HDT index in an ordinal logit regression using changes in the monetary policy rate at the next decision as the dependent variable. We also incorporated gaps and expectations in the analysis, so that the logit estimation can be considered as an ordinal transformation of a Taylor rule augmented by communication.

4.1. Topic Modeling

Topic Modeling is a statistical technique for revealing the underlying semantic structure in large collection of documents (Kherwa & Bansal, 2019). In this field of computer science, the most notable contribution in the past two decades is the LDA algorithm, first proposed by Blei et al. (2003). The intuition behind the model is quite simple: every document can be though as a mixture of topics, and every topic as a mixture of words. In this regard, LDA is a generative probabilistic model that employs an unsupervised learning process: given the number of documents, $N$, the number of unique terms (words) in the corpus, $V$, and the number of topics, $K$, it aims to identify the underlying distribution by estimating the mixture of words that is associated with each topic, while also determining the mixture of topics that describes each document. At the highest level, LDA represents a three-level hierarchical probabilistic assignment model, where each document is modeled as a weighted mixture of the underlying set of topics, and each topic is modeled, in turn, as a weighted mixture of the underlying set of terms in the corpus. Details of the LDA algorithm and statistical estimation can be found in Blei et al. (2003), Hansen et al. (2018) and Hansen et al. (2019).

In the context of CB communication, let’s think of topics as overarching themes that emerge from the diverse array of messages the CB conveys. Just as CBs address a wide range of economic and monetary issues in their communications, LDA identifies these underlying
themes by analyzing the frequency and co-occurrence patterns of words across documents. For instance, a CB’s messages might cover topics like inflation, interest rates, economic growth, and financial stability. LDA helps uncover these latent themes and their proportions in the communication corpus, offering a holistic view of the key subjects being addressed. In our LDA model, documents can be thought of as individual MPS. Each of these documents represents a mixture of different topics covering various aspects of monetary policy and the economy. LDA extracts the underlying topics and their contributions to each document, shedding light on the multifaceted nature of central bank messaging. This process allows to discern the nuanced policy directions and priorities embedded within these communications. Just as certain keywords or phrases signal specific themes in CB communication, LDA identifies words that serve as indicators of topics. For instance, words like “inflation,” “rate,” “growth,” and “stability” might be strong indicators of distinct topics related to monetary policy. LDA’s probabilistic approach captures the likelihood of words appearing within each topic, which aligns with how CBs convey different emphases through specific terminology. By uncovering these word-topic relationships, LDA provides a quantitative foundation for understanding the semantic content of central bank communication, revealing the underlying narrative and policy signals.

Our LDA communication model takes as inputs the data in our DTM (see Appendix A): $N = 131; V = 1,649$; and the number of topics, $K$. Despite the many advantages of using LDA models, they have two limitations. First, determining the optimal number of topics can be challenging due to the unknown value of $K$. Secondly, interpreting the results can be ambiguous since the model only reveals the structure of topic-per-word and document-per-topic probabilities, meaning the results are a weighted bag of words associated with the topics of each document and the words of each topic. However, it lacks the ability to assign labels to each of the topics, thus requiring some prior knowledge to interpret the content and infer an appropriate structure for each of them.

We have effectively addressed the first issue by training a total of 99 models for $K$ values ranging from 2 to 100. We then ran the algorithms developed by Griffiths & Steyvers (2004), Cao et al. (2009), Arun et al. (2010) and Deveaud et al. (2014). This procedure yields four validated metrics to determine the number of topics to consider, which suggest that the optimal value of $k$ lies between 13 and 61 (see Figure 1). When estimating the LDA model, it is crucial to consider the trade-off between the number of topics and accuracy in assigning unique terms.\(^5\) That is, using a large value for $k$ may improve the accuracy in assigning unique terms, which involves a dilemma between interpretability and goodness of fit (Chang et al., 2009).

\(^5\)In LDA model estimation, it is essential to balance the number of topics with the accuracy in assigning unique terms, which involves a dilemma between interpretability and goodness of fit (Chang et al., 2009).
terms to each topic, but it may also lead to a more complicated interpretation. Conversely, using a small value for k may simplify the interpretation, but it comes with a risk of assigning a small number of topics that are too general. After considering the recommended k-range of the four metrics, as well as analyzing previous literature on CB communication (see Section 2), which typically uses between 5 and 30 topics, we evaluated different LDA models for k ranging from 5 to 35. Finally, we selected rather ad hoc 11 topics as the optimal value for our communication corpus.\(^6\)

Figure 1: Optimal Number of Topics

*Source:* Author’s calculations. *Notes:* Standardized values of each metric. The optimal number of topics is found where the metrics are minimized (top panel) or maximized (bottom panel).

\(^6\)This type of selection is supported by the recommendations of Blei (2012), who states that interpretability is a legitimate reason to choose a value of \(K\) different from the one that yields the most efficient model. He highlights the disconnect between how topic models are evaluated and the reasons why we expect them to be useful (Blei, 2012, as cited in Hansen et al., 2018, p. 18).
Table 2: Terms with the highest Probability per Topic

<table>
<thead>
<tr>
<th>Topics Structure</th>
<th>LDA Topics</th>
<th>Terms within Topics (Top 10 with the highest Probability)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monetary Policy</td>
<td>Topic 1</td>
<td>continuous Banxico interest rate Mexico day decision overnight interbank interest rate recent bank first</td>
</tr>
<tr>
<td></td>
<td>Topic 11</td>
<td>monetary policy expectations low decrease good regard monetary balance affect average</td>
</tr>
<tr>
<td>Economic Activity</td>
<td>Topic 2</td>
<td>economy activity contraction narrow Governing Board month purpose emergent last expect</td>
</tr>
<tr>
<td></td>
<td>Topic 3</td>
<td>country product equal gap growth rate development great near behavior</td>
</tr>
<tr>
<td></td>
<td>Topic 10</td>
<td>exhibit shock might domestic particular record tendency process hold special</td>
</tr>
<tr>
<td>International Affairs</td>
<td>Topic 4</td>
<td>recovery year United States although hold previous toward demand annual forecast</td>
</tr>
<tr>
<td></td>
<td>Topic 7</td>
<td>international part anticipate economic growth change minor zone previous prevail still</td>
</tr>
<tr>
<td>Balance of Risks</td>
<td>Topic 5</td>
<td>risk factor environment inform uncertainty large median amount prudent track</td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>Topic 6</td>
<td>price depreciate currency commodity related spoil general service decision possible</td>
</tr>
<tr>
<td>COVID-19 Pandemic</td>
<td>Topic 8</td>
<td>core headline pandemic term effect financial market global trajectory action necessary</td>
</tr>
<tr>
<td>Inflation Risk</td>
<td>Tópico 9</td>
<td>increase inflation pressure target major level base quarter point adjust</td>
</tr>
</tbody>
</table>

Source: Author’s calculation
Note: The table displays the top 10 terms with the highest probability of belonging to each topic
Each term is represented in its root form (see Appendix A).
The LDA model is estimated using the original Spanish documents, and the terms shown in the table are translations by the author.
With the information derived from the LDA model, we identified 7 potential categories into which Banxico directed its language over the period 2008-2022: Monetary Policy, Economic Activity, International Affairs, Exchange Rate, Inflation Risk, Balance of Risks, and COVID-19 Pandemic. As depicted in Table 2, each of the inferred topics can be linked to specific subjects. For example, topics 1 and 11 encompass words closely related to monetary policy (“interest rate”, “decision”, “overnight interbank interest rate”, “monetary policy”, “balance”), making it possible to label these topics as identifiable components of Banxico’s monetary policy language. Topics 2, 3, and 10 are tied to economic activity, as words such as “economy”, “activity”, “gap”, “growth”, to name a few, exhibit a high likelihood of being part of them. Topics 4 and 7 represent international affairs, whereas topics 5, 6, 8, and 9 are associated with the balance of risks, exchange rate, the COVID-19 pandemic, and inflation risk, respectively.

In addition, the document-per-topic probabilities allow us to describe the thematic distribution over time within all MPS (see Figure 2).

![Figure 2: Topics Relative Frequency.](image)

*Source:* Author’s calculations. *Notes:* Each topic is represented by its document-per-topic probability distribution. The topics are labeled using ad-hoc criteria based on the analysis of words with a high probability of occurrence (see Table 2).

Throughout the period, topics related to Monetary Policy show a high prevalence among policy statements. International Affairs and Economic Activity also capture most of the language in specific periods, notably standing out in the post-Global Financial Crisis era.
It is also worth mentioning that the Exchange Rate topic shows a high prevalence between 2014 and 2016, when Banxico acknowledged that external shocks could pose some challenges to the achievement of its objectives. Another important highlight is that we identify themes related to the COVID-19 pandemic and Inflation Risk, which explain most of the language since 2020, in line with the macroeconomic narrative of this period.

4.2. Sentiment Analysis

Since the LDA model alone does not provide relevant measurable information on the semantic content of CB communication, we calculated a measure of the policy bias (hawkish/dovish) for each MPS. Using dictionary-based sentiment analysis, we constructed a Hawkish-Dovish Tone (HDT) index. To this end, we rely on the Loughran-McDonald [LM] (Loughran & Mcdonald, 2011, 2014) and González-Tadle [GT] (Gonzalez & Tadle, 2021) dictionaries. We decided to use an intercept between the bag of words of both dictionaries because the former has been widely validated by the literature on CB communication, while the latter is a novel contribution to the analysis of CB documents written in Spanish in Latin American and other emerging economies.

The LM and GT dictionaries are made up of two types of words: positives/hawkish and negatives/dovish. The positives/hawkish category contains terms that CBs use when implementing a restrictive policy stance, such as 'increase,' 'inflationary,' 'high,' 'accelerate,' and others. On the other hand, the negatives/dovish category includes terms that CBs emphasize when taking an accommodative policy, such as 'adverse,' 'cut,' 'decrease,' 'low,' 'disinflation,' and others. We use these categories to create an average tone index that considers the CB's policy tone. To calculate the index, we use the following formula:

\[
HDT_i = \frac{\sum_{positive\_i} - \sum_{negative\_i}}{\sum_{positive\_i} + \sum_{negative\_i}}
\]

where \(\sum_{positive\_i} - \sum_{negative\_i}\) is the total number of positive words minus the total number of

---

7For instance, on February 17, 2016, Banxico made an unscheduled decision to raise the policy rate by 50 basis points. This move responded to increased volatility in international financial markets and deteriorating external conditions for the Mexican economy, including the continued fall in oil prices. These factors were recognized by the CB as negatively affecting public finances, the current account, and the exchange rate, thus increasing the risk of misalignment of inflation expectations with the target.

8The LM dictionary is a collection of English words represented in their root form. The GT dictionary contains a set of Spanish and English words that have been used to analyze the thematic content of central banks that communicate in a similar writing style to Banco de México, such as Chile, Peru, Brazil, Australia, Israel, New Zealand, among others. To match our analysis, we translated the dictionary using the DeepL software. Then, 5 synonyms are considered for each word, seeking congruence between the dictionary language and the specific wording of Banco de México.
negative words in document $i$, normalized by the total coincidences between the dictionaries and document $i$, $\sum positive_i + negative_i$. This formula results in an index of the average sentiment of each MPS, on a scale of 1 to -1, where 1 represents the exclusive use of hawkish language and -1 the total use of dovish terms.

Following Astuti et al. (2022), we built our HDT weighted index utilizing the subset of documents belonging to $k$ topics identified by the LDA model. Thus, we performed sentiment analysis considering the topic-per-word and document-per-topic distributions. First, we computed the individual sentiment for each topic ($k$) in each document ($i$): $HDT^{k}_i, k = 1, \ldots K$. As a final step, we calculated the weighted average:

$$HDT_{w_i} = \frac{\sum_{k=1}^{K} w_{k,i} HDT^{k}_i}{\sum_{k=1}^{K} w_{k,i}}$$

Figure 3 shows our tone index and Banxico’s policy rate between 2008 and 2022. The variables are expressed in monthly frequency, so that the policy interest rate corresponds to the values observed at the end of each month. In the case of the HDT weighted index, a Last Observation Carried Forward imputation was performed to obtain a monthly series, followed by a 9-month moving average to reduce noise.

**Figure 3:** Evolution of Banco de México’s target rate and communication tone
*Source: Author’s calculations. Notes: The target rate corresponds to the observed values at the end of each month. As for the HDT index, a Last Observation Carried Forward imputation is performed to obtain a monthly series, and a 9 month moving average is applied to reduce noise.*
There are several periods in which joint movements of the variables are observed, such as 2008-2009, 2016-2018, 2019-2020 and 2021-2022. In addition, it is worth noting that the Pearson’s correlation coefficient emphasizes a moderately positive linear relation between the variables, with a value of 0.68.

### 4.3. Econometric Estimation

Our objective is to determine whether CB communication can accurately predict interest rate decisions. Specifically, we should expect the use of restrictive language to be an indicator of an upcoming policy rate hike. Conversely, accommodative language should suggest an imminent interest rate cut. If the language used is neutral or uncertain, it is more likely that there will be no change in monetary policy in the near term.

Following the aforementioned criteria, we decided to include our HDT weighted index into an ordinal logit model. Since policy interest rates typically move by a discrete amount (e.g., by 25 basis points), we selected this type of econometric estimation because it allows capturing the discrete nature of variables. Therefore, to investigate the research question we used the changes in the monetary policy rate ($\Delta r_t$) as the dependent variable. $\Delta r_t$ take values of: $-3 \rightarrow 75$ basis points (bp) cut; $-2 \rightarrow 50$bp cut; $-1 \rightarrow 25$bp cut; $0 \rightarrow$ no change in the monetary policy stance; $1 \rightarrow 25$bp hike; $2 \rightarrow 50$bp hike; $3 \rightarrow 75$bp hike.\(^9\)

Moreover, in our analysis we also incorporated other relevant macroeconomic variables such as the the inflation and output gaps and private inflation and growth expectations. The inflation gap is measured by the difference between the annual percent changes on the Consumer Price Index and Banxico’s inflation target (3%), and the output gap by the cyclical component of the overall indicator of economic activity (IGAE), measured through the Hodrick-Prescott filter. Private expectations are proxied by financial analyst 12-month ahead inflation and year-end GDP growth forecasts, as measured by the average monthly observations from Banxico’s survey of private-sector economic experts’ expectations. Since data on interest rate decisions are not collected on a regular monthly frequency, the macroeconomic variables represent the information available at the time of the decision (e.g., the October 2020 decision considers the September 2020 gaps and expectations).\(^10\)

Let’s start with a discrete representation of a classical Taylor rule for policy rates,\(^9\) Cermeño & Navarrete (2011), Picault & Renault (2017), Baranowski et al. (2021), and Priola et al. (2022) apply a similar methodology for other CB, choosing only -1, 0, +1 for the discrete change in the policy rate. Following Astuti et al. (2022), we employ various categories at different levels of analysis to accurately assess the influence of communication on specific monetary policy changes.

\(^9\)Gaps and Expectations are taken in first differences, which is consistent with similar studies. See Bennani & Neuenkirch (2017), Astuti et al. (2022) and Priola et al. (2022).
considering it as a function of inflation and output gaps:

\[ \Delta r_t = \rho \Delta r_{t-1} + \alpha \Delta (\pi_t - \pi^T) + \beta \Delta (y^*_t) + \epsilon_t \] (3)

where \( r_t \) is the policy rate, \( \pi_t \) is the inflation rate, \( \pi^T \) is the inflation target, \( y^*_t \) is the output gap, \( \alpha, \beta, \rho \) are parameters, and \( \epsilon_t \) is an error term. We also considered one period lagged variable, to control for the smoothing of monetary policy.

Traditionally, this specification is widely accepted as good estimation of the CB reaction function (Orphanides, 2010), so we should expect the parameters to be significant in the regression. Following Apel & Blix-Grimaldi (2014) and Astuti et al. (2022), we augmented this model in two ways. First, we included expectations to represent a forward-looking Taylor rule:

\[ \Delta r_t = \rho \Delta r_{t-1} + \alpha \Delta (\pi_t - \pi^T) + \beta \Delta (y^*_t) + \gamma \Delta E_t(\pi_{t+12}) + \delta \Delta E_t(y^{ye}) + \epsilon_t \] (4)

where \( E_t(\pi_{t+12}) \) is 12-month ahead inflation expectations, and \( E_t(y^{ye}) \) is year-end GDP growth expectations.

Secondly, we augmented the model with communication by including our HDT weighted index in both the classical and forward-looking specification:

\[ \Delta r_t = \rho \Delta r_{t-1} + \alpha \Delta (\pi_t - \pi^T) + \beta \Delta (y^*_t) + \phi HDT w_{t-1} + \epsilon_t \] (5)

\[ \Delta r_t = \rho \Delta r_{t-1} + \alpha \Delta (\pi_t - \pi^T) + \beta \Delta (y^*_t) + \gamma \Delta E_t(\pi_{t+12}) + \delta \Delta E_t(y^{ye}) + \phi HDT w_{t-1} + \epsilon_t \] (6)

If CB communication adds valuable information to anticipate interest rate decisions, beyond that stemming from the other regressors, the tone in \( t \) should be able to predict the change in the monetary stance in \( t + 1 \). Therefore, we should expect \( \phi \) to be positive and statistically significant. Finally, we ran the logit regression considering only the smoothing term and the HDT weighted index, in order to investigate the predictive power of communication alone.
Table 3 shows the results of logit estimations. As can be noted, neither gaps nor expectations show statistical significance in the classical and forward-looking specifications. On the other hand, the communication augmented models display a better performance with higher McFadden Pseudo $- R^2$ and lower (Akaike) information criteria. The tone index parameter is statistically significant at the 5% level across the different specifications, suggesting that it is a relevant variable in anticipating the next policy decision. Moreover, this performance holds when we only consider the smoothing term and the HDT weighted index.

Table 3: Ordinal logit estimation results

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta r_{t-1}$</td>
<td>8.823***</td>
<td>8.174***</td>
<td>8.791***</td>
<td>8.174***</td>
<td>8.157***</td>
</tr>
<tr>
<td></td>
<td>(0.976)</td>
<td>(1.006)</td>
<td>(0.982)</td>
<td>(1.011)</td>
<td>(1.004)</td>
</tr>
<tr>
<td>$\Delta (\pi_t - \pi^T)$</td>
<td>0.400</td>
<td>0.323</td>
<td>0.378</td>
<td>0.312</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.389)</td>
<td>(0.396)</td>
<td>(0.391)</td>
<td>(0.396)</td>
<td></td>
</tr>
<tr>
<td>$\Delta (y_t^*)$</td>
<td>4.516</td>
<td>3.215</td>
<td>4.536</td>
<td>3.143</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.510)</td>
<td>(7.374)</td>
<td>(7.652)</td>
<td>(7.511)</td>
<td></td>
</tr>
<tr>
<td>$HDT w_{t-1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.440**</td>
<td>2.362**</td>
<td>2.597**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.159)</td>
<td>(1.168)</td>
<td>(1.152)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta E_t(\pi_{t+12})$</td>
<td>0.833</td>
<td>0.586</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.986)</td>
<td>(0.955)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta E_t(y^{pc})$</td>
<td>0.047</td>
<td>0.043</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(0.156)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo$R^2$</td>
<td>0.339</td>
<td>0.352</td>
<td>0.342</td>
<td>0.353</td>
<td>0.349</td>
</tr>
<tr>
<td>Parallel Assumption</td>
<td>holds</td>
<td>holds</td>
<td>holds</td>
<td>doesn’t</td>
<td>holds</td>
</tr>
<tr>
<td>LLR</td>
<td>-117.512</td>
<td>-115.244</td>
<td>-117.126</td>
<td>-115.043</td>
<td>-115.738</td>
</tr>
<tr>
<td>AIC</td>
<td>253.024</td>
<td>250.488</td>
<td>256.252</td>
<td>254.086</td>
<td>247.477</td>
</tr>
</tbody>
</table>

Source: Author’s calculations
Ordinal logit models estimated by maximum likelihood.
Asymptotic standard errors are given in parentheses.
***Significant at the 1 percent level; **5 percent level; *10 percent level.
Brant test was performed to validate the parallel lines assumption.
In model D, $E_t(\pi_{t+12})$ parameter violates the parallel lines assumption.
LLR stands for Log-Likelihood Ratio.

Simultaneously, when applying a “from general to specific” approach, taking model D as the starting point, looking for individual significance in the coefficients of the independent variables and the non-rejection of the null hypothesis in the Brant test to verify the fulfillment
of the parallel lines assumption, the estimates lead us to consider model E as the best specification.

In summary, the results suggest that forecasting the monetary policy stance is feasible if we only consider our tone index. Therefore, Banco de México, through its monetary policy statements, sends key signals that contain relevant information for the determination of the next interest rate decision. Moreover, as the tone index remains informative even after accounting for macroeconomic variables, the analysis indicates that this information cannot be captured by inflation and output gaps or private sector expectations.

The estimated coefficients of the logit regression do not directly reveal information about the contributions of independent variables on the dependent variable, unlike the linear models. Therefore, to yield an economic interpretation, we calculated the average marginal effects (AME) related to model E. To facilitate the interpretation of the results, the tone index is standardized and denotes variations in terms of standard deviations. The AME provide information of the estimated change in the predicted probabilities of moving up or down the ordinal response categories for a one-unit change in the independent variable, while holding other variables constant. In our analysis, the latter means we report the effects on the probability of changes in the policy rate (±75bp, ±50bp, ±25bp, or no changes) for a one standard deviation increase in the tone index, or for a unit change in the discrete lagged rate. Table 4 shows the results.

<table>
<thead>
<tr>
<th></th>
<th>Pr(-3)</th>
<th>Pr(-2)</th>
<th>Pr(-1)</th>
<th>Pr(0)</th>
<th>Pr(1)</th>
<th>Pr(2)</th>
<th>Pr(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta r_{t-1}$</td>
<td>-0.013</td>
<td>-0.121**</td>
<td>-0.347***</td>
<td>-0.404*</td>
<td>0.700***</td>
<td>0.174**</td>
<td>0.012</td>
</tr>
<tr>
<td>$HDTw_{t-1}$</td>
<td>-0.004</td>
<td>-0.039</td>
<td>-0.111**</td>
<td>-0.129</td>
<td>0.223**</td>
<td>0.055*</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Source: Author’s calculation.
Note: Average marginal effects of model E.
Statistical significance at 1% (***) and 5% (**). Statistical significance at 10% (*).

A positive AME indicates that an increase in the independent variable is associated with higher odds of moving to a higher category of the dependent variable. A negative AME indicates the opposite, that is, a higher odd of moving to a lower category. For example, when Banxico tightens its monetary policy, the probability of observing a 25bp, 50bp, or 75bp rate hike in the next decision increases by 70%, 17%, and 1.2% (not significant), respectively. On the other hand, when Banxico eases its monetary policy, this probability decreases by 35%, 12%, and 1.3% (not significant).

As for the tone index, we found that a one-standard-deviation increase (decrease)
change in the tone of communication increases on average the probability of a rate hike (rate cut). Accordingly, the probability of observing a rate hike of 25bp, 50bp, or 75bp in the next decision increases by 22%, 5.5% and 0.4% (not significant) when Banxico delivers a hawkish message in the monetary policy statement. Conversely, when the message is dovish, this probability decreases by 11%, 3.9% (not significant), and 0.4% (not significant). These results are consistent with the expected effects of CB communication as a predictor of upcoming short-term interest rate decisions (see Blattner et al., 2008) and with recent research empirically testing the same hypothesis in other CB (see Astuti et al., 2022; and Priola et al., 2022).

During the period under study, Banco de México’s Governing Board met on 131 occasions; on 77 of these meetings, it was decided to leave the policy rate unchanged, on 23 it was cut by at least 25bp, and it was raised by at least 25bp on 31 occasions. Our model is effective in anticipating, on average, 7 out of 10 changes in Banco de México’s monetary policy stance. Specifically, it is highly efficient when the monetary stance remains unchanged, successfully anticipating 93.5% of the time. When large changes occurred (+75bp) the model has a hit success rate of 66% and 75% for negative and positive shifts, respectively. On the other hand, Banxico’s communication anticipates 5 out of 10 times that the policy rate increased by 25bp and 50bp, respectively. It shows similar results in the case of 50bp cuts (4 out of 9). Finally, the model presents its worst performance for changes of −25bp, as it failed to predict even one of the 11 times the CB cut its rate by this amount. Table 5 summarizes these results.

Table 5: Predictive power of Banco de México’s communication

<table>
<thead>
<tr>
<th></th>
<th>-75bp</th>
<th>-50bp</th>
<th>-25bp</th>
<th>hold</th>
<th>+25bp</th>
<th>+50bp</th>
<th>+75bp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>3</td>
<td>9</td>
<td>11</td>
<td>77</td>
<td>16</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>Prediction</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>72</td>
<td>8</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>Success Rate (%)</td>
<td>66.6%</td>
<td>44.4%</td>
<td>0%</td>
<td>93.5%</td>
<td>50.0%</td>
<td>54.6%</td>
<td>75.0%</td>
</tr>
</tbody>
</table>

Source: Author’s calculation.

These findings are due to multiple factors, among the main ones we can identify: during most of the period under study, Banco de México hold the policy rate steady, or was in a tightening cycle, which explains why the model is more effective in anticipating this type of decisions; interest rate cuts were not systemic; there were occasions in which the CB changed its monetary stance without modifying the communication strategy. For example, unanticipated changes were observed, such as in February 2016 (oil price shock) and March-April 2020 (COVID-19 pandemic), when the CB modified its monetary stance in extemporaneous decisions.
Figure 4 presents the fitted values of the ordinal logit model, compared to the observed path of Banxico’s policy rate. The trajectory of the predicted interest rate suggests that Banxico’s Governing Board, through its communication strategy, was able to effectively convey the expected movements for the next monetary policy meeting, however, there were certain periods when it was not able to adequately telegraph its plans. Part of this was due to unforeseen shocks in the economy that could hardly have been anticipated. Overall, our analysis suggests that Banco de México is more effective in telegraphing its decisions when it intends to raise or leave the policy rate unchanged, as compared to when it expects cuts in future decisions. The econometric estimation results present elements to conclude that Banxico’s communication is effective in anticipating 7 out of 10 interest rate decisions.

5. Conclusions

Following the world’s leading CBs and the observed trends in monetary policy making, Banco de México has made significant efforts to improve its communication and transparency strategy over the last 20 years. In this paper, we have measured the role of CB qualitative communication as a monetary policy tool, based on the language contained in the monetary policy statements of this institution.
We have leveraged Natural Language Processing techniques to uncover aspects of CB communication. In particular, using a Latent Dirichlet Allocation model, an unsupervised machine-learning technique, and dictionary-based sentiment analysis, we have developed our Hawkish-Dovish Tone weighted index, which captures the bias in the tone of communication. The LDA model was useful to identify a series of latent topics on which Banco de Mexico’s language focused between 2008 and 2022. Using this information, we could capture CB’s talk on Monetary Policy, Economic Activity, International Affairs, Exchange Rate, Inflation Risk, Balance of Risks and COVID-19 Pandemic. Our findings also suggest that Banco de México’s communication is highly effective in anticipating future short-term interest rate decisions.

In particular, the analysis reveals that the CB, through its communication, sends key signals that contain relevant information for the determination of the short-term monetary stance, information that cannot be reflected in conventional macroeconomic indicators. The latter was an interesting upshot of our study. It is worth mentioning that CB communication can capture prospective and retrospective qualitative information about the CB’s view. Therefore, we interpret these results as follows: CB communications are informative and influential and have the ability to encompass information on important macroeconomic variables in the determination of monetary policy, i.e., by having more and better information on upcoming economic outcomes, and on its own behavior, the CB shares information that by itself is relevant in the short run. Accordingly, our communication model was able to predict almost all the decisions in which the monetary stance remained steady, and was effective when changes of ±75bp, ±50bp and +25bp occurred. However, it fails to anticipate a single one of the 11 decisions in which the central bank cuts its rate by 25bp. These results are consistent with the expected effects of CB communication as a predictor of upcoming short-term interest rate decisions (see Blattner et al., 2008) and with recent research empirically testing the same hypothesis in other CBs (see Astuti et al., 2022; and Priola et al., 2022).

In conclusion, our findings suggest that Banco de México, through its communication strategy, can effectively convey the expected movements for the next monetary policy meeting, especially when it comes to tightening cycles, or when monetary policy holds the rate steady. However, there were certain periods when it was unable to adequately telegraph its plans. Part of this was due to unanticipated shocks to the economy that could hardly have been foreseen, such as the increase in international oil prices in 2016 and the COVID-19 pandemic lockdown in 2020. The econometric estimation results present robust elements to determine that CB communication is effective in anticipating, on average, 7 out of 10 interest rate decisions. In other words, our study suggests that by considering the previous monetary policy decision and a correct interpretation of the information in the monetary policy statement,
it is possible to anticipate with 70% effectiveness what Banco de México will do in its next decision.

Going forward, there are various implications of our analysis. First, the text-processing techniques outlined in this article could be useful to develop further investigation on the predictability of monetary policy. On the one hand, we could leverage the results of the LDA model to explore how different aspects of communication, such as monetary policy, economic activity, international affairs, to mention a few, may be useful to forecast policy and other market interest rates. For example, it would be interesting to study how CB communication impacts on different maturities of the yield curve, or how different subjects of communication are related to real and nominal rates. On the other hand, we could apply the same methodology to other publications, such as inflation reports or minutes, to check if our conclusions hold in all these documents, or even study the news about central banking on the day of the decision, and how analysts and financial markets react to the communications in the very short term.

Likewise, the ability of a CB communication index to forecast policy rate decisions holds profound implications across the economic landscape. This predictive power may reflect the CB’s success in conveying its intentions and economic outlook to stakeholders. By providing accurate guidance, the CB enhances market predictability, reduces volatility, and bolsters its policy credibility. The influence of CB communication may extend to diverse macroeconomic variables, impacting investment, business planning, household behavior, and even international trade dynamics. Ultimately, effective communication could act as a linchpin, fostering a more informed, stable, and responsive economic environment, where policy decisions resonate through interconnected channels, driving growth, stability, and well-informed decision-making. Building upon this notion, it becomes intriguing to evaluate the influence of qualitative communication on financial markets, particularly in contemporary times. Another potential investigation pertains to exploring if CB qualitative communication shapes expectations of professional forecasters. Hence, a feasible approach could encompass integrating indicators akin to our tone index within varied econometric models to examine communication’s impact on private agents’ expectations. It’s reasonable to anticipate that effective central bank communication could affect these variables, even if temporarily.

Overall, our findings show that, similar to what has been observed in other economies, Banco de México’s communication provided by the language of the monetary policy statements is estimated to be powerful and effective in anticipating upcoming interest rate decisions. In terms of monetary policy, these results imply that Banco de México can take advantage of its communication strategy to provide guidance on future actions, potentially anchoring
expectations and reducing noise in financial markets, consequently, improving the transmission of monetary policy. As stated by Ben Bernanke (2015), monetary policy today is 98 percent talk and only two percent action, so the ability to shape market expectations about future policy through public statements is one of the most powerful tools CBs have. Thus, following Gabriel Markhlouf (2020), we should expect the days of “mumbling with great incoherence” to be over.

References


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Appendix A: Text Mining and Document Preprocessing

To apply the techniques implemented in this research to the publications of the central bank, a process of filtering and cleansing the documents must be carried out. This is commonly known as text mining, and it involves extracting useful and relevant information from a set of unstructured text documents. It is used in the field of data mining and artificial intelligence to analyze large amounts of text and discover hidden patterns, trends, and insights.

The objective of text mining is to transform textual data into structured and comprehensible information, enabling deeper analysis and informed decision-making. Various techniques and algorithms are applied during the text mining process, such as natural language processing (NLP), text classification, entity extraction, sentiment analysis, among others. Some common tasks in text mining include identifying keywords, detecting topics, document classification, grouping similar documents, and extracting specific information such as names of individuals, locations, or dates. In summary, text mining is a technique that allows converting large volumes of unstructured data into valuable information, facilitating the understanding and analysis of texts in different contexts and applications.

For our specific case, the first step is to download the publications. This includes all of Banxico’s monetary policy statements from 2008 to 2022. All information was obtained in PDF format from Banco de México’s official website. I chose to analyze the publications in the original Spanish language for two reasons: first, the availability of the documents, and second, to eliminate any bias that might be introduced in the translation. Secondly, before applying any text mining techniques, it is necessary to preprocess the documents to obtain a set of plain text data. The filtering process involves removing all non-text-related objects, such as headers, page numbers, covers, indexes, table of contents, footnotes, appendices, etc. Despite the many efforts made by academics and researchers to develop techniques for including graphics, tables, figures, charts, and other visual elements in linguistic analysis, no such method is available. Therefore, even though such material can add valuable content to the analysis, it is necessary to eliminate them.

With this information, a corpus of central bank documents can be constructed. Specifically, a corpus is a structured and systematic collection of documents or other linguistic data that are gathered and organized for the purpose of analysis and study. The central bank communication corpus provides a valuable data source for the empirical analysis in this research. Our corpus consists of 131 plain text documents, for each monetary policy statement. A second filtering step is performed, which involves converting each letter to lowercase, removing all numbers, punctuation marks, and stop words. Stop words are common
words that are excluded or filtered in natural language processing and text analysis. These words are very frequent in language but often do not contribute substantial meaning to the context or understanding of the text. Common examples of Spanish stop words include “de,” “el,” “y,” “es,” “en,” “a,” “una,” “para,” among others. These words are often adverbs, conjunctions, prepositions, and pronouns that are frequently used in sentence construction but do not provide distinctive or relevant information for text analysis. By eliminating these words, noise or interference in the analysis can be reduced, and the most important and distinctive words (or terms) in the text can be identified more accurately.

The following is an example of what a paragraph from Banco de México’s publications would look like, with and without punctuation marks, numbers and stop words. Specifically, the Monetary Policy Statement of December 12, 2022 is used:

**ORIGINAL STATEMENT:**
La Junta de Gobierno del Banco de México decidió incrementar en 50 puntos base el objetivo para la Tasa de Interés Interbancaria a un día a un nivel de 10.50%, con efectos a partir del 16 de diciembre de 2022. La actividad económica mundial se recuperó moderadamente en el tercer trimestre, aunque las perspectivas para 2023 siguieron deteriorándose. La inflación global se mantiene elevada, si bien la general disminuyó en diversas economías ante menores presiones en los precios de alimentos y energéticos.

**STATEMENT WITHOUT PUNCTUATION, NUMBERS, AND STOP WORDS:**
\text{junta gobierno banco méxico decidió incrementar puntos base objetivo tasa interés interbancaria día nivel efectos partir diciembre actividad económica mundial recuperó moderadamente tercer trimestre aunque perspectivas siguieron deteriorándose inflación global mantiene elevada si bien general disminuyó diversas economías ante menores presiones precios alimentos energéticos}

This process allows us to identify only unique and significant terms for analyzing the lexical diversity of the central bank. It can be argued that removing stop words, numbers, and punctuation makes reading the text slightly more difficult. However, the message and context of the publication remain understandable. Finally, a series of n-grams are collapsed. N-grams are continuous sequences of n elements, which can be words, symbols, or tokens in a document. In the corpus constructed so far, bi-grams and tri-grams are chains of two and three words, respectively, that often appear together in the text. For example, “crecimiento económico”, “tasa de interés”, “política monetaria”, “Estados Unidos”, “tipo de cambio”, “meta de inflación”. etc. The n-grams considered in Banxico publications are a combination
of Toborda’s list (see Taborda, 2015) adapted to the central bank’s style and extended with some terms that the author considers relevant for identification:

- banco central, bancos centrales, banca central → banco_central.
- banco central europeo → bce.
- banco de méxico → banxico.
- crecimiento económico, crecimiento de la economía → crecimiento_económico.
- crisis financiera → crisis_financiera.
- comercio internacional → comercio_internacional.
- covid-19, coronavirus, sarscov2 covid → covid.
- déficit fiscal, déficit público → déficit_fiscal.
- europa, eurozona, europeo, europea, europeos, eurosistema, eurogrupo → europa.
- estabilidad financiera → estabilidad_financiera.
- estados unidos, estadounidense, estadounidenses → estados_unidos.
- internacional, internacionales, mundial, mundiales, mundo → internacional.
- junta de gobierno → junta_gobierno.
- objetivo de inflación, objetivos de inflación, inflación objetivo, meta de inflación, metas de inflación, inflación meta → inflación_objetivo.
- mercados financieros, mercado financiero, sistema financiero, sector financiero → mercado_financiero.
- sistemas bancarios, sistema bancario, sector bancario, sectores bancarios → sector_bancario
- mexicana, mexicano, mexicanos, méxico → méxico.
- política fiscal, políticas fiscales → política_fiscal.
- política monetaria → política_monetaria.
- tasas de referencia, tasa de referencia → tasa_monetaria.
- tipo de cambio, tipos de cambio, tasa de cambio, tasas de cambio → tipo_cambio.
- tipo de interés, tipos de interés, tasa de interés, tasas de interés → tasa_interés.
- tipo de interés objetivo, tipos de interés objetivo, tasa de interés objetivo, tasas de interés objetivo → tasa_monetaria.
- reserva federal → fed.

The following paragraph exemplifies how Banxico’s publications would look like, without punctuation, numbers, stop words, and with collapsed n-grams:
junta_gobierno banxico decidió incrementar puntos base objetivo tasa_interés interbancaria día nivel efecto partir diciembre actividad económica mundial recuperó moderadamente tercer trimestre aunque perspectivas siguieron deteriorándose inflación global mantiene elevada si bien general disminuyó diversas economías menores presiones precios alimentos energéticos amplio número banco_central continuó incrementando tasa_monetaria mencionaron comenzarían moderar magnitud aumentos obstante anticipa dichas tasas permanezcan niveles altos periodo

Finally, it is necessary to stem the words. This step can be applied at the researcher’s discretion, but it is strongly recommended to reduce the remaining words in the corpus. By stemming the words, we collapse similar terms to their root form. For example, “economía”, “económico”, “economista”, “economizar” would be reduced to “econom”. This is useful as it represents a normalization of the elements in the corpus, allowing different variations of words to be counted as a single term. This reduces the amount of information to manipulate in subsequent analysis. In addition, in the lemmatization of the publications, relevant words for synonyms, such as “meta” and “objetivos”, or “incremento”, “aumento” and “elvado”, or “internacional” and “global”, among other words, are reduced to a single root term. The final result of a paragraph in the corpus documents would look like as shown below:

The latter methodology results in a corpus ready to be transformed into a Document-Term Matrix. A Document-Term Matrix (DTM) is a tabular representation used in natural language processing and text analysis. It organizes a collection of text documents into rows and terms (words or phrases) into columns. Each cell in the matrix contains a numerical value representing the frequency or importance of a specific term in a particular document.
DTMs are used to capture the textual content of documents in a format suitable for various analytical techniques, such as topic modeling, sentiment analysis, and machine learning algorithms. Our communication corpus yields a DTM with 131 rows, each representing a monetary policy statement, and 1,649 columns, each representing unique terms in the entire corpus. The DTM entries show the frequency of each unique term in each monetary policy statement.

Table 6: Document-Term Matrix

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Source: Author’s calculation.
Note: This table presents an excerpt of our document-term matrix. Terms are presented in their root form in the original Spanish language. Columns indicate the date of publication of the monetary policy statement.

Finally, the same filtering process was applied to the dictionaries to ensure similar terms for analysis and comparison.