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by Mario Gonzalez and Raul Cruz Tadle

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Monetary Policy Press Releases: An International Comparison*

Mario Gonzalez†‡

Raul Cruz Tadle§

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Abstract

Around the world, several countries have adopted inflation targeting as their monetary policy framework. These institutions set their target interest rates in monetary policy meetings. These decisions are then circulated through press releases that explain the policy rationale. The information contained in the press releases includes current policies, economic outlook, and signals about likely future policies. In this paper, using linguistic methods, such as Latent Dirichlet Allocation (LDA) and semi-automated content analysis, we examine the information contained in the monetary press releases of inflation targeting countries. In addition, we build a custom dictionary for analyzing monetary policy press releases. Using Semi-automated Content Analysis, we then develop a measure, which we refer to as the Sentiment Score index, that quantifies the policy tilt implied in the information provided in the press releases. We find that for a significant majority of the inflation targeting countries, the index provides additional information that helps predict monetary policy rate movements.

Keywords: Central Bank, Financial Market, Monetary Policy, Communication

JEL: E44, E52,E58

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† Correspondence: Central Bank of Chile. Email: mgonzalezf@bcentral.cl

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§ Correspondence: California State University, Sacramento. Email: raul.tadle@csus.edu

1 Introduction

The amount of research work on monetary policy communication has seen rapid growth in the last two decades. This growth reflects a change in the way policymakers think about announcing their decisions and the importance of managing expectations and providing insights into the economy. Policymakers have increasingly emphasized the dual role of communication, first, as a tool that reinforces traditional monetary policy instruments and as a monetary policy instrument that can move financial markets, decrease monetary policy decisions' surprises, and help reach central banks' macroeconomic objectives. A recent strand of this literature has incorporated linguistic tools and analysis to otherwise traditional economic analysis tools. Most of the research work has also focused on individual countries, especially the U.S.

Our current project builds on previous work by examining the monetary policy press releases of inflation-targeting central banks with a relatively long set of policy documents. Using linguistic methods, such as Latent Dirichlet Allocation (LDA) and semi-automated content analysis, we examine the information contained in the monetary press releases of Australia, Brazil, Canada, Chile, Hungary, Iceland, Indonesia, Israel, New Zealand, Norway, Peru, The Philippines, Poland, Romania, South Africa, South Korea, Sweden, and Thailand.

In this work, we follow the methodology presented by Tadle (2021) and Gonzalez and Tadle (2020). We use semi-automated content analysis to develop a measure, which we refer to as the Sentiment Score index, that quantifies the policy tilt implied in the press releases. The methodology utilizes both a custom dictionary built specifically for central bank documents all while accounting for the context in which the words are used. Instead of analyzing documents using single words separately, we examine the combination of nouns and modifiers in sentences to evaluate their embedded sentiments. We contribute to the literature by building custom dictionaries for each country and by analyzing how the resulting sentiment indices compare with one another across time and how they help predict monetary policy changes for the near and medium term. We find that for a significant majority of the inflation targeting countries, the index provides additional information that helps predict policy rate movements. In addition, we find that these sentiments increased their comovement during the Global Financial Crisis.

In our semi-automated content analysis approach, we create a computer algorithm that extract the qualitative information from policy statements. The main advantage of this method is that it is more transparent and replicable, and it accounts for the context of the documents. The resulting analysis is more time efficient in quantifying the policy document information. It is also less subjective, especially when compared to completely heuristic methods. Adopting this approach allows us to examine each press release and determine whether the document sentiment generally leans toward contractionary or expansionary monetary policy. This perceived policy tilt depends on how inflationary pressures and economic conditions are described in the policy text.

Using the continuous sentiment index for each set of policy documents, we study if the monetary policy press releases contain enough information to anticipate monetary policy movements. We also examine if the monetary policy sentiments are correlated at the international level using principal components analysis. We found a heightened amount of co-movement in the policy sentiments during the Global Financial Crisis. The co-movement decreased but remained much higher than the sentiment variance in the pre-crisis period.

This paper is mainly connected to two strands of literature. The first strand focuses on using linguistic tools in economics to evaluate the qualitative content of text documents by transforming them into a more quantitative format.[1] Although this type of methodology is imperfect since we are still not able to capture all of the details from the documents, the current approach is an important step forward. This methodology has been used to analyze communication, construct GDP nowcasting indexes, study social media, and construct uncertainty indexes, among other uses.

The next strand of literature examines how well central banks communicate their monetary policy decisions.[2] This work focuses on how central bank announcements create news, influence expectations, and affect asset prices.[3] They not only evaluate the frequency of communication but focus mainly on the contents of widely-distributed central bank communication.

[1] See Lucca and Trebbi (2009) for an example.

[2] Blinder et al. (2008) presents an excellent survey of this literature.

[3] Pescatori (2018) serves as an illuminating example as he examines the importance of policy predictability and efficacy.

We contribute to these literature strands in two ways. First, we build a dictionary specifically designed to capture the monetary policy sentiment.[4] We then examine the sentiments of central bank policy documents using a semi-automated linguistics approach and evaluate if they increase the predictability of monetary policy decisions.

The rest of our paper is structured as follows. Section 2 explores the literature on central bank communication. Section 3 then details the inflation-targeting countries and the press releases selected for each country. Section 4 explains the linguistic analysis methodology for document readability and the content analysis approach used to calculate the continuous sentiment indices for each set of press releases. Section 5 presents the results. Finally, section 6 discusses some robustness while section 7 presents some concluding remarks.

2 Related Literature

Recently, there has been a surge in the literature that studies central banks' communication strategy, especially since communication has become an integral tool in a central bank's arsenal. Much of the research has focused on measuring the information content of monetary policy documents. Early examples of this are Rosa (2011), which uses a manual approach to extract information from policy documents, and Lucca and Trebbi (2009), which utilize an automated method to analyze the FOMC statements and the VAR framework to estimate the effect of these statements on the macroeconomy.

Building on the need to develop more systematic approaches for examining policy documents, Hansen and McMahon (2016) were the first to adopt the use of Latent Dirichlet Allocation (LDA) to analyze economic policy documents. Hansen et al. (2017) further use this methodology to understand how transparency affects the deliberation of monetary policymakers.

Following this line of research, many more projects that use LDA in analyzing monetary policy documents have emerged. These include Lee et al. (2018) who use LDA to analyze the Bank of Korea's minutes. They build a text-based indicator that helps explain current and future monetary policy decisions. Kawamura et al. (2019) also use LDA to analyze the ambiguity of

[4] Unlike other dictionaries, our dictionary is divided into keywords, words that narrow the topic of a sentence, and modifiers, words that give intention to a sentence.

expressions in Bank of Japan's Monthly Monetary Report. The authors find that ambiguous expressions tend to appear more frequently in recessions. Using a similar LDA approach, Hansen et al. (2019) examine the effect of Fed communication on long-run rates. Their study concludes that monetary policy communication affects long-run uncertainty, which in turn affects the long-run premium and long-run rates.

A growing body of work uses other linguistic tools to analyze communication materials from central banks. Hendry and Madeley (2010) extract information from the Bank of Canada statements using Latent Semantic Analysis to find the type of information that affects returns and volatility of interest rate markets over the 2002-2008 period. For Brazil, Carvalho et al. (2013) use Google search queries to build a time series that measures whether each monetary policy statement is perceived as more *hawkish* or *dovish*. They examine the impact of these time series on the changes in the term structure of interest rates.

For the Swedish Central Bank, Apel and Grimaldi (2014) build a custom dictionary to analyze the information content of the monetary policy minutes. For the ECB, Picault and Renault (2017) manually analyze the press releases of that central bank between January 2006 and December 2014. Nardelli et al. (2017) use two different approaches, semantic orientation and Support Vector Machines, to construct an index that measures the tone perceived by the media regarding ECB press conferences. Gonzalez and Tadle (2020) utilize the dictionary method to build a tone index for the Central Bank of Chile. They then use that index to establish its relationship with the monetary policy rate and its effect on the Chilean financial markets and macroeconomy. The results show that the tone index precedes the monetary policy rate movements by about twelve months, that it has a strong effect on the stock market after 2008, and that it has a decreasing effect on the yield curve.

Although there has been a burgeoning interest in examining policy documents, only a handful of papers look at the communication documents of central banks from an international perspective. The closest to our work is Armelius et al. (2020), who utilize LDA to evaluate the policy communication from 23 central banks over the 2002-2017 period. They found that central bank sentiments generate spillovers to other countries in terms of sentiment, policy rate, and macroeconomic variables. In contrast to our work, they look at the speeches from board members while we look at monetary policy meeting press releases. Another paper that is closely related to our work is the research by International Monetary Fund (2018). They assess the minutes and monetary press releases of five Latin American countries. Using the Latent Dirichlet Allocation methodology, they build a tone index, similar to our Sentiment score index, to analyze the relationship between press releases and monetary policy changes. Their results show that the tone is a good predictor of future monetary policy changes. They also find that the tone of press releases explains a significant share of the market rates' variation.

3 Data

3.1 Data

Our data is comprised of the monetary policy press releases that are published shortly after monetary policy meetings. In particular, we use the that inform the public the rationale monetary policy rate (MPR) decisions. In addition, we use more traditional macro data as the effective MPR, the expected MPR according to the survey in Bloomberg, the inflation rate for each of the countries, the GDP growth for each of the countries and the U.S. CPI, U.S. GDP and the international price of a group pf commodites: WTI oil, gold and copper. The monetary policy press releases was obtained from the webpages of the individual central banks while the macro data was obtained from bloomberg.

As will be explained later, our methodology includes the use of machine learning techniques, in particular LDA. Althought this tools are very powerful they require a lot of data to have good estimates, so use three criteria to ensure that we have enough data for the analysis.[5]. First, the selected countries must have adopted inflation targeting in their monetary policy framework by 2005. Second, the monetary policy press releases must be published in English or translated to English by the central bank. This criteria is related to the fact that the dictionaries we build are language specific, so having multiple languages may alter our results.

Finally, the central bank must have started publishing regularly informative monetary policy press releases by 2009. Those documents that we refer to as informative press releases are those

[5] In their study Hansen et al. (2017) applied LDA to around 128 FOMC documents published between 1998 and 2014

that not only mention the monetary policy decision but also the main reasons for these decisions. These explanations include the current economic outlook, both domestic and international, and the expected future developments. With this criteria, we ended up with 18 countries: Australia, Brazil, Canada, Chile, Hungary, Iceland, Indonesia, Israel, New Zealand, Norway, Peru, The Philippines, Poland, Romania, South Africa, South Korea, Sweden, and Thailand.

We collected a total of 3184 press releases. Referring to the descriptions of these press releases in Table 1, we found some interesting observations about the change in monetary policy communication. For example, Australia adopted an IT framework in 1993 but did not systematically publish informative press releases until November 1997. Before that, it only delivered an informative press release when it changed its MPR. Without any MPR changes, the press releases state the policy decision without economic explanations. Another interesting case is Israel, which started publishing monetary press releases in Hebrew in 1997 but waited until June 1999 to deliver a translated version of their press releases. We also found similar cases for Mexico and Colombia, which started publishing press releases in English only after 2009. For this reason, these countries were excluded from our sample.

Table 2 shows the different formal communications tools used by each of the central banks in the sample. Most countries have between 8 and 12 monetary policy meetings per year. The only exceptions are Sweden and South Africa, both of which have six policy meetings, New Zealand with 7, and Hungary with 24. As can be expected, all countries do not have the same monetary policy meetings frequency, this is not a problem when one is interested in doing a country by country analysis. However, when one wants to make a monthly comparison of the countries and their monetary policy meetings it creates a problem, because there is not only a mismatch in frequency but also those that have similar frequency may have meetings in different months. Therefore to overcome this problem, once the sentiment score is calculated, we average the index quarterly son all our econometric analysis done from an international perspective is quarterly.

Table 1: Press Releases Descriptive Statistics

Country	Year IT Adopted	Press release avalaible in.... since... Native	English	Informative since	Total number of press releases
Australia	1993	Jan-90	Jan-90	Nov-07	183
Brazil	1999	Mar-06	Mar-06	Mar-06	111
Canada	1991	Jun-97	Jun-97	Mar-99	163
Chile	1999	Sep-97	Sep-97	Jan-01	220
Hungary	2001	Dec-01	Jan-03	Apr-03	316
Iceland	2001	Mar-01	Mar-02	Mar-09	89
Indonesia	2005	Aug-05	Aug-05	Aug-05	169
Israel	1997	Nov-97	Jun-99	Jun-99	234
New Zealand	1989	Dec-96	Dec-96	Dec-96	145
Norway	2001	Mar-01	Mar-01	Mar-01	124
Peru	2002	Feb-01	Feb-01	Feb-01	211
The Philippines	2002		Dec-01	Dec-01	176
Poland	1998	Feb-98	Jan-01	Jul-98	220
Romania	2005	Jul-05	Oct-03	Oct-03	127
South Africa	2000	Oct-99	Jan-00	Jan-00	129
South Korea	1998	Jan-99	Jan-00	Jan-00	229
Sweden	1993	Jan-96	Jan-96	jan-96	161
Thailand	2000	Apr-00	May-00	May-00	174
Total					3,184

Table 2: Main Central Bank Communication Tools

	Adopted on	Meetings per year		Press	Minutes (weeks	MP Report	MPR
		Current	Previous (time)	Release	after meeting)		Forecast
Australia	06-1993	11		Yes*	2	Feb, May, Aug, Nov	No
Brazil	06-1999	8		Yes	4	Mar, Jun, Sep, Dec	No
Canada	02-1991	8	not defined	Yes	No	Jan, Apr, Jul, Oct	No
Chile	06-1999	8	12 (02-17)	Yes	2	Mar,Jun, Sep, Dec	No
Hungary	06-2001	24		Yes	20-15 days	Mar, Jun, Sep, Dec	No
Iceland	03-2001	8		Yes	2	Feb, May, Aug, Nov	Yes
Indonesia	07-2005	12		Yes	No	Jan, May, Aug, Nov	No
Israel	06-1997	8	12 (97-17)	Yes	2	Feb, Aug	No
New Zealand	12-1989	7	8 (99-15)	Yes	No	Feb, May, Aug, Nov	Yes
Norway	03-2001	8	6 (13-17)	Yes	No	Mar, Jun, Sep, Dec	Yes
Peru	01-2002	12		Yes	2	Mar, Jun, Sep, Dec	No
The Philippines	01-2002	8	9 (07-10)	Yes	4	4	No
Poland	02-1998	11	12 (01-09)	Yes	4	Jan, Apr, Jul, Oct	No
Romania	08-2005	8		Yes	1	Feb, May, Aug, Nov	No
South Africa	02-2000	6	5-9 (00-02)	Yes	No	Apr, Oct	Yes
South Korea	04-1998	8	12 (00-16)	Yes	2	4	No
Sweden	01-1993	6	8 (00-05)	Yes	10 days after	Feb, Apr, Jul, Sep, Oct, Dec	Yes
Thailand	05-2000	8	9 (00-03)	Yes	2 (since 2011)	Feb, May, Aug, Nov	No

Source: Web page of central banks

4 Methodology

The first steps in our linguistic analysis are similar those in any other linguistic paper and consists in cleaning the documents to be used. Then we use LDA, which is a Bayesian model used to analyze a group of data, specifically text information, to build the our keywords dictionary. This dictionary contains the nouns that will determine which sentences will be studied. At the same time, we use a frequency analysis to build our modifiers dictionary. These modifiers are the most used adjectives and verbs in the documents.

We then conduct sentiment analysis to measure the evolution of the policy bias or sentiment in the monetary press releases. We use the Dictionary Method of Content Analysis since it is widely used in measuring document sentiment in the finance literature.[6] It has also been used in previous economics work evaluating the impact of policy documents and social media text.[7] As Hansen and McMahon (2016) points out, the main benefit of this approach is that it is scalable to a given type of document with much less concern about consistency and transparency. At the same time, our approach incorporates the context and usual syntax of the policy documents so that more of the nuances that are lost with fully automated methods are captured in our methodology.

This analysis is becoming more common in the literature and consists of classifying the sentences in a particular document into corresponding sentiments. To do this, we first construct a dictionary used to classify the sentences in the press releases. We utilize Latent Dirichlet Allocation to select nouns and frequency analysis for the choice of verbs and adjectives.

Although there are several dictionaries for the analysis of document sentiments, ours contain two innovations. It is the first to evaluate the press releases of inflation-targeting central banks.Apel and Grimaldi (2014) also build a custom dictionary for the analysis of the Swedish Central bank minutes, however, they use their knowledge about the topic to build it. Another dictionary is built by Loughran and McDonald (2011) and Henry (2008), but their focus is on finance and accounting. Still, since these dictionaries are used extensively in the literature, we also re-calculate our sentiment indexes with the help of these dictionaries as a robustness check.

[6]See Tetlock et al. (2008) and Loughran and McDonald (2014) for additional references.

[7]For additional examples, see Rosa (2011).

Finally, we use the sentiment index calculated for each country to conduct more traditional econometric analyses. In these analyses, we incorporate cross-correlograms, panel analysis, and local projections. We also apply Principal Components Analysis to examine how the sentiments of the press releases of different central banks move together over time.

4.1 Sentiment Analysis: Dictionary

As an initial step to conducting our Content Analysis, we modified the text to ensure a consistent approach. We removed the capitalization of words, separated the sentences, and removed all punctuation and stop words. We chose not to stem the words, however, to maintain the semantic meaning of the terms.[8]

Our implementation of the Dictionary method requires that a selection of words to be classified into two types: *Keywords* and *Modifiers*. Our chosen *Keywords* are the nouns that indicate the economic subject of the sentences. On the other hand, the *modifiers* we utilize are adjectives and verbs that state what is happening to the sentence's subject.

To build the *keywords* dictionary, we run a country by country analysis using Latent Dirichlet Allocation (LDA). LDA, which was developed by Blei et al. (2003), is a probabilistic approach to text analysis. In this methodology, each set of documents has a probability distribution of terms over a specified number of topics.[9] As a result, keywords in each document set receive topic assignments. Then, conditional on the topic, a given keyword is assigned a weight relative to how semantically significant it is to the topic. In terms of economics, this methodology has been used by Hansen et al. (2017) and Hansen and McMahon (2016), among others. The main advantage of this methodology is that it is a fully probabilistic method. Therefore, it allows words to be assigned to more than one topic, making the approach more flexible than deterministic methods.

For each set of central bank policy documents, we then choose the number of topics that maximizes the Coherence Score, which objectively evaluates how semantically interpretable the given sets of words are as topics.[10] In particular, we examine the range of results from two to

[8] In particular, we need to be able to identify and separate nouns from verbs and adjectives.

[9] In particular, we use the Gibbs Sampling method to establish the posterior distribution of words in each topic.

thirty topics and choose the topic number that leads to the highest Coherence Score.

After conducting the LDA method using the chosen topic number for each country, we interpret the semantic topics based on the terms connected to them and then collect the topics related to inflation, economic growth, and financial markets. From the words within the topics, we compile a set of nouns that have relevant economic meanings.[11]

On the other hand, the *modifiers* are positive or negative words that provide information about the *Keywords*. In our study, the *modifiers* are adjectives and verbs. We combined all the press releases in the sample and selected all the verbs and adjectives that could have economic meaning in the context of a monetary policy press release. Once we obtained an initial list of modifiers, we added all of the verbs' different tenses to the list. In addition, we added the British spelling variant of the verbs and adjectives when they existed. We then categorized the modifiers as being positive or negative depending on the semantic meaning of the words in the policy discussions.[12]

There are two reasons for building separate dictionaries for each set of press releases. The first considers the method we use. The algorithm searches for the presence of a *keyword* in a sentence. If it finds a *keyword*, then it searches for *modifiers*. Therefore, when using *keywords* in our methodology, we want to use the most important words in the press releases by country. Once a sentence is selected to be analyzed, we then want to make sure that the modifiers convey the messages about the economic subjects that the press releases discuss.

A second reason is that using a single dictionary for all countries may lead to other issues. We tried creating a dictionary by combining those used in Tadle (2021) and Gonzalez and Tadle (2020). However, we found that a significant number of relevant sentences were missed as this combination did not have the keywords specific for each country. The results showed us that to have the appropriate dictionary for a given set of policy documents, it has to be built based on the words used by the policymakers of that specific country.

[10] A brief explanation of the Coherence Score appears in the Appendix.

[11] We discard proper nouns. Although they may be relevant in another context, we believe they are not in our current work.

[12] As a robustness check for our dictionary, we compared the classified modifiers with a combined version of the positive and negative dictionaries by Loughran and McDonald (2016) and Hendry and Madeley (2010). The results end up being almost identical.

4.2 Sentiment Analysis: Index

When calculating the sentiment index, we adopt a similar methodology used in Tadle (2021) and Gonzalez and Tadle (2020). We define three distinct sentiments for each of the sentences of a press release. The first sentiment refers to a higher likelihood of contractionary monetary policy since its semantic meaning positively correlates to escalated inflationary pressures. We refer to these as hawkish-leaning and call them *hawkish*, for simplicity.

On the other hand, the second type of sentiment is dovish-leaning as it conveys lower inflationary pressures and leans more toward expansionary monetary policies. Sentiments that fall under this category are denoted as *dovish*. Finally, we also categorize sentences as neutral, and those refer to sentences that do not have a clear sentiment.

Each individual *keyword* is categorized as either *hawkish* or *dovish*. The categorization of each of the keywords depends on the policy tilt that results when it is associated with a positive *modifier*. For instance, the keyword 'wage' is categorized as a hawkish key term since it signals more support for contractionary policy. This is because when the term 'wage' is attached to a positive modifier, such as 'improving,' we have the phrase 'improving wage,' which signals higher inflationary pressures. In contrast, when the term 'wage' is attached to the negative term 'declining,' we obtain 'declining wage,' which relates to more subdued inflationary pressures. The opposite effect occurs to the semantic meaning of dovish keys when attached to positive and negative modifiers.

Once we have categorized the *keywords* for each country, we analyze the press releases by separating them into individual sentences. For a given sentence, if it has a hawkish *keyword* and more positive than negative modifiers, then its sentiment is taken as hawkish and is given a score of '+1'. If the sentence with a hawkish *keyword* has more negative than positive modifiers, then its sentiment is taken as dovish and is given a score of '-1'. The opposite scoring is given for a sentence with a dovish *keyword*. For this sentence, if there are more positive than negative modifiers, it is deemed dovish and given a score of '-1'. If it has relatively more negative modifiers, it is treated as hawkish and is given a score of '+1'. Sentences with the same number of positive and negative modifiers are given a zero score, while those with both hawkish and dovish keys are scored the same as sentences with only hawkish keys.

Table 3: Example of Sentence Evaluations

Sentence Example 1

'global economic $\underbrace{\text{growth}}_{\text{hawkish}}$ continues to $\underbrace{\text{improve}}_{\text{positive}}$'

- Source: Reserve Bank of New Zealand's February 8, 2018 Policy Statement
- Sentence Score: +1 (hawkish keyword and more positive than negative modifiers)

Sentence Example 2

'but the near-term outlook for the $\underbrace{\text{global}}_{\text{hawkish}}$ $\underbrace{\text{economy}}_{\text{hawkish}}$ is the $\underbrace{\text{weakest}}_{\text{negative}}$ for many years'

- Source: Reserve Bank of Australia's February 3, 2009 Policy Statement
- Sentence score: -1 (hawkish keywords and more negative than positive modifiers)

Table 3 presents some examples of the sentence-level evaluations. In Sentence Example 1 extracted from the February 8, 2018, Policy Statement of the Reserve Bank of New Zealand, we observe one hawkish keyword and only one positive modifier. Based on the scoring metric, this sentence receives a score of '+1' for its hawkish-leaning sentiment. In contrast, the second sentence example from the February 3, 2009, Policy Statement of the Reserve Bank of Australia has two hawkish keywords and one negative modifier. Following the scoring procedure, this sentence receives a score of '-1' due to the dovish sentiment of its information.

After conducting the sentence-level scoring, we aggregate the individual sentence scores for each document. We then divide the sum by the number of evaluated sentences. We scale the resulting value by 100 to create a continuous sentiment measure that ranges from -100 to 100.

5 Results

In this section, we present the results for building of the dictionary, and the sentiment score analysis. We also present the results of using traditional econometric tools with the sentiment score to understand how each country publishes its monetary policy decision.

5.1 Results: Dictionary

For each country, we run the LDA using the number of topics that maximize the coherence score.[13] We then analyzed the words in the LDA topics and selected those that are related to economic and financial conditions. The results of this analysis appear in tables 4 and 5.

We also find some interesting observations about the dictionaries. First, the size of each dictionary differs broadly among the countries. This variation may arise since the optimal number of topics, given by the coherence score, differ broadly among countries. Second, we categorized more keywords as *hawkish* than *dovish*. We do not think this is a problem as this categorization depends on how we classify the modifiers.

The sets of modifiers appear in Table 6. We notice that there are 215 words in the positive modifiers category and 229 words in the negative modifiers section, making the dictionary relatively balanced. Although some of the words in the modifiers list were not used in this study, the dictionary was built as general as possible, so it can be used in the future for studies that analyze policy documents.

5.2 Results: Sentiment Index and Econometric Analysis

We present the results of building the sentiment scores using our methodology. We show them as six-month moving averages since the gross indexes show high volatility. These sentiment scores, along with their respective monetary policy rate, are shown in Figures 1 and 2. Referring to Figure 1, we show the results for Australia, Brazil, Chile, Hungary, Iceland, Indonesia, Israel, Norway, and New Zealand. We find that these indices are more volatile than their respective MPR. This difference in volatility may be driven by the fact that each press release varies with every meeting because it is expected that there would be some variation in the evolution of these indexes.

Interestingly, the countries that show the highest volatility are Chile and Israel, which are the countries that have the smallest sets of keywords. This may be due to the coherence score indicating that their LDA should run with only two and five topics, respectively. The low number

[13] We also examined the results using the same number of topics for all countries. However, we found that many relevant sentences were missed as they did not have the appropriate keywords for each country. The results showed us that building a dictionary must be created separately for each country.

Table 4: Dictionary Analysis Results: Coherence Score and Keywords

	Hawkish	Dovish	Number of topics
Australia	business, businesses,commodity_price, condition, confidence, credit, demand, economic, economy, employment, exchange_rate, expansion, expect, expected, expectation,financial_market, global, growth, household, housing, housing_market, inflation, international, investment, lending, market, pressure, price, prospect, recovery, spending, stance, trade, trend, wage, world	risk, spare_capacity, uncertainty	23
Brazil	economy,economic_activity, expectation, inflation, inflation_projection, inflation_prospect, inflation_trajectory, recovery supply, total_cpi, trade	disinflation, monetary_easing	7
Canada	activity, anticipate, bank, condition, core_inflation, demand, deposit_rate, economy, global, growth, inflation, price,		11
Chile	inflation, growth, price		2
Hungary	activity, assessment, condition, consumer_price, core_inflation, cost, cost_shock, councils_assessment, demand, development, domestic, domestic_demand, economic_agent, economic_growth, economy, euro_area, financial_market, growth, household_consumption, hungarian_economy, inflation, inflation_expectation, inflation_target, inflationary_pressure, labour_market, market, output, price, price_stability, private_sector, wage	disinflationary_in reduction, risk, slowdown, unused_capacity	28
Iceland	appreciation, banks_forecast, capital_account, current_account, demand, domestic_demand, economic_activity, economic_development, economic_recovery, economy, exchange_rate, foreign_currency, foreign_exchange, growth, inflation, inflation_expectation, inflation_outlook, krona, labour_market, market, monetary_stance, output, output_growth, private_consumption, recovery	demand_pressure, disinflation, risk, slack, spare_capacity, uncertainty	27
Indonesia	banking_industry, banking_system, capital_adequacy, consumption, core_inflation, credit_expansion, credit_growth, current_account, demand, development, domestic_economic, economic, economic_growth, economic_recovery, economy, exchange_rate, financial_market, financial_system, foreign_capital, global_economic, global_economy, global_financial, growth, inflation, inflation_target, inflationary_pressure, inflow, investment, market, price, recovery, rupiah, surplus	debt, import, risk, volatile_food	24
Israel	activity, government, growth, inflation, interest, interest_rate, market		5
New Zealand	activity, annual_cpi, bank, capacity, commodity, commodity_price, confidence, construction_sector, consumption, cost, demand, depreciation, dollar, economic_activity, economy, employment, exchange_rate, export, export_commodity, export_price, firm, fuel, growth, headline_inflation, house_price, housing, housing_market, income, inflation, inflation_expectation, inflation_pressure, investment, market, ocr, oil, pace, price, rate_ocr, reconstruction, recovery,repair, resource, sentiment, spending, supply, tradables_inflation, trade, upside, view	import	29

Source: Authors' calculations

Table 5: Dictionary Analysis Results: Coherence Score and Keywords

	Hawkish	Dovish	Number of topics
Norway	activity, assessment, bank, consumer_price, development, economy, employment, euro_area, expectation, growth, house_price, inflation, inflation_report, interest_rate, norway, norwegian, norwegian_economy, outlook, price, project, projection, wage_growth	risk	15
Peru	credit, dollar, domestic, domestic_currency, domestic_demand, economic_activity, financial_system, food_product, foreign_currency, foreign_exchange, global_economic, growth, inflation, inflation_determinant, inflation_forecast, international_financial, market, price, recovery, supply_shock		28
The Philippines	assessment, growth, inflation, inflation_outlook, price	pressure, risk	2
Poland	activity, demand, deposit, economic_condition, economy, employment, exchange_rate, growth, growth_rate, household, inflation,inflation_expectation, interest, loan, price, price_growth, production, wage	deposit_rate	21
Romania	banking_system, consumer_price, credit, credit_institution, current_account, development, domestic, economic, economic_growth, financial_stability, foreign_currency, foreign_exchange, global_economic, growth, inflation_expectation, inflation_report, lending, liquidity, loan, price, stability	deficit, disinflation, risk, uncertainty	23
South Africa	bank, consumption_expenditure, core_inflation, country, cpix_inflation, demand, development, domestic, economy, electricity, employment, environment, exchange_rate, expenditure, food, food_price, forecast, global, growth, inflation, inflation_expectation, inflation_outlook, inflation_target, inflationary_pressure, mining_sector, outlook, petrol_price, price, rand, recovery, upside_risk		24
South Korea	consumer, consumption, demand, expectation, export, financial, growth, housing, inflation, lending, liquidity, market, oil, petroleum, price, recovery, sentiment, stock, surplus	risk, slowdown, uncertainty,	22
Sweden	assessment, demand, development, economic_activity, economic_development, economy, energy_price, growth, inflation,inflation_report, inflationary_pressure, market, price, recovery, resource_utilisation, swedish_economy		19
Thailand	recovery, economy, export, policy_rate, growth, expect, investment, outcome		2

Source: Authors' calculations

Table 6: Modifiers Dictionary

Positive Modifiers: 215
above, accelerate, accelerated, accelerates, accelerating, accommodate,accommodated, accommodates, accommodating, added, augment, augmented,augmenting, augments, benign, best, better, biggest, boost, boosted, boosting, boosts, brighter, buoy, buoyant, buoyed, buoying, buoys, calm, calmed, calming, calms, climb, climbed, climbing, climbs, depreciate, depreciated, depreciates, depreciating, dynamic, elevate, elevated, elevates, elevating, encouraging, escalate, escalated, escalates, escalating, exceed, exceeded, exceeding, exceeds, expand, expanded, expanding, expands, expansionary, expansive, fast, faster, fastest, favorable, favourable, firmer, good, great, greater, greatest, grew, grow, growing, grown, grows, healthier, high, higher, highest, improve, improved, improves, improving, impulse, impulsed, impulses, impulsing, increase, increased, increases, increasing, inflationary, large, larger, largest, lift, lifted, lifting, lifts, loose, loosen, loosened, loosening, loosens, looser, maximum, mitigate, mitigated, mitigates, mitigating, more, mount, mounted, mounting, mounts, optimistic, outperform, outperformed, outperforming, outperforms, peak, peaked, peaking, peaks, pick, picked, picking, picks, positive, raise, raised, raises, raising, ramp, ramped, ramping, ramps, rapid, recover, recovered, recovering, recovers, reinforce, reinforced, reinforces, reinforcing, restore, restored, restores, restoring, rise, risen, rises, rising, rose, satisfactory, skyrocket, skyrocketed, skyrocketing, skyrockets, spike, spiked, spikes, spiking, spur, spurred, spurring, spurs, stabilise, stabilised, stabilises, stabilising, stabilize, stabilized, stabilizes, stabilizing, stable, steady, stimulate, stimulated, stimulates, stimulating, stimulative, stimulatory, strengthen, strengthened, strengthening, strengthens, strong, stronger, strongest, successful, surge, surged, surges, surging, swifter, upper, upside, upswing, upswinging, upswings, upswung, uptrend, upturn, upturned, upturning, upturns, upward, vigorous, widen, widened, widening, widens, wider
Negative Modifiers: 229
adverse, aggravate, aggravated, aggravates, aggravating, appreciate, appreciated, appreciates, appreciating, appreciatory, bad, bottom, bottomed, bottoming, bottoms, concern, concerned, concerning, concerns, conservative, constrain, constrained, constraining, constrains, contract, contracted, contracting, contractionary, contracts, cut, cuts, cutting, dampen, dampened, dampening, dampens, decelerate, decelerated, decelerates, decelerating, decline, declined, declines, declining, decrease, decreased, decreases, decreasing, deepen, deepened, deepening, deepens, deflationary, descend, descended, descending, descends, destabilizing, deteriorate, deteriorated, deteriorates, deteriorating, difficult, diminish, diminished, diminishes, diminishing, disappointing, disinflationary, dovish, down, downside, downsize, downsized, downsizes, downsizing, downward, downwards, drop, dropped, dropping, drops, erode, eroded, erodes, eroding, fade, faded, fades, fading, fail, failed, failing, fails, fall, fallen, falling, falls, fell, fewer, flatten, flattened, flattening, flattens, fluctuate, fluctuated, fluctuates, fluctuating, fragile, harm, harmed, harming, harms, inconsistent, jeopardise, jeopardised, jeopardises, jeopardising,jeopardize, jeopardized, jeopardizes, jeopardizing, lackluster, least, less, low, lower, lowered, lowering, lowers, lowest, mild, minimal, minimum, minor, moderate, moderated, moderates, moderating, modest, negative, pessimistic, poor, recessionary, reduce, reduced, reduces, reducing, restrictive, riskier, risky, sank, shorten, shortened, shortening, shortens, shrink, shrinking, shrinks, shrunk, shrunken, sink, sinking, slow, slowed, slower, slowest, slowing, slows, sluggish, small, smaller, smallest, soften, softened, softening, softens, speculate, speculated, speculates, speculating, stress, stressed, stresses, stressing, stringent, subdued, subprime, sunk, suppress, suppressed, suppresses, suppressing, threaten, threatened, threatening, threatens, tighten, tightened, tightening, tightens, tighter, tougher, turbulent, uncertain, unclear, undermine, unfavorable, unfavourable, unstable, volatile, vulnerable, wane, waned, wanes, waning, weak, weaken, weakened, weakening, weakens, weaker, weakest, worse, worsen, worsened, worsening, worsens, worst

Source: Authors' Calculations

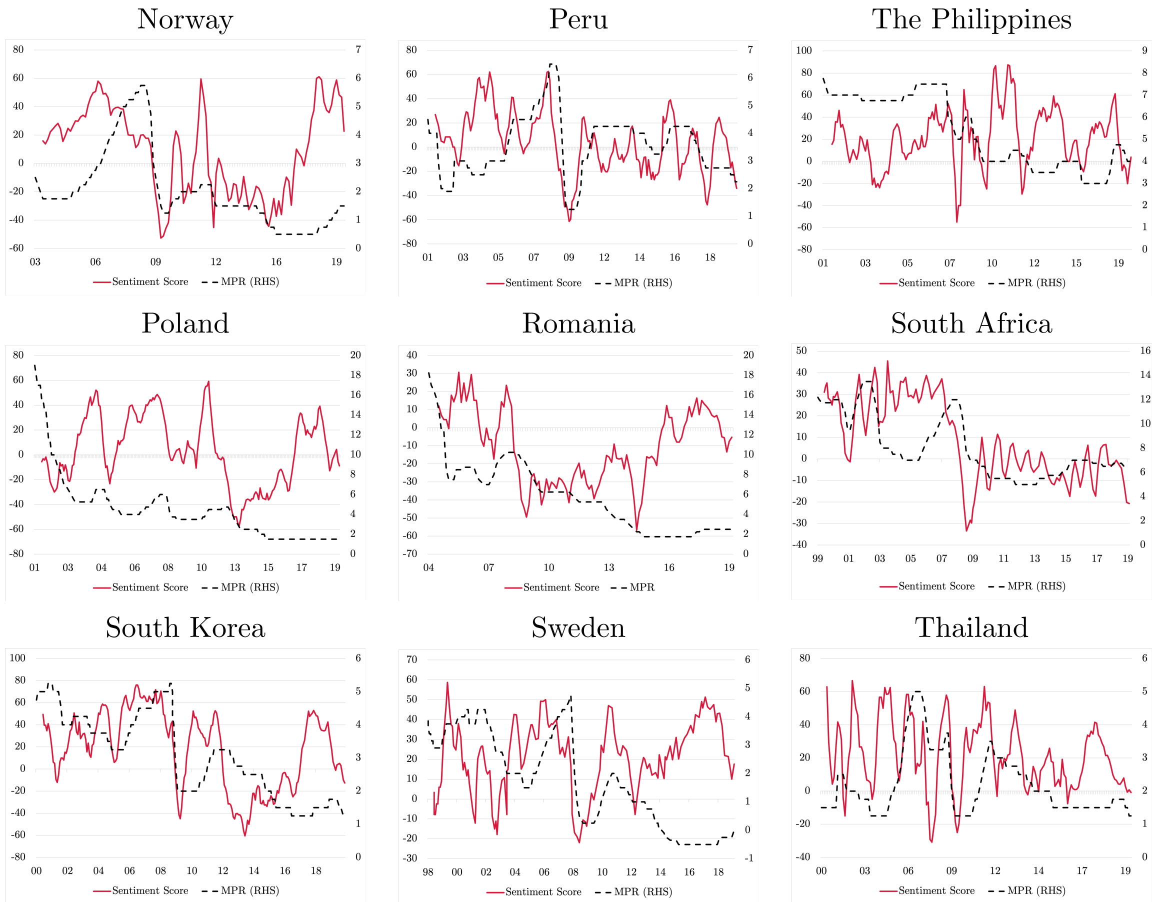
Figure 1: Sentiment Scores

of keywords and, therefore, evaluated sentences for the corresponding press releases may push the volatility higher.

Despite this high volatility, some patterns can be obtained with visual analysis. First, there is a significant decrease in the index in all countries during the Global Financial Crisis, signaling higher monetary policy expansion in 2008. In most cases, this period saw the single most substantial decrease in the index. This drop towards increased monetary expansion is usually followed by an increase in the index, signaling possible increases in the MPR. After this increase, there is a period of decreased volatility, starting around 2010, when most countries have maintained relatively stable MPRs.

Similar dynamics can be found in Figure 2, which shows the sentiment score indexes and MPR for Peru, The Philippines, Poland, Romania, South Africa, South Korea, Sweden, and

Figure 2: Sentiment Scores

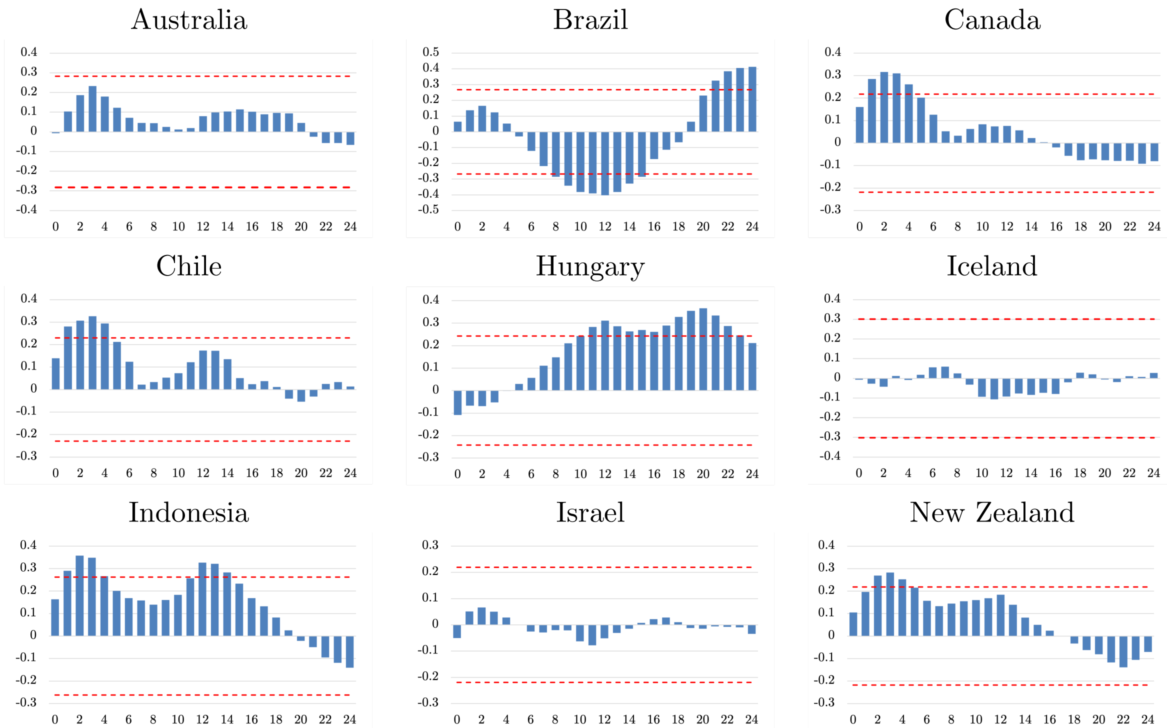


Thailand. As before, the countries whose indexes show higher volatility are those with the smallest dictionaries: The Philippines and Thailand. As in Chile's case, examining the coherence scores indicates that both countries should have only two topics.

Consistent with earlier observations, the evolution of each country's sentiment score is related to the evolution of the MPR. Recall that central banks not only publish their decision in the monetary policy press releases, but they also explain the reasons for that decision. Noting this, the central banks are communicating relevant information that allows the public to evaluate their assessments of the economy. Such information can also help predict the future evolution of the MPR.

To further evaluate the informativeness of the monetary press releases, especially in understanding the policy path, we calculate the cross correlograms between the MPR and the Sentiment Score in quarterly frequency. Figure 3 and 4 illustrate our findings.[14] They incorporate the upper and lower confidence bounds that reflect values that are two standard deviations away from 0 and help to objectively evaluate the statistical relationship between the sentiment score and the MPR. If a central bank first announces its intention to increase its monetary policy rate and act on those intentions, the sentiment score will then lead the movement of the MPR with a positive and significant correlation coefficient.

Figure 3: Sentiment Score and MPR Cross-Correlation



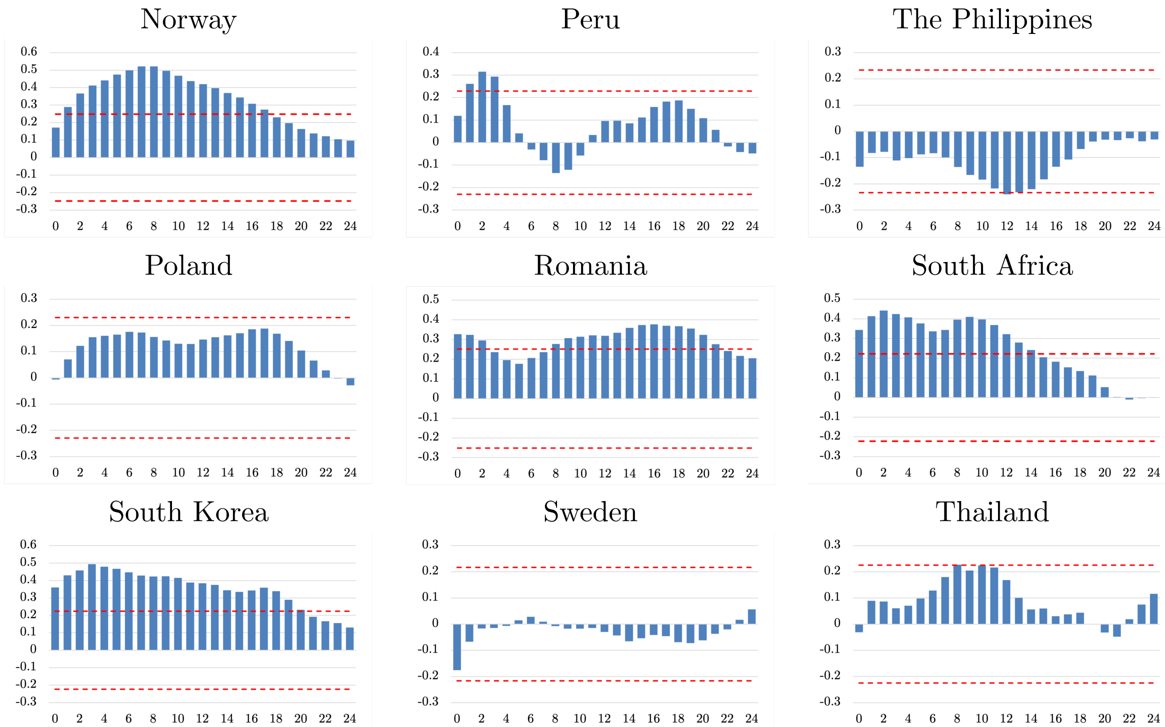
Note: Quarterly Frequency

Source: Author's calculations

Figure 3 shows the cross-correlogram for the first set of countries: Australia, Brazil, Canada, Chile, Hungary, Iceland, Indonesia, Israel, and Norway. For many of these countries, the graphs show that the movements of their sentiment scores anticipate the movements in their respective MPR. For example, the correlogram of Canada is maximized at the third quarter. This finding implies that movements on the sentiment score are followed by movements on the

[14] We change the frequency of the correlograms to quarterly frequency because the timing of the monetary policy press releases is different across countries and comparing these policy documents becomes difficult without quarterly aggregation.

Figure 4: Sentiment Score and MPR Cross-Correlation



Note: Quarterly Frequency
Source: Author's calculations

MPR three quarters ahead. This finding suggests that the monetary press releases contain enough information to anticipate movements of the MPR.

We also find that although the correlogram is positive for Australia, it is not statistically significant. In addition, Iceland and Israel show correlograms that are close to zero. This observation points to the lack of a statistically significant relationship between the sentiment index and their MPR for these two countries.[15]

Figure 4 shows the cross-correlogram graphs for the second set of countries: New Zealand, Peru, The Philippines, Poland, Romania, South Africa, South Korea, Sweden, and Thailand. In this case, New Zealand, Peru, Romania, South Africa, South Korea, and Thailand show a positive and significant correlation between the movements of their MPR and the respective sentiment scores, while The Philippines, Poland, and Sweden show no significant correlation.[16]

[15]Brazil's case is puzzling since it initially had a negative and statistically significant relationship that turned positive and statistically significant over time.

[16]The conclusions of this section are robust to using the sentiment scores that will be presented in the robustness

Much of the comovement between the sentiment index and monetary policy rates may simply reflect the economic data discussed in the press releases and used in the determination of monetary policy. So, if we want to analyze if there is additional information in the monetary policy documents, it necessary to filter this common information. By filtering the sentiment score indexes, we can focus our study in the information that is not explained by the publicly-available economic data. We then examine how the information from the press releases affects the predictability of monetary policy.

Following Jordà (2005), we use local projections to estimate the impact that surprise changes in the sentiment index has on the predictability of monetary policy. To examine this, we first evaluate the unexpected change in the sentiment index. We estimate the surprise element by running the following equation for each country[17]

$$ss_t = \beta_0 + \beta_1 ss_{t-1} + \beta_2 ss_{t-2} + \beta_3 \pi_{t-1} + \beta_4 \pi_{t-2} + \beta_5 \pi_{t-3} + \beta_6 \pi_{t-4} + \epsilon_t \tag{1}$$

where ss is the central bank policy document sentiment and π represents the inflation rate over the previous year. ϵ, the residual in this specification, is taken as the surprise element of the sentiment index. This residual represents the information in the sentiment index not explained by the economic variables of interest and the sentiment score of previous periods. We then implement the local projections methodology using the specification

$$mpr_{t+h} = \gamma_{0,h} + \gamma_{1,h} mpr_{t-1} + \gamma_{2,h} mpr_{t-2} + \gamma_{3,h} \epsilon_t + u_t \tag{2}$$

Some central banks hold meetings more frequently than others. To account for this, we examine the impact of the surprise sentiments on the predictability of mpr on the following policy meetings. We then evaluate the impact on the local projections up to 24 meetings in the future.

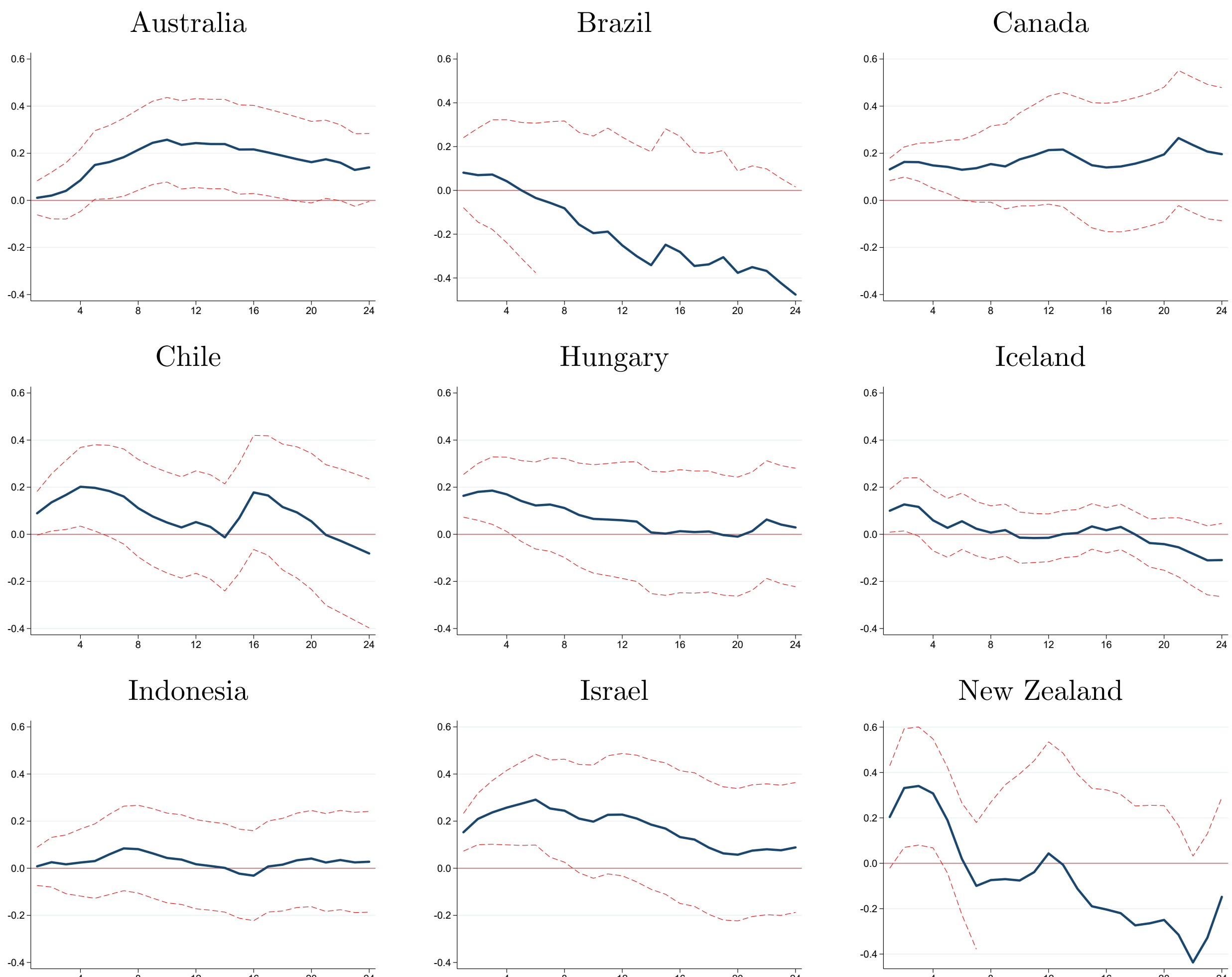
The results are shown in figures 5 and 6 together with confidence bands at the 10% significance level. We find that for a significant number of inflation-targeting countries that we evaluated,

section.

[17]We evaluated different specifications, including lag of growth, but those variables we examined were statistically insignificant in this analysis.

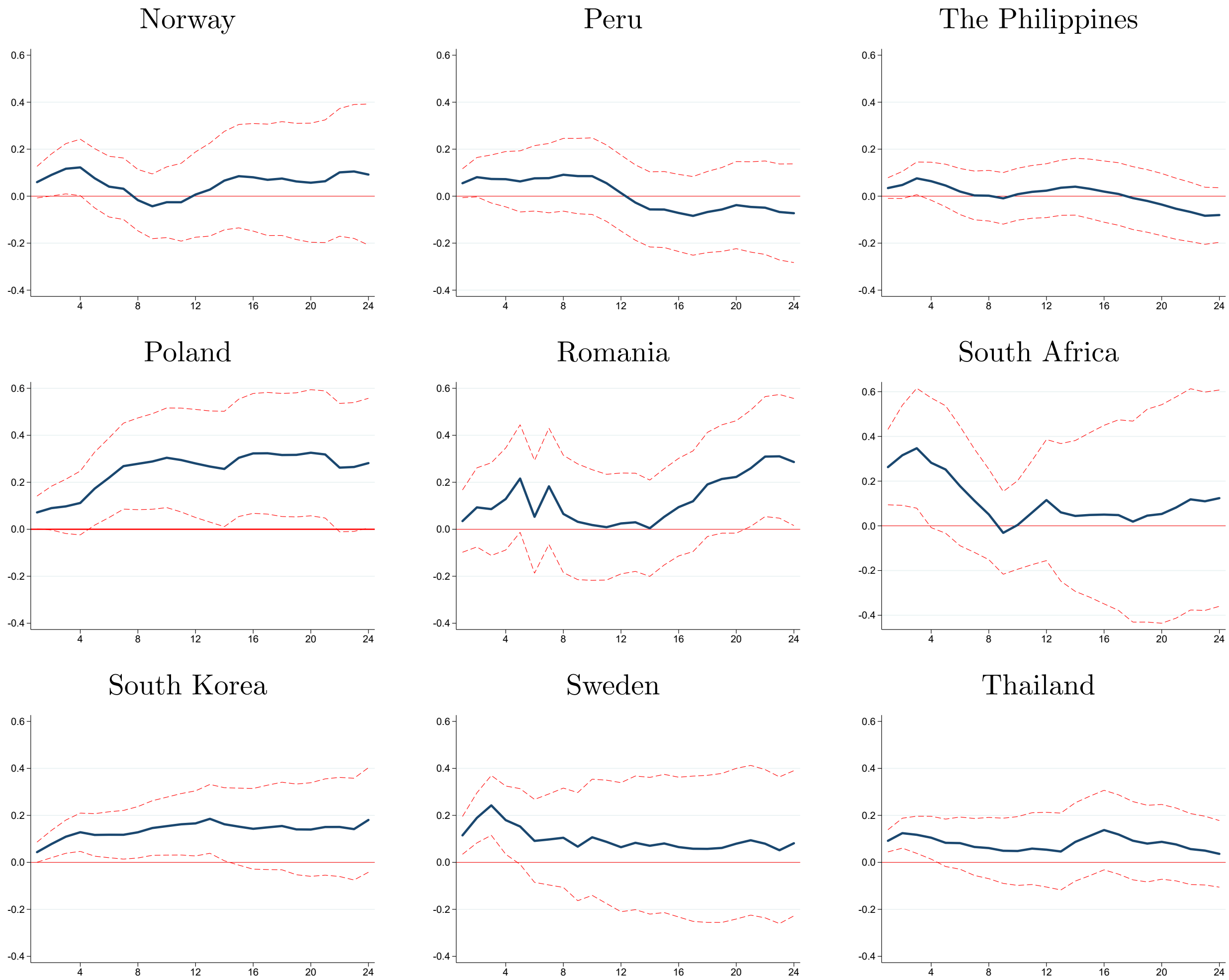
the sentiment surprises are positively related to the near-term changes in the policy rate. This finding supports the claim that for many of the inflation-targeting economies, sentiment surprises increase the predictability of near-term changes in the monetary policy rate. The results in this section are in line to other papers that study the effect of communication on the predictability of monetary policy rates in the U.S. and the E.C.B., The results in this section are in line to other papers that study the effect of communication on the predictability of monetary policy rates in the U.S. and the E.C.B., some of these papers include Pakko (2005), Hayo and Neuenkirch (2015), Sturm and De Haan (2011), and Hubert and Labondance (2021).

Figure 5: Local Projections of MPR using Sentiment Index



Also, we make a brief assessment of whether there is a global factor that moves all of the sentiment scores analyzed. We conduct simple principal component analysis to obtain what

Figure 6: Local Projections of MPR using Sentiment Index



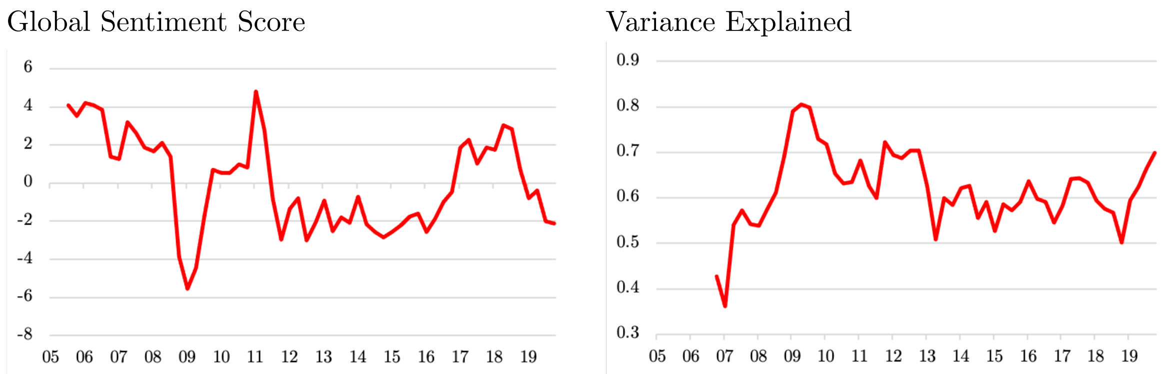
we call the Global Sentiment Score.[18] For this, we use 15 out of the 18 countries, leaving out Australia, Brazil, and Iceland because of their shorter sentiment score series. We define the Global Sentiment Score as the first principal component of the 15 sentiment scores starting in June 2005. This can be seen in the left panel of Figure 7. We can see that the sample was previously hawkish but decreases to the most dovish point in the sample for the 2008-2009 Crisis. Then it stays relatively constant between 2012 and 2016. It began to increase toward a more hawkish sentiment during 2017.

In the right panel of Figure 7, we run a two-year moving-window principal component analysis

[18]The first principal component is a direction in a coordinate scalar projection of the data. It is the direction that covers the most variance of the scalar projections.

to obtain the percentage of the variance explained by the first principal component at different points in time. The results show an important percentage of the sentiment scores that can be explained by a common global factor. Although the percentage explained starts low at close to 40%, it rapidly increases to its peak at 80% during the Global Financial Crisis. It then decreases to move within a band between 50 and 60%. In 2019, the percentage explained began increasing again as the trade war between the US and China started to impact the real economy.

Figure 7: International Sentiment Score Comparison



In addition to examining a global common factor among the sentiment indices, we evaluated whether sentiments of influential central banks, such as those from the Federal Reserve, may move closely with others. We focus on Fed documents since prior literature findings indicate that U.S. monetary policy shocks have impacted the economies of other countries.[19] Because of the significance of U.S. policy decisions, the policy discussions embedded in Fed documents may also help forecast how foreign monetary policy discussions evolve. For this reason, we consider the relationship between Fed policy document sentiments and the sentiments of central bank documents from the other economies.

In this analysis, we adopt the local projections methodology used by Iacoviello and Navarro (2019) in a panel dimension. We examine the average effect of Fed *ss* shocks on the projections for the ss of inflation-targeting countries.

[19]See Kim (2001), Ehrmann and Fratzscher (2009), and Georgiadis (2016) for further discussions.

We estimate the surprise element of the US ss using the equation

$$ss_t = \delta_0 + \delta_1 ss_{t-1} + \delta_2 ss_{t-1} + \delta_3 \pi_{t-1} + \delta_4 \pi_{t-2} + \varepsilon_t \tag{3}$$

where ε is the unexplained part of the variation in Fed ss and serves as the surprise component of the policy document sentiments. We then evaluate how the US ss is related to foreign ss using the following specification:

$$ss^i_{t+h} = \eta_{0,h} + \eta_{1,h} ss^i_{t-1} + \eta_{2,h} \pi^i_t + \eta_{3,h} g^i_t + \eta_{4,h} Z_t + \eta_{5,h} \varepsilon_t + \xi^i_t \tag{4}$$

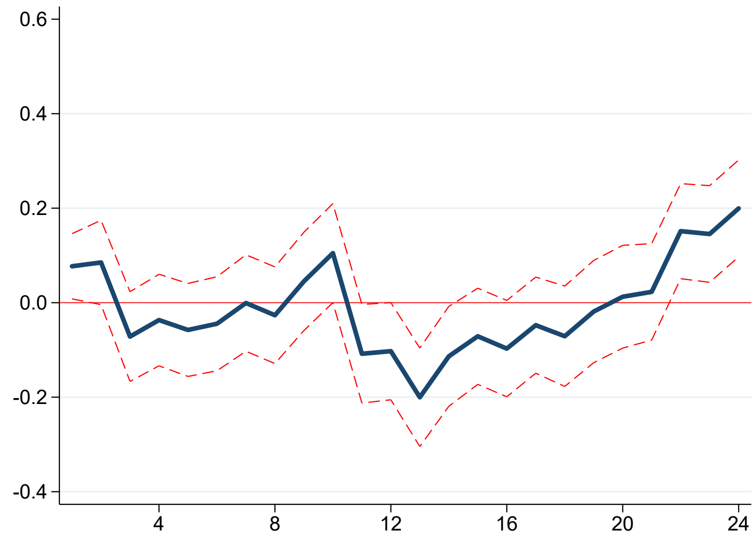
In this equation, $\eta_{5,h}$ captures the average impact of the US ss index on the ss projections after h quarters. π^i and g^i are the inflation and growth rates, respectively, of country i. Moreover, Z represents a set of control variables, namely, the U.S. CPI, U.S. GDP, oil price, gold price, and copper price.

Figure 8 shows the results with confidence bands at the 10% significance level. We find that the U.S. sentiment surprise has, on average, a statistically significant relationship with foreign sentiment indices at the very immediate horizon of about one quarter. This finding highlights that the U.S. sentiment surprises may not necessarily spill over to other central banks. Our results support the idea that the Federal Reserve discusses similar economic indicators that foreign central banks also incorporate in their policy documents.

5.3 Comparison of Results with Prior Literature

As previously mentioned, there are several papers that build sentiment indexes for central banks, among them we can find Apel and Grimaldi (2014) and Picault and Renault (2017). In this section, we recognize the advantages of these methodologies while highlighting the improvement over theirs. These papers add to the literature by studying the sentiment of central banks documents by studying the ideas that can be obtained by using a combination of words instead of just studying unigrams (single words). We agree with the notion that more than one word is required to give meaning to an idea, our methodology is improves on theirs as is explained in the following lines.

Figure 8: Average Impact of U.S. Sentiment Surprise



In Apel and Grimaldi (2014), the authors combine nouns with a modifier, in their case adjectives, to get the meaning of ideas. Their nouns dictionary contains the words “inflation”, “cyclical position”, “growth”, “price”, “wages”, “oil price” and “development” while the adjectives dictionary includes “decreasing”, “slower”, “weaker” and “lower”, “increasing”, “faster”, “stronger” and “higher. Although in terms this is big improvement in terms of methodology, this dictionary allows for only a limited number of ideas to be captured. We add to this methodology in several ways. First, we include a larger number of adjectives, but, more importantly, we add verbs, which allow us to capture ideas such as “inflation has decreased” which would not be captured in their dictionary. Second, the nouns that we use are classified into two categories, Hawkish and Dovish. This allows to include concepts that show a deterioration of the economy when they increase. For example, we have the keyword (noun) “inflation” that, when paired with words such as “higher” or “increased”, can be categorized as being hawkish. However, we also have the keyword (noun) “unemployment” that can be categorized as Dovish when paired with the same modifiers mentioned previously. In that sense, our methodology is able to capture more nuances in the topics. Finally, we select the nouns using a machine learning procedure to capture the main nouns in the documents instead of choosing the nouns based on our knowledge of the topic.

In Picault and Renault (2017), the authors manually analyze all the sentences in all ECB press releases between January 2006 and December 2014. The main disadvantage of this methodology is that it depends on a manual analysis of the sentences, which is both time-consuming and can be affected by subjectivity issues. The time-consuming dimension translates into that it is very costly to do the same analysis for another central bank. The dictionary they build is based on how the press releases are written in the ECB. For example, one entry is "accommod fiscal monetari polici put upward pressur inflat" after removing stopwords and stemming the words. This entry would work only if the sentence is written in the same way as it is written in the ECB. To analyze another central bank, it is, most likely, necessary to do the same manual analysis.

In contrast, our analysis looks for specific words in each sentence to mark them as hawkish and dovish. Since a computer does it, it can be used easily in any central bank. Although, at this point, we have a dictionary for each country, we are working on building a master dictionary for all central banks.

Several papers in the literature that studies central bank communication use the dictionary built by Loughran and McDonald (2011), among them we can find Armelius et al. (2020), Benchimol et al. (2020).This dictionary consists only of unigram terms that are divided into sentiments: negative, positive, uncertainty, litigious, strong modal, weak modal, and constraining, which in the context of monetary policy does not make much sense. So in this section I present a short comparison of the analysis that one would get by using the Loughran and McDonald (2011) and ours.

For Loughran and McDonald (2011) we follow their procedure by searching only unigrams terms in the positive and negative category and adding (or substract) them at the document level. While our methodology consists of using two separate dictionaries (keywords and modifiers) to search at each of the sentences, a combination of keywords and modifiers allowing us to obtain a score per sentence. The comparison results appear in Table 7 and 8. The first table shows how each methodology work for press release of the central bank of Sweden published in October 2008. It can be seen that the LM11 methodology recognizes the words decline, diminishing, and slowing as negative, but in the context of monetary policy those words can have different meaning

Table 7: Comparing Results of Methodologies: Sweden Oct-2008

LMD2011		
cut, crisis, threatens, slowdown, diminished, dampen, strains, decline, diminishing, stability, easing, strong, weaker, slowing, weakening, downturn, positive, opportunity		
GT2022		
Keyword	**Modifiers (category)**	**Sentence**
inflation	down (N)	the riksbank's forecast for both inflation and gdp will therefore be revised down.
inflation, price	diminishing (N)	inflation expectations are diminishing and remain anchored to price stability.
growth, price	augmented (P) downside (N) diminished (N) upside (P)	the recent intensification of the financial crisis has augmented the downside risks to growth and thus has diminished further the upside risks to price stability.
assessment, growth	weaker (N) slowing (N) down (N) inflationary (P) diminishing (N)	the executive board of the riksbank makes the assessment that economic growth in sweden is slowing down and that inflationary pressures are diminishing as an effect of the financial crisis.
growth	threatens (N) reinforce (P) diminished (N) inflationary (P)	the global financial crisis threatens to reinforce the current slowdown in economic growth with diminished inflationary pressures as a result.
market	weakening (N)	the labour market is also showing clearer signs of weakening.

if they are combined with words such as growth or inflation, Dovish, or unemployment and risk in the other, Hawkish. Table 2 shows the correlation coefficients between LM11 sentiment index and our index. It can be seen they go as high as 0.7 in the case of Hungary to as low as 0.2 in the case of Brazil, showing very different results between each other.

6 Robustness: Altering the Modifier List by Country

In our current work, we build sentiment scores for the monetary policy press releases of a set of inflation-targeting countries. These indexes are built using new dictionaries designed for studying monetary policy documents. The dictionaries are divided between keywords and modifiers. The keywords' dictionaries are country-specific, while the modifiers' dictionary is general. Although the selection of the words to be included in the modifiers dictionary follows an objective procedure, the selection of how to classify the each of the modifiers as positive or

Table 8: Correlation between Sentiment Indexes LM2011 and GT2022

Country	ρ	**Country**	ρ
Hungary	0.70	Australia	0.47
South Africa	0.69	Thailand	0.46
South Korea	0.66	Chile	0.38
Sweden	0.66	Philippines	0.38
Poland	0.62	Israel	0.36
Norway	0.61	Romania	0.32
Nueva Zealand	0.57	Iceland	0.30
Canada	0.51	Peru	0.26
Indonesia	0.48	Brazil	0.20

negative is more subjective. To examine the robustness of our selection criteria we replaced our modifiers dictionary with a combination of the dictionaries presented in Loughran and McDonald (2011) and Hendry and Madeley (2010), which are dictionaries developed to analyze financial texts that also were classified using the same criteria.

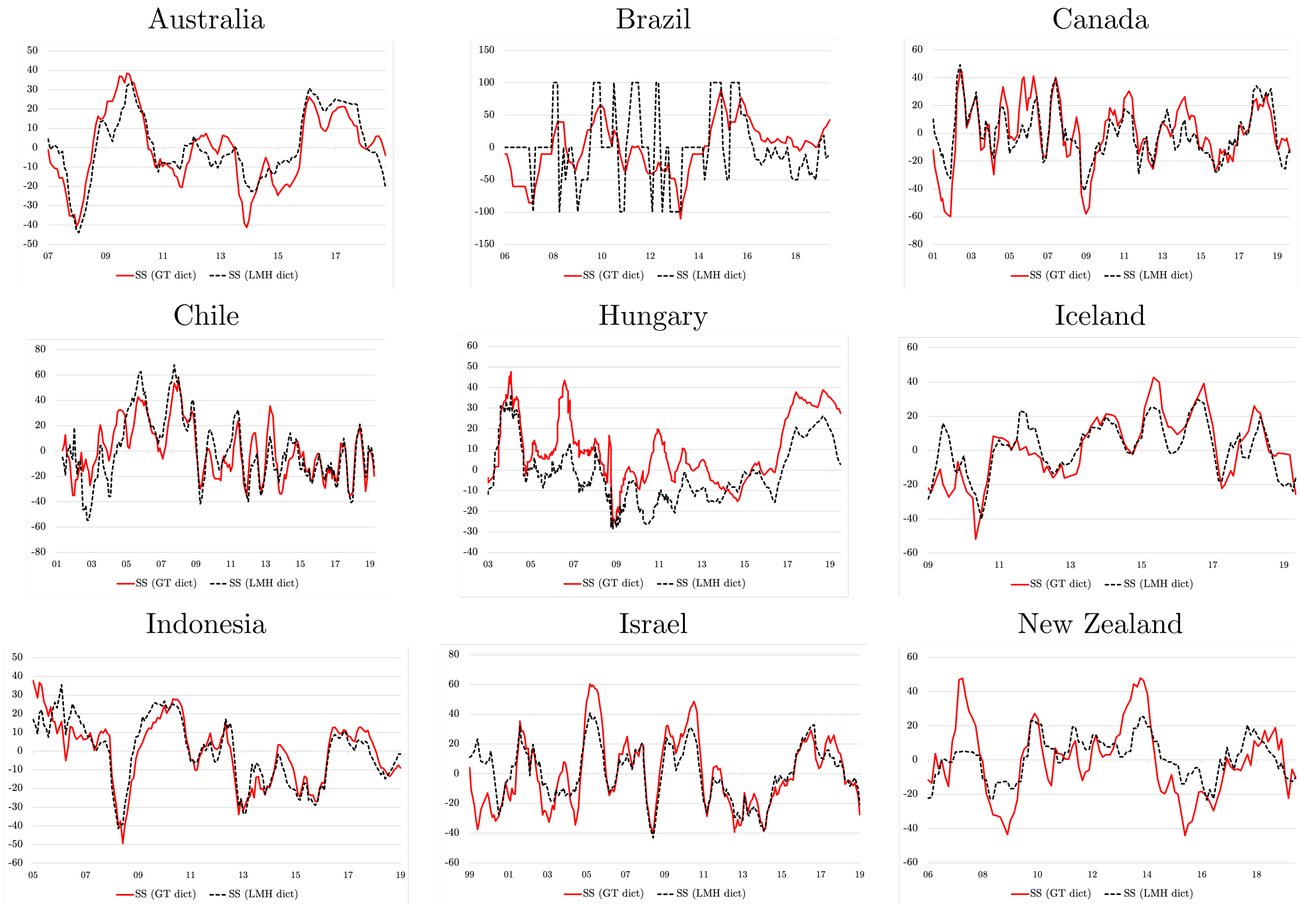
The comparison appears in Figures 9 and 10. The lines labeled as *GT dict* show the sentiment scores calculated using the Gonzalez-Tadle (GT) Dictionary while the *LMH dict* show the sentiment scores calculated using the combined dictionary from Loughran and McDonald (2011) and Hendry and Madeley (2010), which is referred to as LMH. In most cases, the two lines move close to each other, signaling that our classification criteria into positive and negative is consistent with the classification used in general.

7 Conclusion

This paper examines the monetary policy decision communication strategy of a group of inflation-targeting central banks by studying the monetary policy press releases using linguistic analysis, LDA, term frequency, and Semi-automated Content Analysis. We follow the literature that brings linguistic analysis into economics. The use of linguistic analysis tools helps analyze a text document's qualitative content by transforming it into a more quantitative format. We incorporate such tools in our analysis to contribute to the literature that studies the central banks' communication by basing the analysis on the monetary policy's predictability and efficacy.

Using LDA and term frequency analysis, we build a new dictionary that we use combined

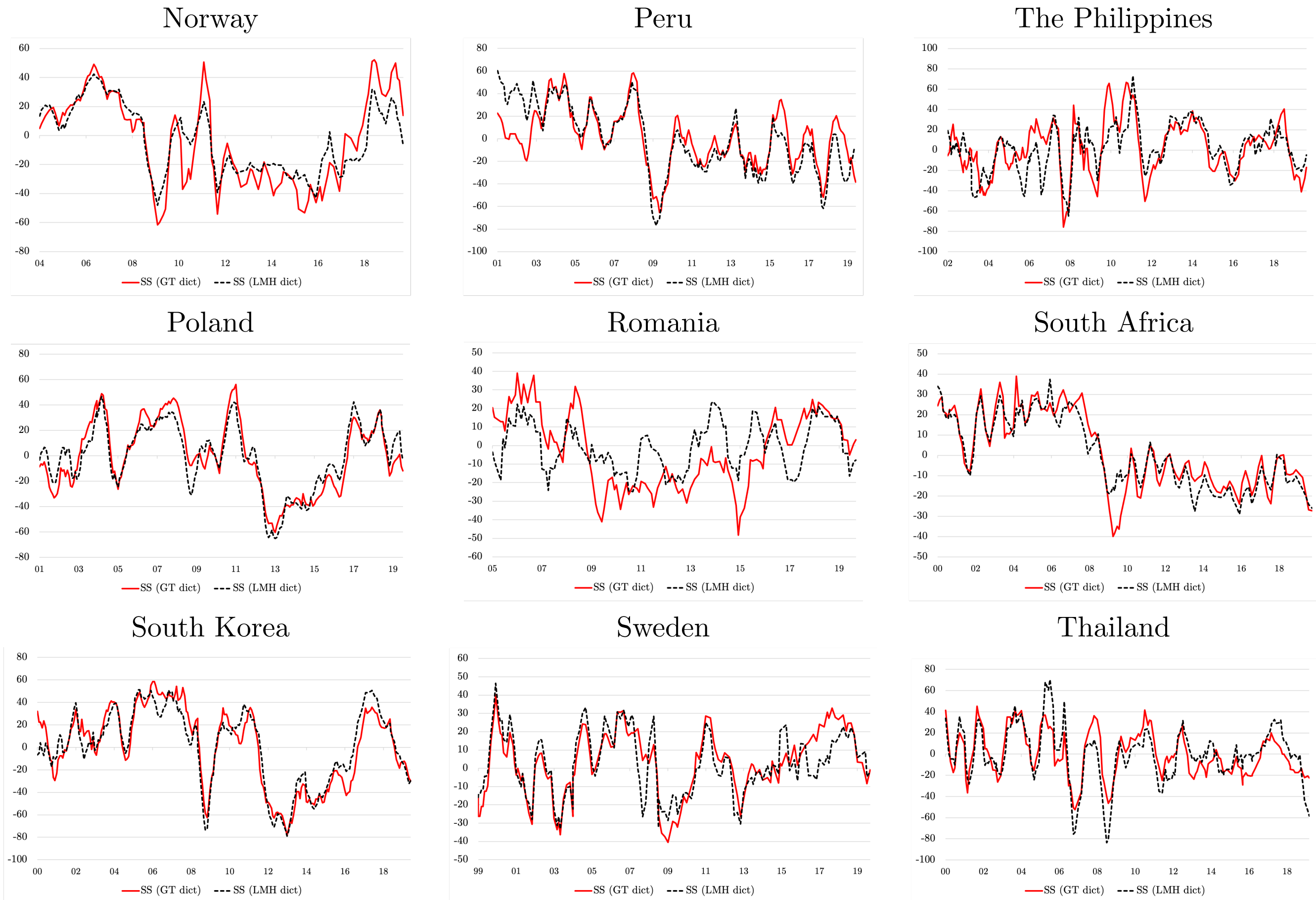
Figure 9: Sentiment Scores Robustness: Gonzalez Tadle Dictionary vs LMH Dictionary



with Semi-automated Content Analysis to measure each monetary policy statement's tone. We find that most central banks reveal information that can help anticipate the evolution of the MPR. Also, we find that during periods of international crisis, the press releases' tone tends to move closer together.

The tools and conclusions found in this paper can help guide communications used by central banks. Central banks can utilize the sentiment index to fine-tune their monetary policy press releases and convey more appropriate information about their monetary policy expectations.

Figure 10: Sentiment Scores Robustness: Gonzalez Tadle Dictionary vs LMH Dictionary



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A Appendix

A.1 Coherence Score

The Coherence Scores, CS, is an alternative way to measure the understandability and interpretability of a given set of textual topics. To compute the CS, we compile the relevant documents into a corpus of texts. The corresponding text of words D are split into topic subsets.

We take the 20 most relevant tokens (unigrams and bigrams) from each topic as the top topic tokens. This selection creates a set of n top tokens. For each token t_i, we calculate the relationships with the other selected tokens. Using Boolean Sliding Window-based Detection, we count the co-occurrence of the tokens in the corpus of examined documents and assign probabilities based on the counts within five tokens (± 5 tokens) around t_i. We then note the probability for tokens t_i and t_j as $p(t_i, t_j)$. For each token, we create a vector of these co-occurrence probabilities using Normalized Pointwise Mutual Information (NPMI). The j-th element of this context vector $\vec{v}_i$ is given by

$$v_{i,j} = NPMI(t_i, t_j)^\gamma = \left(\frac{\log\left(\frac{P(t_i,t_j)+\epsilon}{P(t_i),P(t_j)}\right)}{\log\left(P\left(t_i, t_j\right) + \epsilon\right)} \right)^\gamma$$

Note that ϵ (equated as 10^{-12}) is added to avoid the logarithm of zero. The corresponding context vector for token t_i is given by

$$\vec{v}_i = \{NPMI(t_i, t_i)^\gamma, NPMI(t_i, t_{i+1})^\gamma, NPMI(t_i, t_{i+2})^\gamma, \ldots, NPMI(t_i, t_{n-1})^\gamma\}$$

Given our notation, higher γ values place more weight on higher NPMI values (default value of $\gamma = 1$ is used).

To calculate the coherence scores, we take the average of the cosine similarity confirmation measures among pairs of context vectors. These confirmation measures evaluate the context vector and accounts for their similarities. The coherence score based on the number of topics is then given by

$$CS = \frac{1}{(n-1)!}\Big[\cos\left(\vec{v}_i, \vec{v}_{i+1}\right) + \cos\left(\vec{v}_i, \vec{v}_{i+1}\right)$$
$$\Big]$$

Table A1: Linguistic Analysis Results: Beginning Sample to Dec-2017

	Beginning of sample	Number of words (mean)	Number of Sentences (mean)	Words per Sentence (mean)	Word Length	Gunning Score	SMOG Score	Flesch-Kinkaid Score	Flecsch Score
Australia	Jan-90	468	25	19	5.2	15	14	11	10th-12th G
Brazil	Mar-03	160	8	19	5.4	15	14	12	College
Canada	Mar-99	416	18	23	5.1	17	15	13	College
Chile	Jan-01	238	12	20	5.4	18	16	13	College
Hungary	Jan-03	423	21	18	5.2	15	14	11	College
Iceland	Mar-09	386	19	20	5.2	16	14	12	College
Indonesia	Jul-05	889	42	21	5.5	18	16	13	College
Israel	Jun-99	1457	55	28	5.1	19	16	15	College
Korea	Jan-00	347	16	21	5.4	18	16	13	College
New Zealand	Dec-96	348	16	21	5.3	16	15	13	College
Norway	Oct-10	1445	81	18	5.1	14	13	10	10th-12th G
Peru	Feb-01	427	31	14	5.0	14	13	9	10th-12th G
The Philippines	Dec-01	327	13	25	5.5	19	17	15	College
Poland	Jan-01	873	40	22	5.0	17	15	12	College
Romania	Oct-03	695	21	34	5.4	23	20	19	College grad
South Africa	Jul-14	2187	102	21	5.1	15	14	12	College
Sweden	Jun-98	716	43	17	4.9	14	13	10	10th-12th G
Thailand	May-00	333	19	17	5.4	16	15	12	College
Average		674	32	21	5	17	15	12	
Max		2187	102	34	5	23	20	19	

Source: Authors' calculations

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