Payoff of the credibility and the communication strategy of the central banks on the inflation expectations: case of study for Latin America based in text mining and neuronal networks

César Iván Díaz Tavera[1] Juan Salvador Quiñonez Wu[2]

Lisette Josefina Santana Jiménez[3]

Abstract †

From the perspective of economic agents, the perception of the balance of risks inherent to the most relevant macroeconomic variables and the credibility of monetary policy are crucial elements in the process of expectations formation, which represent one of the main transmission mechanisms of monetary policy. The purpose of this research is to establish the impact of the communication strategy and the credibility of the discourse of central banks in a group of Latin American countries (*i.e.* Chile, Perú, Colombia, and the Dominican Republic) on economic agents' inflation expectations and, consequently, on the decisions taken over a given time horizon, $\boldsymbol{t+n}$ ($\boldsymbol{n} \in \mathbb{N}$). A text mining approach is used to extract the underlying tone of the monetary policy communications issued by the central banks of the countries considered in this study. A multilayer neural network model is estimated for each country to simulate a metric inherent to inflation expectations that is aligned with the information and sentiment reported in the policy communications issued by each central bank. This exercise allows to observe the discrepancies between central banks' expectations, which are reflected in their discourse, and the public's expectations (entropy of expectations). The preliminary results are consistent with the findings of other authors (Carriere-Swallow and Pescaroti, 2018), detecting a certain level of heterogeneity across countries when observing the transparency-communication binomial in the selected countries. In some cases, the forward-looking nature of monetary policy communications and its influence on the process of minimizing the entropy of expectations is emphasized. The simulations performed highlight the role of the credibility of central banks' actions on the behavior of domestic prices, the predictability of the monetary authority's management, and the potential slack that a countercyclical monetary policy fosters, as long as continuous monetary surprises do not occur.

Keywords: text mining, expectations, monetary policy, dictionary, neural networks.

JEL classification: C02, C14, D81, F01.

[1] Central Bank of the Dominican Republic; cesar.diaz@bancentral.gov.do.
[2] Secretary of the Central American Monetary Council (SECMCA); jquinonez@secmca.org.
[3] Central Bank of the Dominican Republic; lj.santana@bancentral.gov.do.
† The opinions expressed by the authors do not necessarily represent the views of the Central Bank of the Dominican Republic or the SECMCA. Any errors are the sole responsibility of the authors.

1. Introduction

The expectations of the economic agents regarding the behavior of the main macroeconomic variables represent one of the key transmission mechanisms of monetary policy, playing a fundamental role in the variations of the interest rate, the exchange rate, wages, aggregate demand and domestic prices (Taylor, 1982). Bems *et al*. (2018) find that longer-term inflation expectations were particularly important in exerting inflationary pressures in countries where this variable has remained above target; these authors also emphasized the role of expectations in building greater resilience to external shocks (*e.g*. during the tantrum episode in 2013, countries with more anchored inflation expectations experienced larger short-term exchange rate depreciations than those with less anchored expectations).

The objective of this research is to establish the impact of the decisions of the monetary authorities on the degree of entropy and anchoring of economic agents' inflationary expectations, in order to analyze under which circumstances there might be greater impact on inflation expectations and the potential outcomes derived from the consistency between policy makers' decisions and central banks' communication strategy (especially in times of high uncertainty). A text mining approach is used to extract the underlying tonic from the monetary policy communications issued monthly by the central banks of the selected countries (*i.e.,* Chile, Colombia, Peru, and Dominican Republic). A dictionary-based analysis is made, considering the idiosyncratic factors of each country.

A multi-layer neural network (MLP) model is estimated, for each country, to generate an artificial metric of "inflation expectations" entirely aligned with the underlying tone of monetary policy communications, in order to establish how the divergence between this artificial metric and inflation expectations[4], allows characterizing the level of entropy in inflation expectations.

[4] The data for the inflation expectations is published officially by each central bank. This information is based on surveys oriented to get the opinion of a sample of businesses and economists, regarding the expected behavior of different macroeconomic variables in a time horizon $t+n, (n \in \mathbb{N})$.

The motivation to carry out the construction of metrics that allow quantifying the underlying tone of communications is given by the fact that a transparent and consistent communication strategy serves as a tool for the management of an optimal monetary policy (Castillo *et al,* 2018), considering its direct impact on the behavior and the decisions adopted by the economic agents.

The results suggest that, after the Covid-19 crisis as well as other subsequent shocks (in less than five years) (*e.g.* Covid-19 crisis, geopolitical conflict between Russia and Ukraine, uncertainty and increased volatility in financial markets, instability in the banking system of the United States of America, among others), there has been a significant change both on the structure of the communications of each central bank, considered on this research, and on the entropy of the inflation expectations. The credibility of the central banks' communication strategy acquires more importance, given their potential effects on the balance of risks of different macroeconomic and financial variables, as well as the fact that the consistency between actions taken by the monetary authority at t has a direct effect on decisions at $t+n$ $(n \in \mathbb{N})$, in terms of the response of domestic prices and the path of economic growth.

Peru is the country that shows a higher correlation coefficient, $\boldsymbol{\rho = 0.87}$, among the inflation expectations and the simulated metric on the frame of the MLP model, while Chile reflects the lowest degree of correlation $\boldsymbol{\rho = 0.68}$. The higher coherence between the inflation expectations and the simulated metric, after the Covid-19 crisis, is consistent with a more explicit and credible communication, in terms of its congruence with the underlying macroeconomic conditions, during this period of time. Additionally, considering the high degree of uncertainty that prevailed during the referred period, it is logical that expectations depend to a lesser extent on the inflation observed in $t-n, (n \in \mathbb{N})$, and that the public appeal to forward-looking information provided by central banks.

The monetary authorities must contemplate both the heterogeneity of the public to whom this information is addressed and in transmitting, in an efficient manner, the perception of the economic outlook (external and internal) and how the prevailing conjuncture can impact the decisions of policy makers. Transparency in the management of monetary policy fosters a better understanding of central banks' objectives, from the public's perspective, as well as of the elements that incentivize their decisions, making it possible to minimize the volatility of expectations (Carrière-Swallow and Pescaroti, 2018; Benchimol *et al,* 2020). Optimal monetary policy management is based on a forward guidance strategy (Carney, 2013), conveying a message about future intentions and actions to be taken to mitigate the potential effects of shocks or sources of uncertainty on the behavior of the economy.

In this paper, it is emphasized the potential derived from a higher degree of transparency and credibility on the communication strategy of the central banks, acting as drivers in the decision-making processes and mapping the impact of these elements on the inflation expectations and the additional effort that the central bank would need to make (more hawkish or dovish monetary policy) in order to maintain the inflation within the target range. Also, it is noted that, especially in periods of high uncertainty, the minimization of noise in the expectations' channel provides a reward in terms of the speed of recovery and economic resilience as well as more slack to implement counter-cyclical policies.

This paper is structured as follows: the next section provides a review of the theoretical and empirical literature on the impact of communication strategies on inflationary expectations, also considering the empirical tools used in previous research to quantify the underlying tone of central bank communications; section 3 describes the data and methodology applied to achieve the objective of this research; section 4 presents the results of both the text mining exercise and the simulations performed within the framework of the specified multilayer neural network topology. The last section shows the conclusions derived from these exercises.

2. Literature review

The literature on the transformation and quantification of qualitative and unstructured information into quantitative information is relatively recent and has become more popular given the availability of machine learning models that enable the estimation of a spectrum of metrics, taking advantage of the growing volume of information available from different sources, at high frequency and in real time. In this order, text mining-based algorithms have emerged as promising alternatives to carry out the construction of proxies to capture economic and political uncertainty over time (Tobback, 2016; Celi *et al*, 2016; Davis, 2016; Baker *et al*, 2015); Nyman *et al,* 2018). Bholat *et al* (2015) emphasized the importance of machine learning tools from the perspective of central banks to exploit the available stock of information and complement modeling techniques based on traditional methods, making the solution of various research problems plausible. The authors discuss how the gradual implementation of data mining techniques has enriched the analytical framework for decision-making processes in different central banks.

Hendy and Madeley (2010) use unsupervised text mining techniques, in this case Latent Semantic Analysis (LSA), to extract information from the Bank of Canada communication statements and explore what kind of information affects yields and volatility in the short term, as well as long-term interest rate markets over the period 2002-2008. Discussions on geopolitical risk and other external shocks, major domestic shocks (SARS and BSE), the balance of risks to the economic projection, and various forward-looking statements significantly affect market returns and volatility, especially for short-term markets.

Castillo *et al.* (2018) construct the European Central Bank (ECB) monetary policy tone index using a compilation of ECB documents and natural language processing (NLP) techniques with the purpose of identifying the most relevant topics within the ECB monetary policy discourse. The objective of generating an index to quantify the tone of ECB communication stems from the fact that central banks have adopted concrete commitments, credible and transparent communication as monetary policy tools. It is emphasized that an objective analysis of ECB discourse is a key tool for tracking changes and forecasting monetary policy expectations.

Since the establishment of inflation targeting regimes in different countries, several studies, dating back more than a decade, have emphasized the role of central bank communication as a monetary policy transmission mechanism, establishing that efficient communication minimizes distortions in the expectations channel, thus minimizing the level of entropy[5] of expectations (Ehrmann and Fratzscher, 2005; Hendry and Madely, 2010). In addition, unsupervised text mining techniques are used to investigate the type of information that affects returns and volatility in the short and long term. In particular, it is identified that discussions about geopolitical risks and other external and internal shocks, the balance of risks in economic projections and various forward-looking statements have a significant effect on market behavior.

Other research focuses on the impact of the structure of monetary policy announcements on various macroeconomic variables, mainly in periods of crisis (European Central Bank, Monetary Dialogue-2018). In this sense, the effectiveness and scope of these communications are evaluated in terms of several components, such as the number of words, the inclusion of clear explanations of both the external and domestic outlook, and how this information translates into the behavior of inflation and economic growth.

Under the Covid-19 crisis, the role of the expectation channel, as one of the most efficient mechanisms for transmitting the decisions of policy makers, became evident. For this reason, more weight is being placed on writing explicit statements that can be understood not only by an audience specialized in economic issues (for example, the Central Bank of Ireland has presented cartoons explaining the functioning of the central bank as a political currency

[5] In this case, the term entropy refers to the divergence between the inflation expectations (based on surveys) and the implicit inflation expectations in the communications of the central bank.

regulator and its incidence in controlling the price level of the economy). Likewise, different central banks have increased their presence in social networks, with the purpose of broadening the scope of information and decision-making processes.

Benchimol *et al*. (2022) show that Federal Reserve (FED) communications regarding the Covid-19 pandemic address issues of financial volatility, contextual uncertainty, and financial stability, and that they emphasize health, social welfare, and unemployment. The authors also show that the Fed's communication policy changed dramatically during the Covid-19 crisis compared to the global financial crisis (2008) and the dotcom crisis (1999) in terms of content, sentiment, and timing. The actions taken by central banks in response to the Covid-19 shock pose greater challenges and demands on monetary policy communication (Unsal and Garbers, 2020). In this sense, safeguarding the credibility of monetary policy requires transparent, consistent and coherent explanations of the crisis through the communication channel.

In the case of Latin America, Carrière-Swallow *et al* (2018) assess the correlation between the tone of monetary policy announcements for a set of countries (*i.e.* Chile, Colombia, Peru, Brazil, Mexico). The results indicate that central banks in the region show a heterogeneous picture in this context so there could be a benefit from a policy of greater transparency. The success of a communication strategy depends more on the quality of the information than on the number of words. Central banks that use a clear and unambiguous communication strategy tend to be among the most predictable.

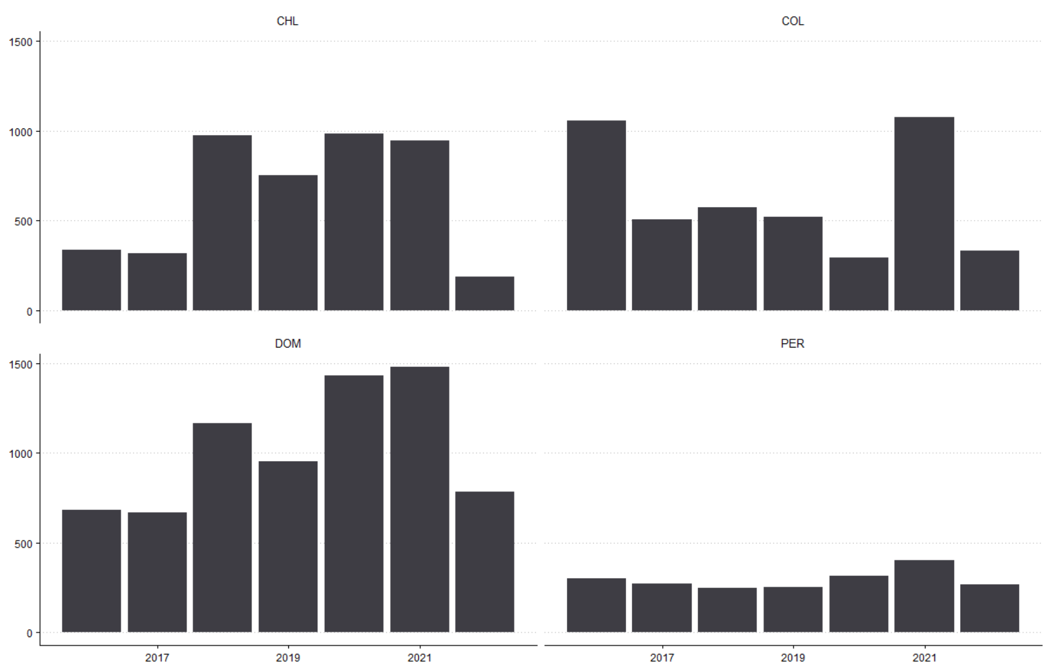
It should also be noted that the use of a monetary policy bias, explicitly conditioned to current forecasts, increases the transmission of monetary policy changes in inflation expectations. The implementation of a forward-looking monetary policy requires a communication strategy that influences the expectations formation process of economic agents. The convergence of these expectations to the target range depends on the effectiveness, transparency and clarity with which the central bank's discourse and position are transmitted at t, factors that combine to promote greater credibility of the entity at $t+n$ $(n \in \mathbb{N})$ to the extent that monetary surprises are minimized, generating greater slack for monetary policy management (Quiñonez *et al*, 2019; Quiñonez and Santana, 2021) and to accommodate internal and external shocks.

3. Data and Methodology

3.1. Data

This research uses information from the monetary policy minutes of the Central Bank of the Dominican Republic, Peru, Chile and Colombia for the period January 2016- May 2022, as well as data on inflation, inflation expectations, monetary policy rate and interbank interest rate for the analogous period. Figure 1 shows the number of words per year for each country in the monetary policy communications. It highlights the fact that the monetary policy minutes of the four countries became longer in the context of international and drastic shocks from 2020 onwards.

Figure 1. Word counting of the monetary policy communications for the considered countries (2016-2022).



*Source: authors' estimations using data from different central Banks.

This is to be expected considering that the goal of the central banks' communication strategy is to keep confidence and expectations anchored through forward guidance. It is also noted that the Peruvian central bank minutes are comparatively short, while those of the Dominican Republic are longer than those of the rest of the countries.

3.2. Methodology

The generation of metrics that allow the transformation of qualitative (unstructured) information into quantitative (structured) information represents one of the main benefits of Natural Language Processing (NLP), specifically the text mining techniques (both supervised and unsupervised learning). In this sense, during the last years and, given the prevailing situation under the Covid-19 crisis, in which high frequency information from non-conventional sources has been demanded, the role of this kind of tools has become increasingly relevant. Within the set of text mining techniques, the contextualization of documents (e.g. newspaper articles, minutes, monetary policy communication, speeches), based on dictionaries, constitutes one of the most efficient techniques for quantifying unstructured information. However, one of the obstacles encountered in the semantic process is the identification of dictionaries that fit the content, subject matter and idiosyncratic component of the document bank under consideration.

This research follows the approach used by Gonzalez and Tadle (2022) and Tavares *et al.* (2021), who constructed sentiment indices using dictionaries in which they defined distinct sentiments for each sentence of the press release that was then used to explain the monetary policy stance of different countries. Since each country has a different communication strategy, that contemplates idiosyncratic components inherent to local situations, a sentiment indicator is developed for each country, following a similar strategy. The sentiment indicator is constructed using supervised machine learning techniques, where a sample of four communications per year is taken and divided by sentences. Each sentence is ranked according to its tonic (1 if the sentence is dovish, -1 if it is hawkish or 0 if it is not possible to rank).

Once the texts have been analyzed and classified, a cleaning process of this information of a qualitative nature is carried out. This pre-cleaning stage is crucial for the accuracy of the results, considering the noisy nature of the unstructured data, and includes several steps that allow us to dispense with irrelevant information, for the purpose of extracting the sentiment consigned in the documents. Modifications are made to the corpus to homogenize the information contained in each text.

First, punctuation marks and special characters (such as percent signs) and numbers are removed. In addition, common English words, that do not provide specific information, are eliminated. This list was expanded to include other common words in the releases, such as names of months of the year, countries and institutions (*e.g.* International Monetary Fund, Consensus Forecast, World Bank and others).

This is followed by a process where words are transformed to the "root" that corresponds to them (also known as "lemmatization" or "stemming"), aligned with the words of Tavares et al (2021). Some words, such as "economy" and "economics", have a common root ("econom-" in this example). By deriving these words to a common root, the number of possible tokens in the texts is considerably reduced and a better token classification can be performed.

For the calibration of the model, 70% of the tokens used are used, while the remaining proportion (30%) is used as a test set. A logit model and a decision tree are used to obtain the probability that a token belongs to a certain class; in the considered context the classes would be hawkish and dovish. Both models are computed through unigrams (one-word tokens) and bigrams (two-word tokens); thus, one has a set of four models to build a sentiment indicator.

Once the model is calibrated, the probability that a word is linked to an underlying positive or negative tonic is obtained. Considering this information, the tokens of each monetary policy release are ranked and a sentiment index given by the following expression is constructed (Vega and Lahura, 2020):

$$sentiment = \frac{P_i - N_i}{P_i + N_i}$$

Where P_i represents the number of tokens with a positive tonic and N_i is the set of tokens with negative tonic.

Analogously to Tavares *et al.* (2021), reference dictionaries are used to construct sentiment indices that are estimated to compare the computed sentiment indicator using logistic and decision tree models.

3.2.1. Neural Networks

A neural network is a structure of layers interconnected through units called nodes. In a neural network there are inputs to which weights are assigned; within each node, the weights of the inputs are aggregated and an activation function is applied to obtain the results derived from the model, which represents the output variable of the network. For an *n*-dimensional input the first layer will have *n*-nodes and the output will have t neural units.

The architecture of a neural network is intended to emulate the functioning of the human brain and the way the neurons are organized is directly linked to the training algorithm; if the network has learned the underlying structure of the problem at hand then it is able to classify and subsequently predict patterns (Gurney, 1997).

In general terms, the structure of a neural network is given by the following expression:

$$Y_t = \sum_{j=1}^{j} X_j \alpha_j \quad \alpha_j > \acute{\alpha}_J \qquad (6)$$

Where Y_t represents the output variable and X_j is the vector of input variables. In addition, α_j is a hyperparameter of the network, which is responsible for activating the neuron to transmit information and is generally represented by a logistic function (in this case by a sigmoid function) given by the expression:

$$f(\mu) = \frac{1}{1+e^{-\mu}} \qquad (7)$$

Considering that, under this specification, there is only one hidden layer, H_j, the equation (6) can be rewritten as follows:

$$H = f\left[\sum_{j=0}^{j} x_j \alpha_j\right] \qquad (8)$$

Denoting θ_j as the weight that links the *input* and the *output* of the model, then:

$$Y_t = \sum_{j=0}^{j} H_j \theta_j \qquad (9)$$

Replacing (8) in (9), we obtain the hidden layers function, including the function g:

$$Y_t = h\left[\left(\sum_{k=1}^{k} \alpha_k\right) f\left(\sum_{j=0}^{j} \theta_{ik} X_j\right)\right], \quad (10)$$

j= a network input with one layer;

k= two neurons with one layer;

The empirical literature does not provide a definitive rule for optimal selection of hidden layers and neurons. However, it is pointed out that one of the strategies used to determine these hyperparameters is linked to the performance of the model in the training phase, as well as to the specification of an unsaturated network, which would lead to an overfitting or under-fitting problem. Similarly, one of the essential rules (Hornik, 1991) is that the number of neurons must be bounded by the number of inputs and outputs of the model. With respect to the number of hidden layers, the theorem of Cybenko (1989) is followed, which states that, given a finite number of neurons, it is possible to approximate the behavior of continuous functions with certain assumptions about the activation function.

Once the number of hidden layers is set and the number of neurons is set, we seek to minimize the function:

$$min_{\alpha k\theta(j,k)}SSD = \sum_{t=1}^{T}\left[Y_t - h\left(\sum_{k=1}^{k}\alpha_k f\left(\sum_{j=0}^{j}\theta_{ik}X_{jt}\right)\right)\right]^2 \qquad (11)$$

For this optimization process, a training sample is required, from which the network learns from the data provided as inputs. Empirical literature estimates that, approximately, the training set is composed of 66%-70% of the total data, while the remaining proportion of the information allows verifying the accuracy of the specified model (test data) (Tkacz and Hu, 1999; Basihos, 2016; Geron, 2017; Chollet, 2018).

4. Results

4.1. Dictionary construction

As noted in the methodological approach (section 3.2), logistic regression models and decision trees have been applied to perform the token collection of the documents compiled for each central bank considered in this study. The results obtained show that, in general, the models trained with bigrams and in which stemming is applied achieve a higher accuracy, as well as a better F1-Score; the latter is true for the releases of all countries, except Chile, whose performance is better with unigrams. It is also observed that while the models for the Dominican Republic have the best accuracy, the metrics are more uniform in the cases of Colombia and Peru.

Figure 1 shows the estimated sentiment indicator for each country and its co-movement with inflation and interest rate expectations. In general terms, both models (logistic and decision tree) and tokens (unigrams and bigrams) yield high volatility indicators. Logistic models using either token generate similar results with similar volatility, unlike decision tree models, which generate fewer volatile indicators using unigrams, rather than bigrams.

Table 1. Performance metrics by model.

	Logistic		Decision Tree	
	Unigrams	Bigrams	Unigrams	Bigrams
	DOM			
accuracy	0.736	0.816	0.729	0.797
precision	0.524	0.614	0.502	0.552
F1 score	0.404	0.568	0.442	0.583
	PER			
accuracy	0.719	0.743	0.705	0.759
precision	0.746	0.659	0.742	0.711
F1 score	0.568	0.642	0.529	0.64
	CHL			
accuracy	0.56	0.518	0.56	0.512
precision	0.528	0.474	0.525	0.465
F1 score	0.51	0.463	0.532	0.448
	COL			
accuracy	0.54	0.639	0.543	0.645
precision	0.548	0.629	0.572	0.632
F1 score	0.551	0.638	0.479	0.648

*Source: authors' estimations.

Table 2. Standard deviation for each model considered.

Country	Logistic		Decision Tree	
	Unigram	Bigram	Unigram	Bigram
Chile	0.189	0.210	0.202	0.205
Colombia	0.240	0.225	0.243	0.225
Peru	0.237	0.251	0.232	0.259
Dominican Republic	0.274	0.266	0.265	0.283
Average	0.261	0.266	0.251	0.276

*Source: authors' estimations.

Since the selected countries use the inflation targeting scheme for monetary policy, inflation expectations are important for policy makers. A Granger test was conducted to verify the causality between the sentiment indicator and the inflation expectations for each country, in order to analyze the co-movements of the indicators and the expectations. The results of these tests are shown in Table 3. In general, the sentiment index does not cause Granger inflation expectations, except for the cases of Colombia and Chile, where the first and second lags were significant, respectively.

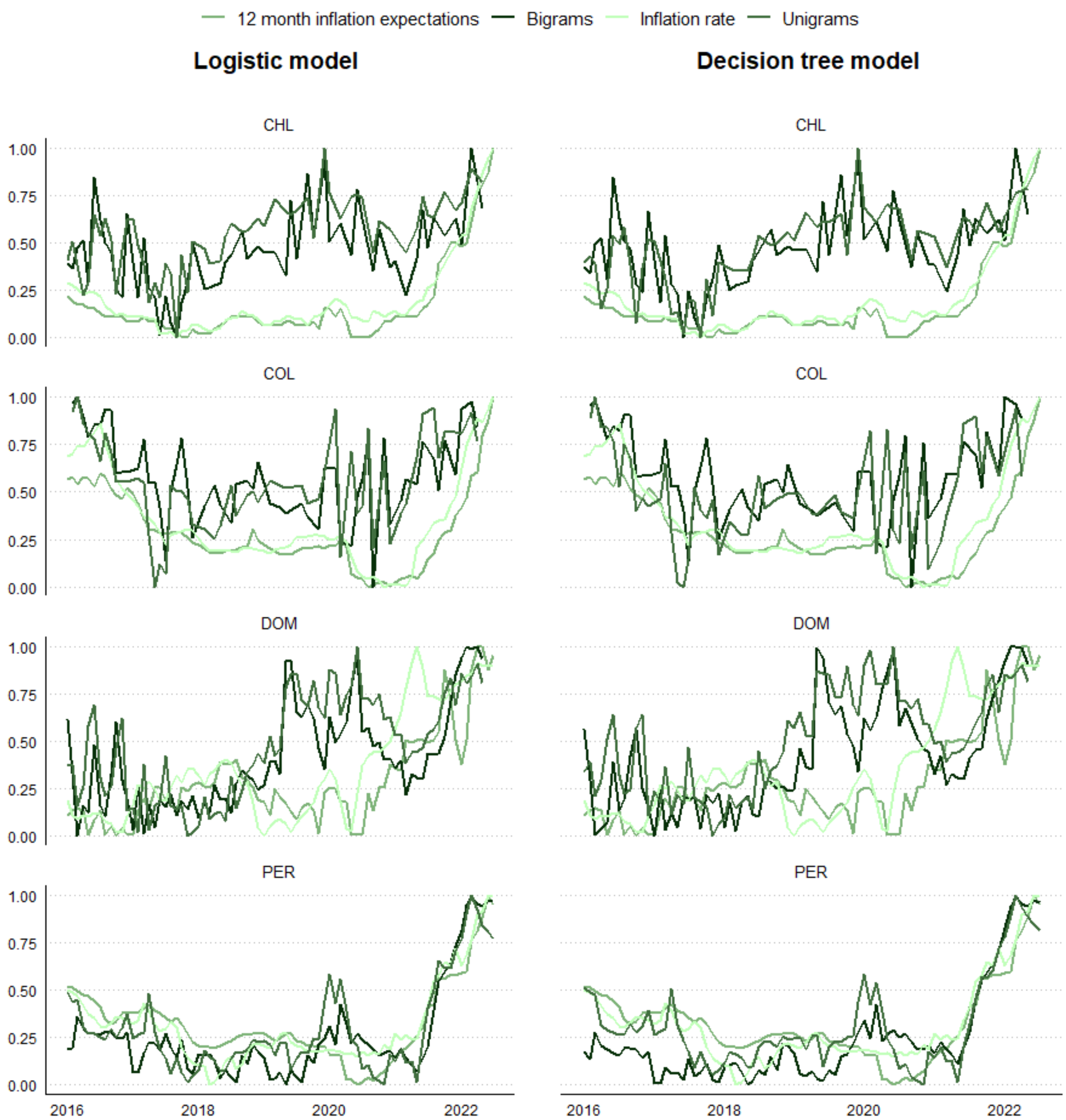
Table 3. P-value of the Granger causality test between the sentiment index and inflation expectations.

Lags	Logistic		Decision Tree	
	Unigrams	Bigrams	Unigrams	Bigrams
	DOM			
1	0.4406	0.2938	0.8119	0.5372
2	0.6765	0.4040	0.8719	0.4778
3	0.7967	0.4454	0.8233	0.4742
	PER			
1	0.9391	0.7660	0.6842	0.8825
2	0.6015	0.8838	0.7137	0.6000
3	0.8075	0.9762	0.8572	0.8124
	CHL			
1	0.3911	0.4485	0.5268	0.4521
2	0.3157	0.0102	0.4432	0.0107
3	0.5379	0.0149	0.6086	0.0177
	COL			
1	0.0056	0.0851	0.0263	0.0341
2	0.0411	0.1533	0.0545	0.0866
3	0.1144	0.6256	0.1599	0.5108

*Source: authors' estimations.

One of the possible explanations for these results is that the expectations of economic agents were highly distorted by the shocks associated with the Covid-19 pandemic, considering that, under such a context of high uncertainty, individuals formed their expectations with additional information that was not necessarily consigned in the monetary policy statements of each central bank.

Figure 2. Sentiment indicators by country and co-movement with inflation and interest rate expectations.



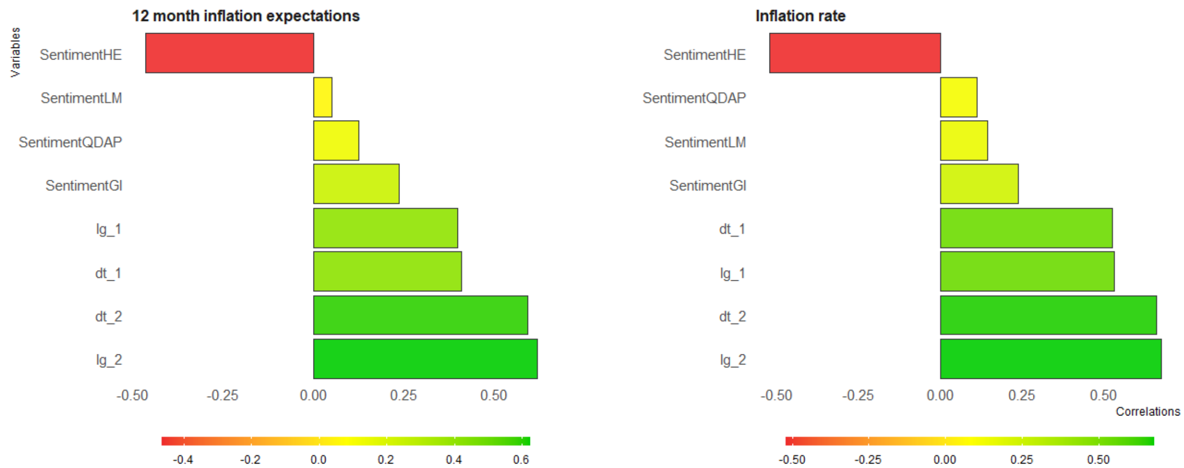
*Source: authors' estimations.

The correlation coefficients of each model with inflation and inflation expectations are shown in Figure 3. For benchmarking purposes, the sentiment index is computed for each of the countries considered using other dictionaries: Henry's Financial dictionary, Loughran-McDonald

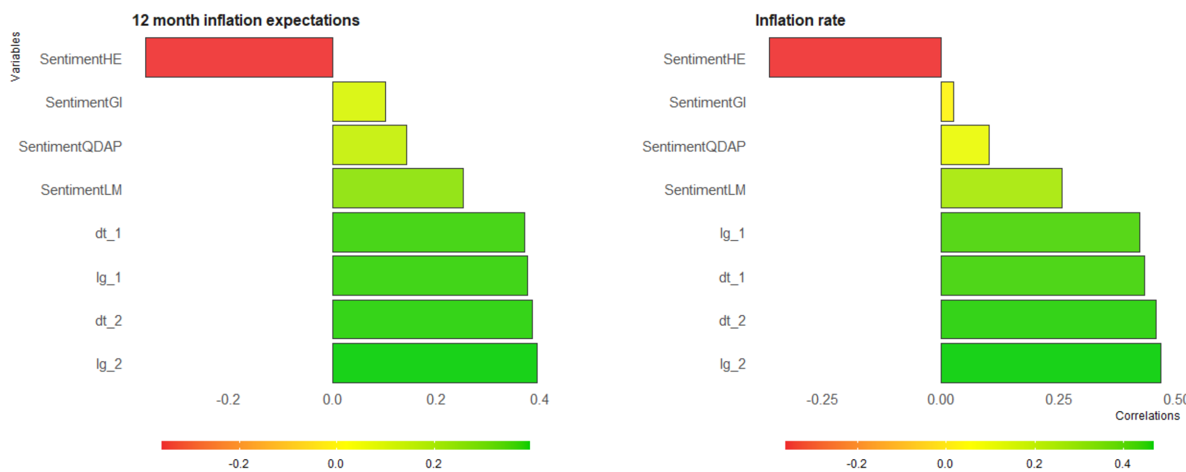
Financial dictionary, Harvard-IV dictionary and the QDAP dictionary. The benchmark indicators, constructed with the alternative dictionaries, show lower correlation with inflation expectation than the indicators generated from the logistic and data tree models. In general, models using bigram tokens show the highest correlation with inflation expectation, except in the case of Peru.

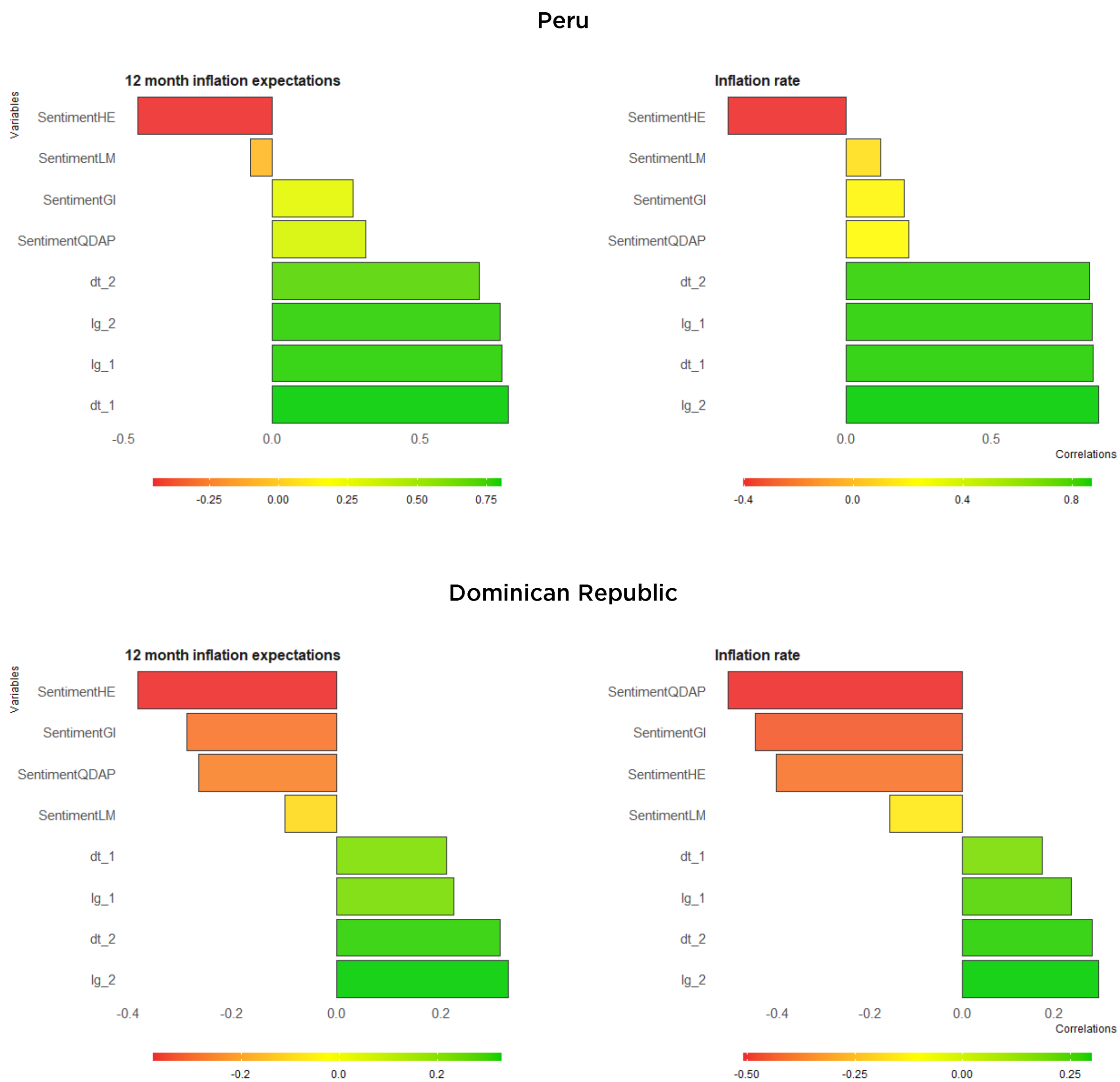
Figure 3. Correlation between sentiment indicators and inflation and interest rate expectations.

Colombia



Chile





*Source: authors' estimations.

4.2. Simulations with neural networks

In this section the results of the simulations based on multilayer neural network (MLP) structures are presented (section 3.2.1). The variables used as inputs in the model are the metrics inherent to the tonic[6] of the monetary policy communications for the central banks of each country considered in this research (*i.e.* Dominican Republic, Colombia, Chile and Peru), and the output variable corresponds to the inflation expectations for the period $t + 12$.

Specifically, the following functional specification is considered:

$$E_{\pi+12}(t) = f(dt1_{i,t}) \quad (12)$$

where:

$E_{\pi+12}(t)$ = inflation expectations for $t + 12$.

$dt1_{i,t}$ = tonic derived from the decision trees for period t and the country i.

The hyperparameters used are a logistic activation function, a hidden layer and two hidden layers. A normalization of the input and output data is carried out, considering the sensitivity of the neural network models with respect to the scale of the information used.

Based on the simulations performed, the impact of the underlying tone in the monetary policy statements of each central bank on the inflation expectations of economic agents is mapped, starting from the dictionary-based contextualization carried out in the first stage of this research. A metric of inflation expectations is constructed, $\boldsymbol{E}^*(\boldsymbol{\pi}_{t,i})$, which is aligned with the tone of the monetary policy statements issued by each central bank. The discrepancy between these metrics represents the degree of entropy[7] of inflation expectations (Quiñonez *et al.*, 2021); let S be the entropy of inflation expectations, then:

$$S = E(\pi_t^*) - E(\pi_t)$$

$E(\pi_t^*)$ = inflation expectations simulated on the MLP model.

[6] En el caso de Chile y Colombia, se llevó a cabo un proceso de interpolación para homogeneizar las series con los otros países (*i.e.* República Dominicana y Perú), puesto que los comunicados de política monetaria no se publican con frecuencia mensual.

[7] In the areas of physics and chemistry, the term "entropy" refers to states of chaos and uncertainty. In this case, the concept of entropy is extrapolated to this economic application to allude, precisely, to processes of uncertainty, as well as to oscillations in the balance of inflation risks, derived from the (recurrent) incoherence between the discourse of central banks and the actions adopted.

The assessment of the entropy of expectations makes it possible to identify whether the central bank's perception of the underlying economic outlook reliably reflects macroeconomic and financial behavior, both domestically and externally and, secondly, whether the appreciation recorded in monetary policy communiqués represents a guideline for decisions to be taken on monetary policy rate movements. Finally, it provides additional information on the expectation formation processes of economic agents, the degree to which domestic and external conditions are weighted, the impact of a forward-looking communication strategy and whether the appreciation of the central bank's risk balance, at the level of the prevailing economic outlook and at the multidimensional level, is consistent with the expectations of economic agents.

Why would these considerations be relevant from the point of view of monetary policy makers? To the extent that there is greater convergence between the monetary authority's discourse and the actions adopted in a given period, economic agents would expect greater credibility, which translates into a reduction of distortions in the expectations channel. The minimization of monetary surprises to economic agents, in general terms, favors a convergence between $\pi_t^* \ y \ \pi_t$. In the opposite scenario, distortions are generated in the expectations channel, since credibility is lost in the central bank's actions and, consequently, it will be necessary to make a greater sacrifice with respect to monetary policy rate movements (which may be larger depending on the health of each economy) than in the counterfactual scenario in which the central bank would have stuck to its discourse.

Likewise, to the extent that such credibility is maintained in $t + n$ ($n \in \mathbb{N}$), the implementation of a forward-looking monetary policy (forward guidance) is more efficient, since it serves as one of the guidelines for the public's choices at t and conditions its decisions on consumption and investment at certain time horizon. In this sense, a forward-looking communication technique can influence economic and financial decisions made at t (Federal Reserve, 2020). Additionally, given that this strategy helps to reduce the entropy of macroeconomic expectations, it would be expected that the effects of monetary policy would be visible in a timely manner, favoring optimal management, mainly in scenarios of high uncertainty, under which the monetary authority could have slack to accommodate shocks (Quiñonez *et al*, 2021), through counter-cyclical measures.

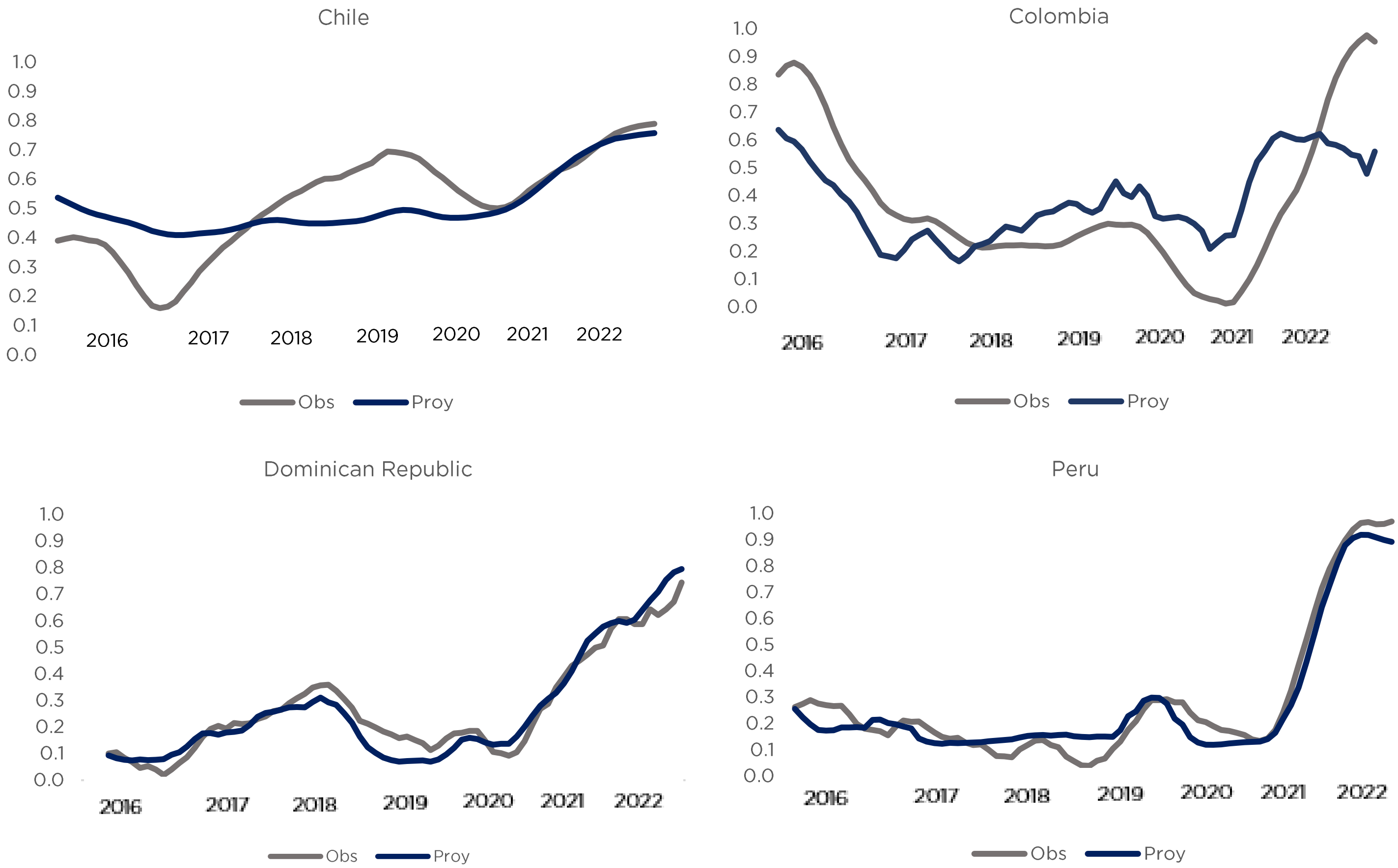
After the Covid-19 crisis, as well as the occurrence of other subsequent shocks (*e.g.*, the Russia-Ukraine geopolitical conflict, etc.), there would be more room to accommodate countercyclical measures. Russia-Ukraine geopolitical conflict, financial market volatility, instability of the banking system in the United States, among others), the effort of central banks to optimize their communication strategies, in terms of effectiveness, transparency and scope, became more visible and more intense, to the point that some central banks made use of didactic[8] tools, extended the discourse, explanations and characterization of the global macroeconomic scenario, and its impact on the decisions adopted by policy makers.

In addition to the challenge posed by the Covid-19 crisis, globally, other factors that have driven the use of an efficient and transparent communication strategy have been the changes in central bank mandates, as well as the use of alternative and more complex monetary policy measures, which generated greater controversy and placed monetary policy decisions. These developments made the effectiveness of central bank communication with the general public imperative (Blinder *et al.*, 2022).

On the other hand, the emergence and refinement of techniques for processing and quantifying text has created new opportunities for public and private entities, making plausible the integration of quantitative and qualitative information, as well as traditional and non-traditional data. In this sense, text mining is a multi-purpose tool that allows the evaluation of aspects such as the economic outlook in which central banks operate (being considered as an innovative methodology to measure inflation expectations) and to approximate the balance of risks associated with different macroeconomic and financial variables.

[8] For example, the Central Bank of Ireland used cartoons on its social networks to make explanations of the management and operation of monetary policy in the crisis period clearer and more far-reaching.

Graphic 1. Simulated inflation MLP model versus inflation expectations.

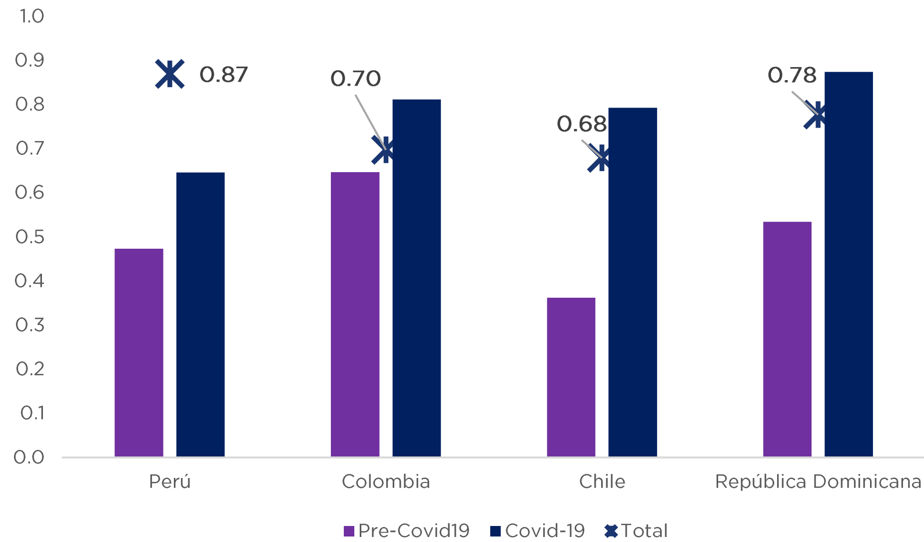


*Source: authors' elaboration.
**Notes:

1/ The simulated inflation was generated within the framework of the multilayer neural network model.
2/ The data are normalized under the min-max criterion in the interval [0,1] and are presented using a moving average.

The results of the simulation exercises reflect (Graphic 1), in general terms, a greater convergence between the tone of monetary policy statements and the inflationary expectations of economic agents than the results presented in other studies that also analyze the underlying sentiment in central bank statements in the region (Carriere-Swallow and Pescarotti, 2018) and for the Dominican Republic (Quiñonez *et al*., 2020). However, it is important to note that these studies were conducted for different periods and using other classification and contextualization techniques. On the other hand, it is observed that this convergence is more visible since the year 2020, considering the factors previously mentioned, with respect to the changes in the communication strategy of central banks after the onset of the Covid-19 crisis (Table A1).

Graphic 2. Correlation between inflation expectations and the inflation metric simulated in the MLP model (inflation expectations entropy).



*Source: authors' elaboration.
**Note: 1/ Moving average; normalized values under the min-max criterion in the interval [0,1].

Heterogeneity is observed in the results of the simulations for the countries considered. In this sense, Peru is the country with the highest correlation coefficient, $\boldsymbol{\rho} = \mathbf{0.87}$, between inflation expectations and the inflation metric simulated in the MLP model (Graph 2), while Chile shows the lowest degree of correlation $\boldsymbol{\rho} = \mathbf{0.68}$. In general, the results derived from this exercise reflect greater discrepancies between $\boldsymbol{\pi_t}$ and $\boldsymbol{\pi}^*$ (Graphic 2) in the pre-Covid 19 period. However, after the onset of the Covid-19 crisis, greater consistency is observed between the two series for all the countries considered. This is consistent with a more explicit and credible communication strategy, in terms of its congruence with underlying macroeconomic conditions, during that period. In addition, considering the high degree of uncertainty that prevailed during the referred period, it is logical that expectations depend, to a lesser extent, on the inflation noted in $\boldsymbol{t - n}\,(n \in \mathbb{N})$, and to use forward-looking information provided by central banks.

The degree of entropy of expectations is largely conditional on the monetary authority's discourse being sustainable, at an inter-temporal level, and that no surprises are generated that could cause distortions in the expectations channel. In this sense, a higher degree of entropy would imply: a) a lower predictability of the monetary policy rate in $t + n$ ($n \in \mathbb{N}$); b) a higher cost, considering the effort that would be required to keep inflationary pressures within the target range; c) less slack to accommodate shocks, mainly shocks of an exogenous nature.

The degree of entropy of the expectations reflects, at certain level, the effort that the central bank must undertake in a scenario in which credibility was not maintained. More explicitly, if simulated expectations are fully aligned with the tone of monetary policy statements, the results obtained from the MLP model point directly to what would have happened in a counterfactual scenario in which the public would have guided its expectations solely on the basis of that discourse. If there is a significant decoupling between the generated metric and the inflation expectations, it is because there was a distortion in the expectations channel or that these were formed based on factors exogenous to the discourse.

MLP models are estimated for each country, using the same hyperparameters as in the previous exercise (equation 11). The following functional specification is considered:

$$E_{\pi+12}(t) = f(dt1_{i,t}, dt1_{i,t-1}, dt1_{i,t-2}, \pi_{t,i}, \pi_{t-1,i}\ ) \quad (12)$$

Donde:

$E_{\pi+12}(t) =$ inflation expectations for $t + 12$;

$dt1_{i,t} =$ tonic derived from regression trees for period t and country i;

$dt1_{i,t-1} =$ tonic derived from regression trees for period $t - 1$ and country i;

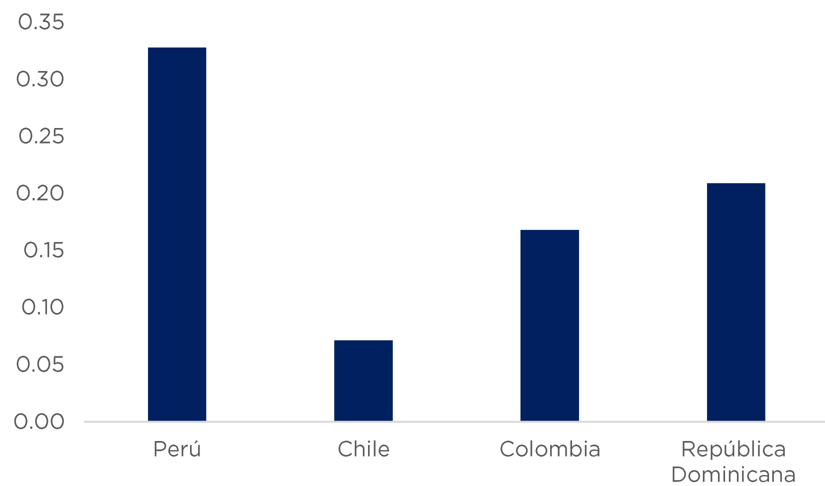
$dt1_{i,t-2} =$ tonic derived from regression trees for period $t - 2$ and country i;

$\pi_{t,i}$ = inflation rate for period t and country i;

$\pi_{t-1,i}$ = inflation rate for period $t-1$ and country i.

Thus, a topology of neural networks yields results with minimal forecast errors to generate inflation expectations forecasts (Graphic 3):

Graphic 3. Mean square error (MSE) projections of inflation expectations (alternative specification).



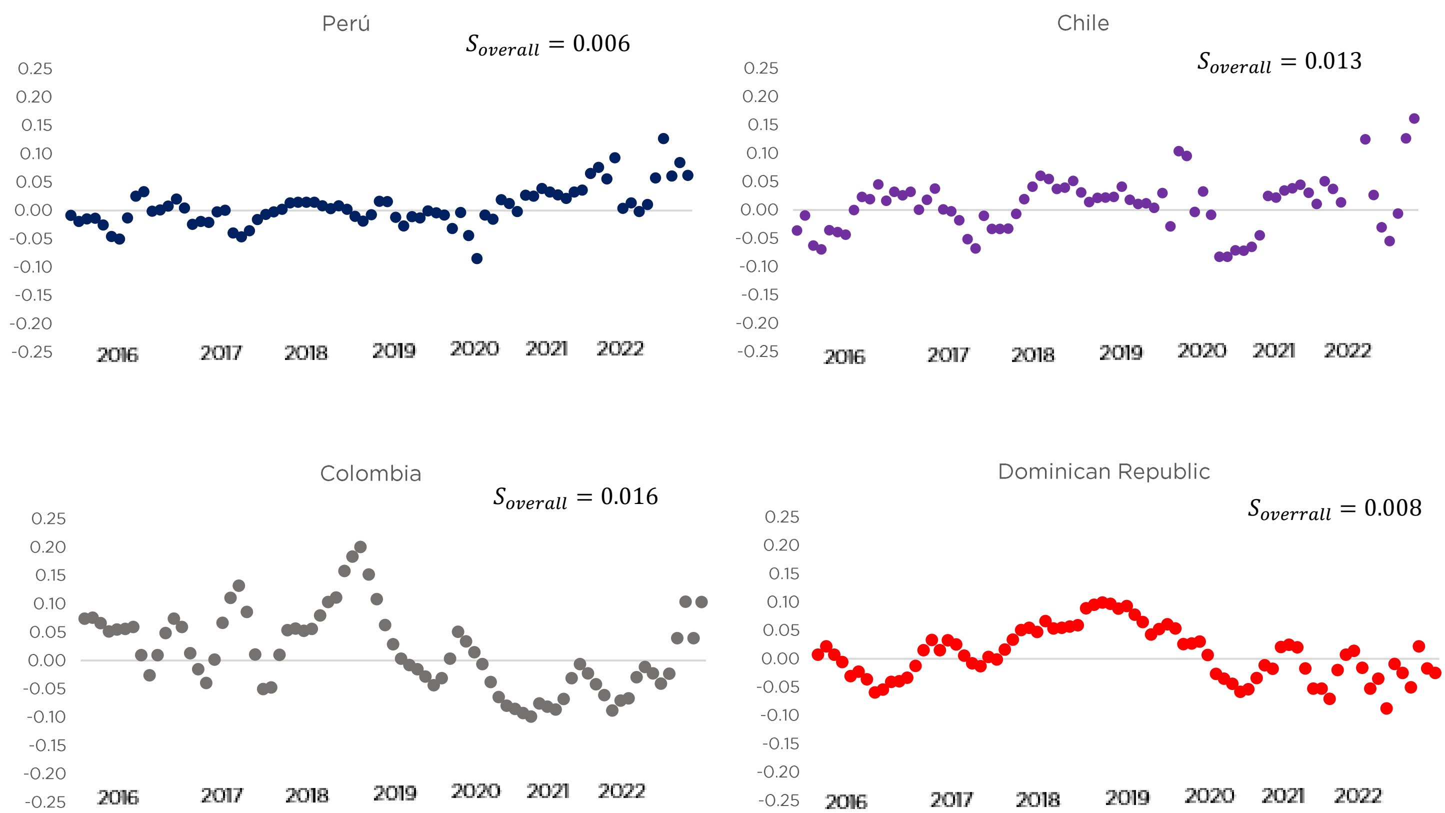
j*Source: authors' elaboration.

Under a forward-looking communication scheme, the monetary authority seeks to guide the public's inflationary expectations to the target range. However, this purpose can only be achieved to the extent that the central bank tries to safeguard the credibility of its discourse. In the countries considered for this research, such an effort is evident after the onset of the pandemic, given that in non-linear and highly uncertain scenarios, distortions in the expectations channel can exacerbate problems concerning the macroeconomic outlook, both domestically and externally.

In this regard, it is worth asking what was the level of effort made by each of these countries in the crisis and post-crisis periods, considering both their communication strategy and the conditions prevailing before the crisis? This question is complex. However, one approach to the answer lies in the discrepancies between the results of the simulations and the inflation expectations compiled through surveys on the expected trajectory of this variable.

In other words, the degree of entropy of expectations is a metric that captures the possible costs of the central bank, since it suggests what would have happened in a counterfactual scenario in which the public would have guided its expectations by the monetary authority's discourse (Graphic 4). The countries with the lowest entropy of inflationary expectations (on average 0.006 and 0.008, respectively) are Peru and the Dominican Republic.

Graphic 4. Entropy of inflation expectations.



*Source: authors' elaboration.

To the extent that a higher degree of entropy of expectations is verified, there will be a greater de-anchoring of economic agents' expectations in $t + n$ ($n \in \mathbb{N}$). This divergence will be more pronounced if monetary surprises are recurrent, considering that the monetary authority would be losing credibility with the public. In this case, a greater effort would be required to reorient inflation expectations, ensuring their convergence to the target range.

5. Conclusions

A central bank's communication strategy represents one of the main tools to strengthen the confidence of economic agents and keep expectations anchored, increasing the effectiveness of monetary policy. In this context, the application of machine learning and text mining techniques to economic theory has allowed researchers to answer new questions of interest, while significantly advancing the understanding of central banks' communication strategies and policy recommendations (Warsh, 2014).

An optimal communication strategy is essential to minimize distortions in the expectations channel. In a scenario where this consistency and transparency is not maintained, a higher degree of entropy is generated between the central bank's expectations and the expectations of economic agents. This translates into an eventual de-anchoring of expectations or deviation of inflation from the target range. This divergence will be more pronounced if monetary surprises are recurrent, considering that the monetary authority would be losing credibility with the public.

The monetary authority's discourse should reflect the central bank's perception of the underlying outlook, both domestically and abroad, and reliably reflect the potential effects of these elements on the balance of risks of the main macroeconomic and financial variables. In periods of high uncertainty, the importance of the credibility and transparency with which central banks operate becomes more evident, considering that these factors have an impact on the speed and effectiveness with which the actions adopted by policy makers are transmitted. In addition, in a scenario in which inflation expectations deteriorate further, it is highly probable that a more aggressive response will be required, in terms of an increase in the monetary policy rate (this response is also subject to the initial conditions of the economy).

From an empirical perspective, it is important to note that, as the interdisciplinary nature of computational learning and economics has strengthened, central banks have benefited significantly from the linkage of these tools with large data sets, both quantitative and qualitative (traditional and non-traditional). In particular, the empirical literature emphasizes the benefits of text mining algorithms, highlighting that as polyvalent tools, they have become a complementary technique for policy makers to have a better understanding of the impact of their statements, as well as to address other aspects concerning forward-looking communication, the process of expectation formation, the balance of risks of different macroeconomic variables and financial stability.

In addition, to the extent that central banks consider other thematic axes as part of their mission and institutional plan, such as the climate challenge and digital currencies, text mining is emerging as an appropriate technique for assessing the potential risks and different aspects associated with these issues. It is important to emphasize that this type of technique seeks to complement, rather than replace, the usual indicators and procedures of central banks. In this way, artificial intelligence is drawing new frontiers for the use of non-traditional information.
This paper employs a methodological approach based on text mining and neural networks. The communication strategy of the central banks of Colombia, Chile, Peru and Dominican Republic during the period January 2016-May 2022 is evaluated through the analysis of their monetary policy communiqués. For each country, the communiqués are tokenized into sentences and new unigram and bigram word dictionaries are constructed and used to classify their underlying tone and create country-specific sentiment indices using supervised machine

learning techniques. The results show that, in general, models trained with bigrams and stemming achieve higher accuracy as well as an improved F1-Score.

A high correlation is identified between the sentiment index built with different models, monetary policy rates and inflation expectations, for each country. The sentiment benchmarks, constructed using the Henry's financial dictionary, the Loughran-McDonald financial dictionary, the Harvard-IV dictionary and the QDAP dictionary, achieved a lower correlation with these macroeconomic indicators.

In the second stage of this paper, we use as inputs the results derived from the text mining exercise, in the framework of a multilayer neural network model, with the purpose of mapping the underlying tone of monetary policy statements on inflation expectations in period t+12. We start from the premise that monetary policy communiqués reflect the monetary authority's appreciation of the balance of risks (both domestic and external) of the main macroeconomic and financial variables and, under a forward-looking communication scheme, the information contained in them is intended to be one of the main guidelines in the process of forming the public's expectations.

In the framework of multilayer neural network models, for each country, a metric of inflation expectations is simulated. The difference between this metric and inflationary expectations is the degree of entropy of expectations. Peru and the Dominican Republic are the countries with the lowest average entropy for the period January 2019-May 2022. This degree of entropy reflects the potential loss or additional costs that central banks would incur in terms of the additional effort they would have to make to keep expectations anchored and minimize inflationary pressures.

It stands to reason that if the anchoring of expectations represents a crucial element in determining the slack with which central banks can accommodate the effect of internal and external shocks, how can this anchoring be strengthened and the distortions in the expectations channel minimized? The economic literature has provided an answer to this question: central banks gain credibility and confidence by fostering price level stability, as well as by maintaining transparency and consistency between their actions, the perception about the underlying macroeconomic outlook, and the actions taken in line with latent risks (Bordos and Siklos, 2015).

Future extensions of this paper intend to explore other methods for the construction of the dictionaries or to create a system in which different supervised and unsupervised learning techniques are weighted. On the other hand, an alternative to simulate expectations may be to use Fourier transform finite impulse response (FIR) exercises, which would also be performed in the framework of a neural network topology and simultaneously allow noise isolation during the estimation process.

Finally, in the framework of this exercise, it is feasible to compute an implicit interest rate that is consistent with both inflation expectations and the prevailing inflation rate for a given period. This interest rate can be estimated as an inverse function of a model in which both expectations and simulated inflation are introduced as inputs according to the tone of the monetary policy statements of each central bank.

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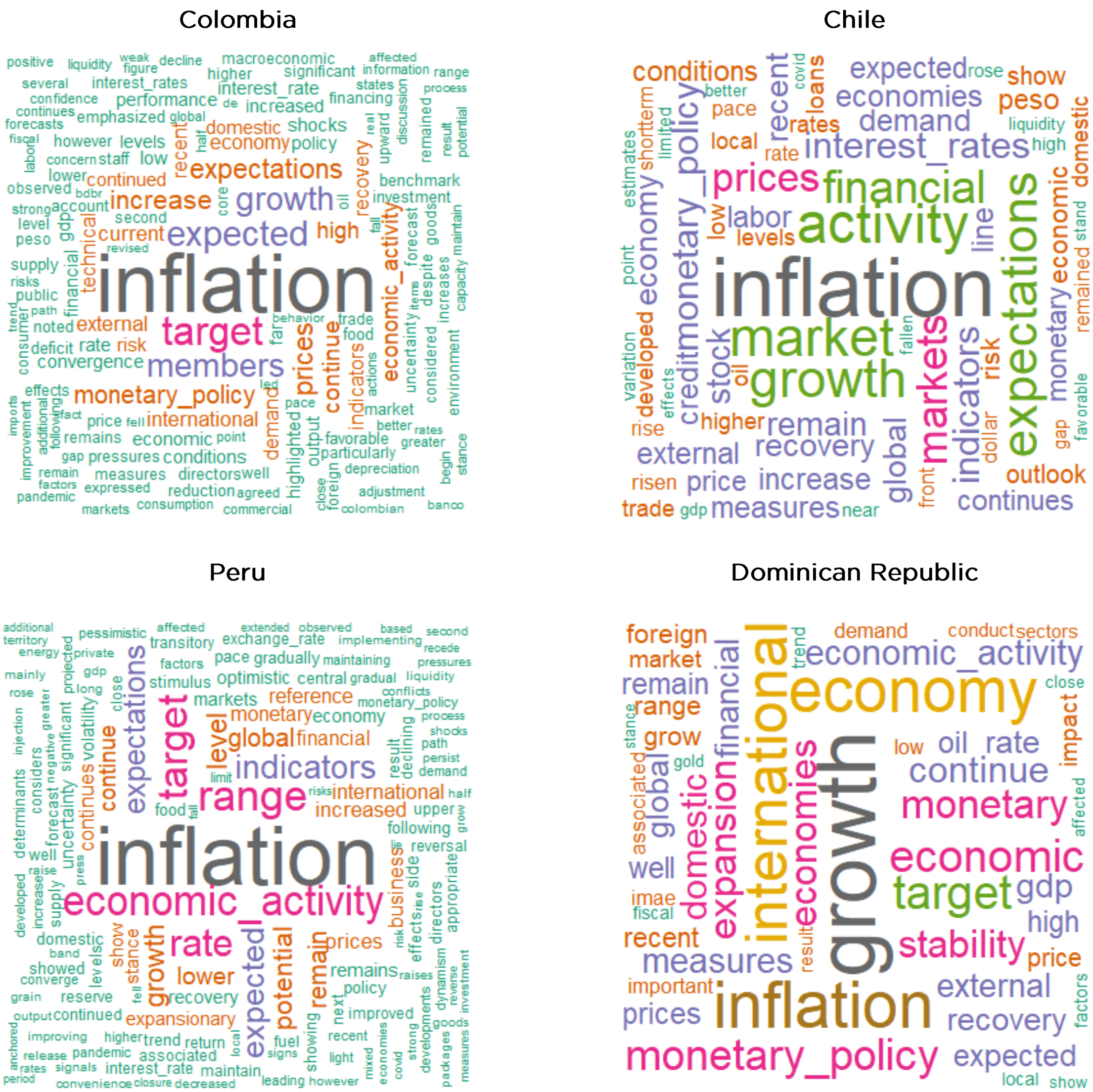
Appendix I

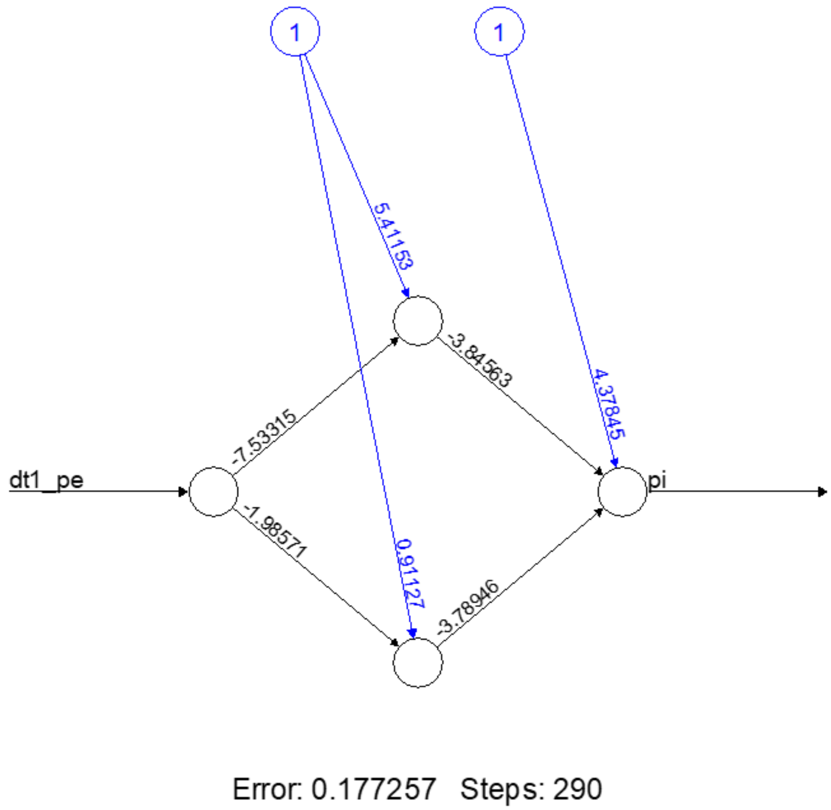
Figure A1. Word clouds per country.



*Source: authors' elaboration.

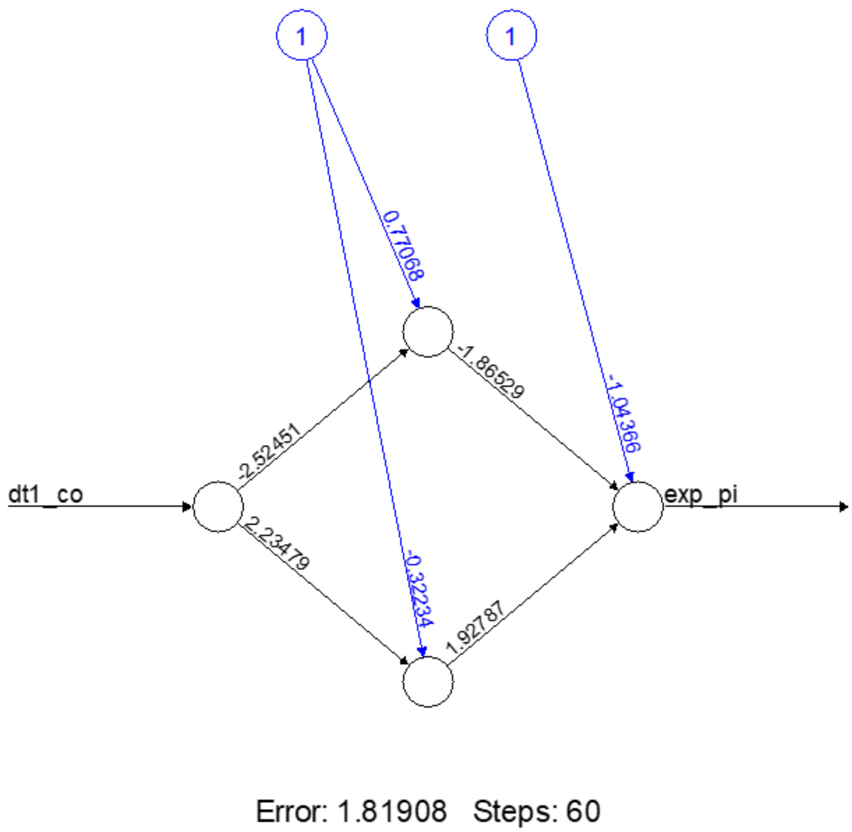
Appendix II. Entropy of inflation expectations by country (January 2016-May 2022).

Figure A2. 1. Entropy of inflationary expectations in Peru.



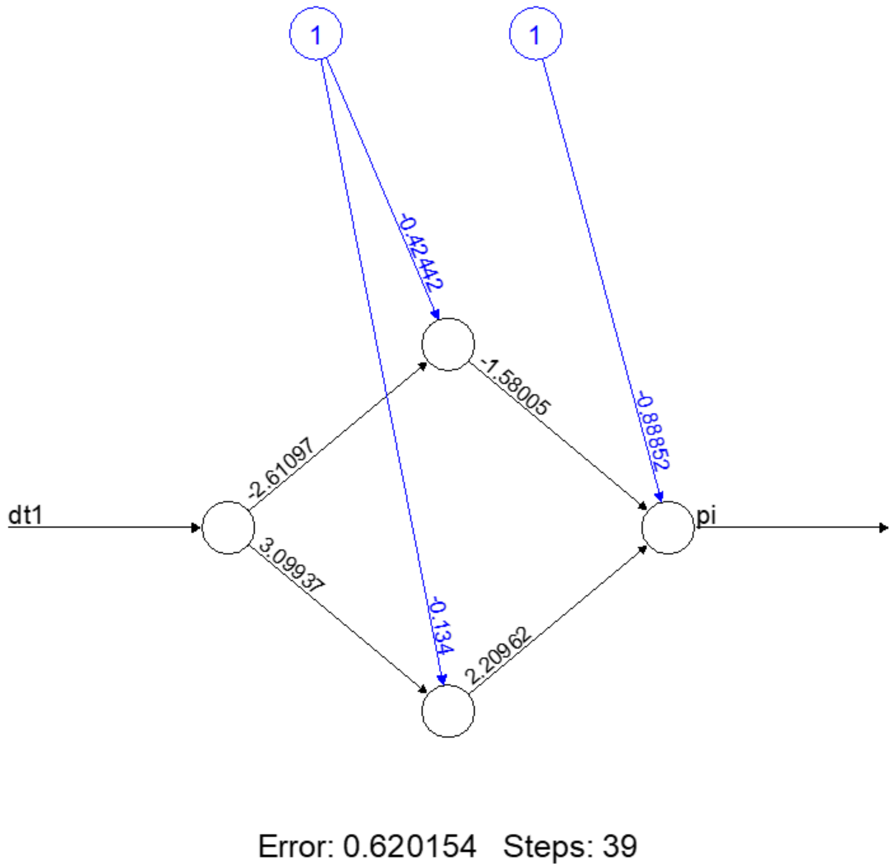
*Source: authors' estimations.

Figure A2. 2. Entropy of inflation expectations in Colombia.



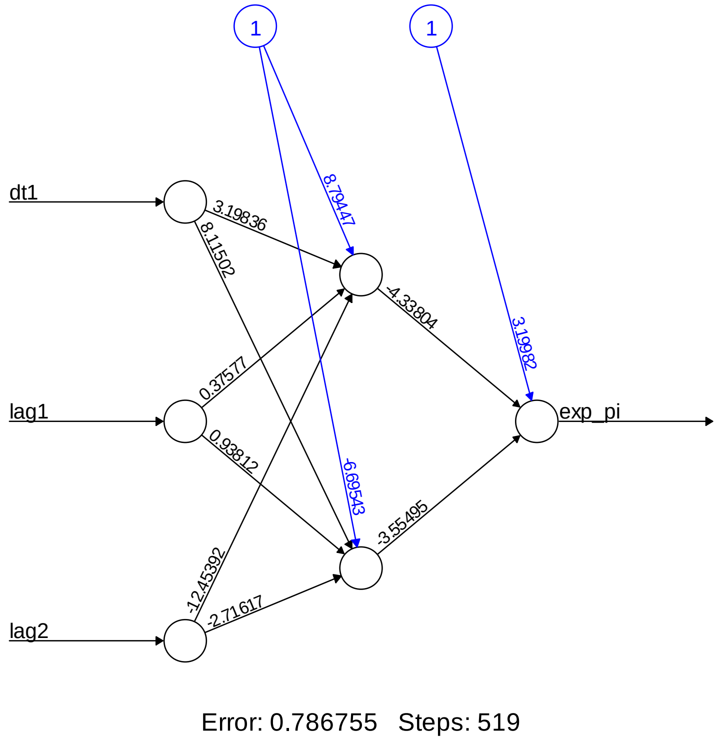
*Source: authors' estimations.

Figure A2. 3. Entropy of inflation expectations in Chile.



*Source: authors' estimations.

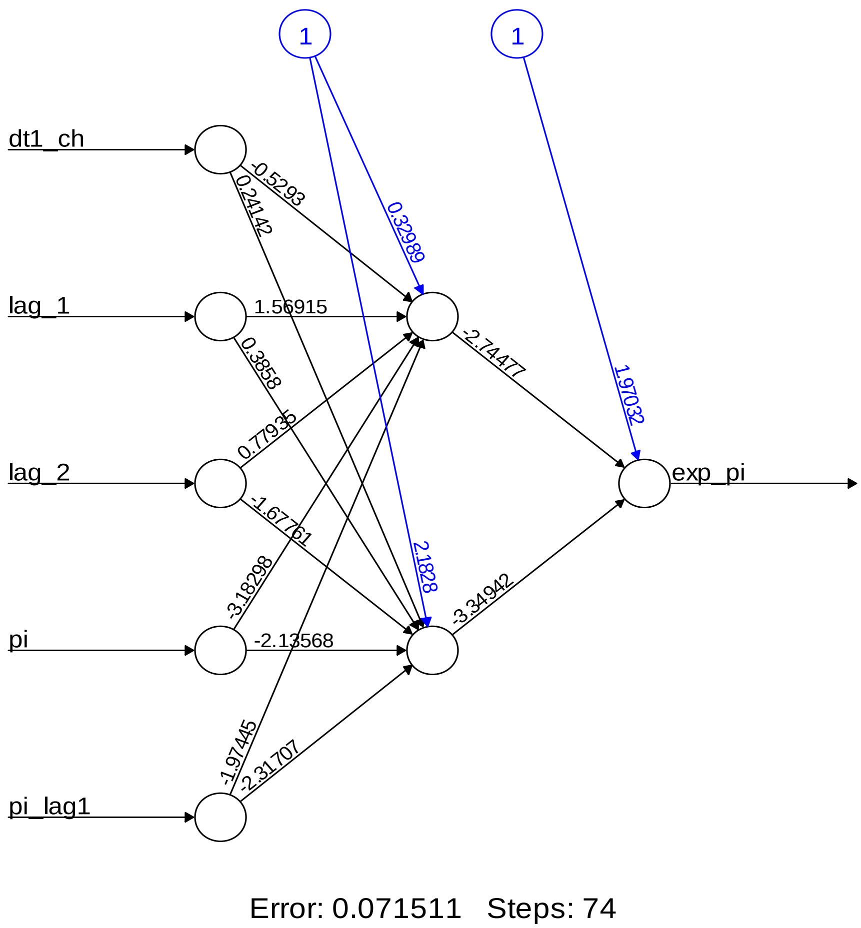
Figure A2. 3. Entropy of inflation expectations in the Dominican Republic.



*Source: authors' estimations.

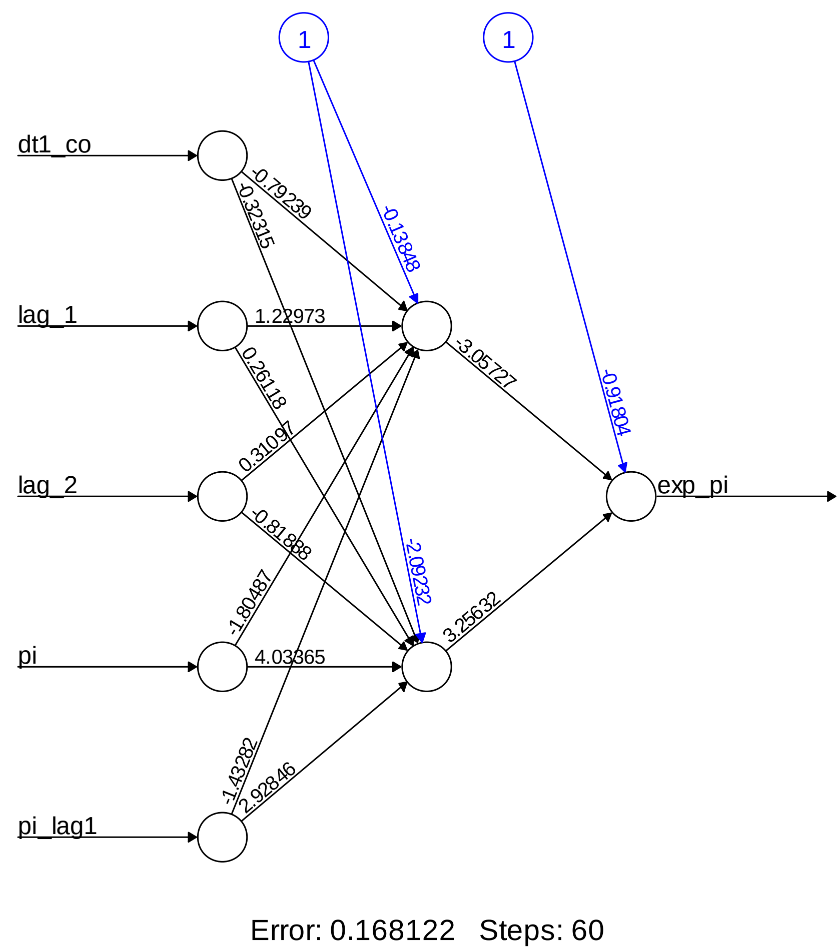
Appendix III. MLP models to simulate inflation expectations by country (January 2016-May 2022).

Figure A3. 1. Simulated inflation expectations for Chile.



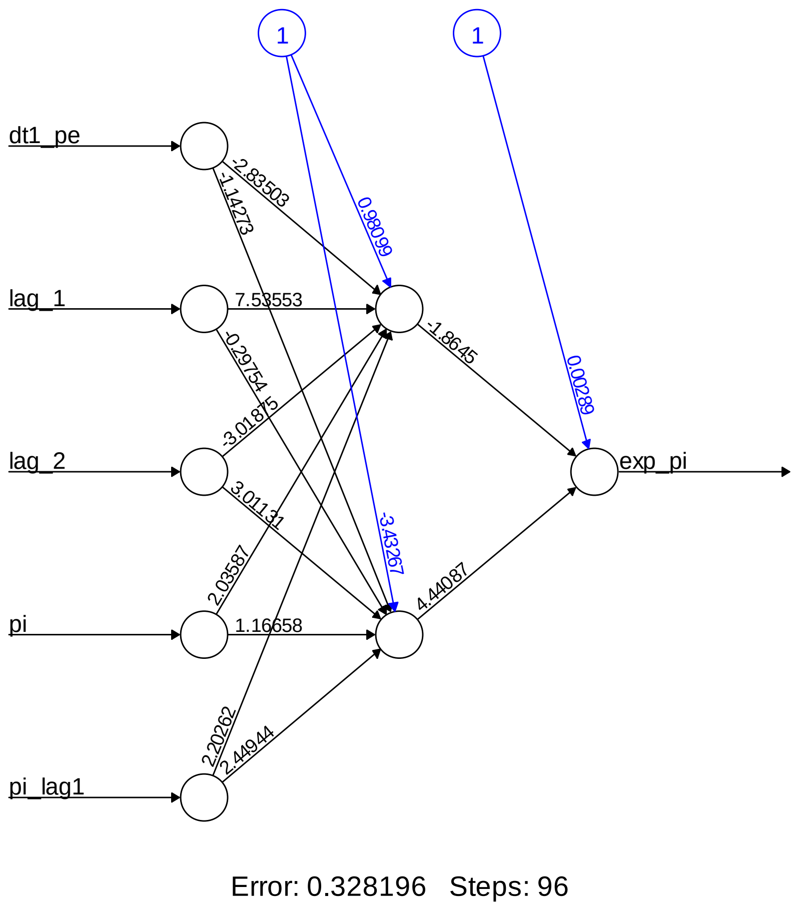
*Source: authors' estimations.

Figure A3. 2. Simulated inflation expectations for Colombia.



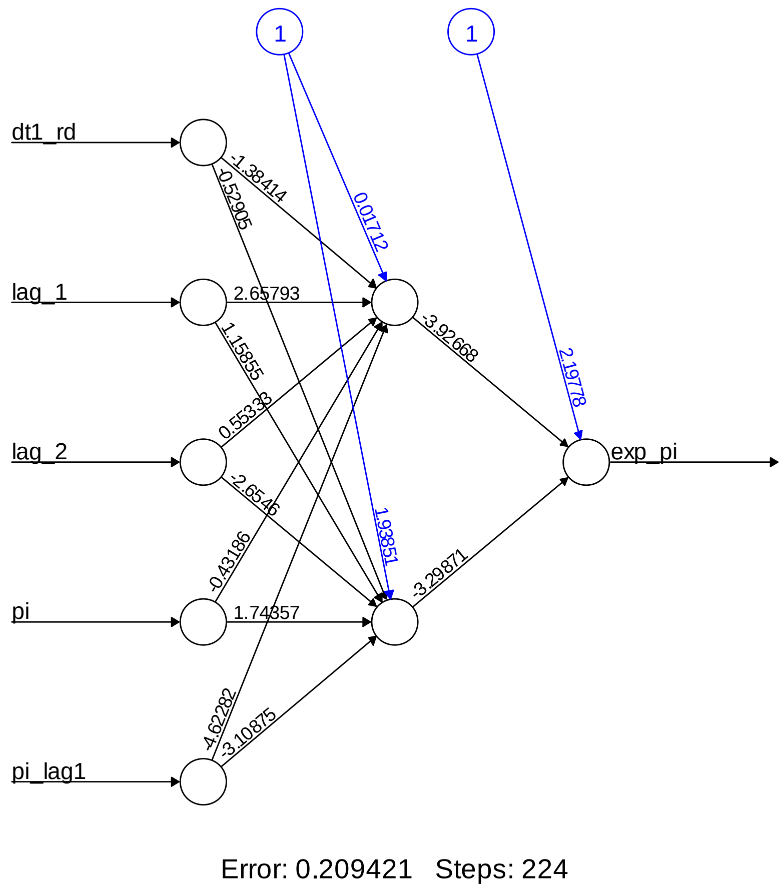
*Source: authors' estimations.

Figure A3. 3. Simulated inflation expectations for Peru.



*Source: authors' estimations.

Figure A3. 4. Simulated inflation expectations for the Dominican Republic.



*Source: authors' estimations.